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Assessing the housing market incentives from residential building energy efficiency regulations

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Abstract

If buyers are willing to pay a price premium for more energy efficient homes, this can act as a market incentive for investment in improvement, supporting net-zero goals in the housing sector. While the effectiveness of energy labels as signals of energy efficiency and hence the basis for house price premiums has been extensively examined, the mixed evidence and methodological issues (including omitted variables bias (OVB), undetermined mechanisms, price premium heterogeneity) have undermined the robustness of findings and their ability to inform decision-making. The overall aim of this thesis is to advance understanding and research practice of the price premiums of housing energy efficiency as represented by Energy Performance Certificates (EPCs). The thesis carries out three progressive steps from knowledge synthesis to application of innovative methodology to address the above research gaps.

Beginning with a systematic scoping review summarising 68 European studies of the price premium from EPCs covering published research to May 2024, it outlines research gaps and synthesises the evidence to guide the empirical analyses. It finds that studies are largely limited to countries where EPC data are openly available, and that OVB is a major methodological issue among studies. Findings show that each additional EPC band contributes to 1-3% increase in house prices, offering a solid benchmark for the following empirical analyses.

Second, focussing on the second-hand house sales market of Greater Manchester, UK, between 2017 and 2024, a multilevel hedonic model (MLM) is developed at the property scale using Zoopla listings, EPC data, and several neighbourhood-level datasets. The MLM uses a natural experiment, modelling the change in the price premium after the 2022 energy crisis. It offers novel insights into both omitted variables issues and the mechanisms underpinning willingness-to-pay (WTP). It confirms the causal interpretation of the relationship between housing energy efficiency and house prices, and suggests that a desire for energy cost saving forms at least part of the mechanism underlying WTP.

In the final analysis, causal machine learning approaches are integrated into the hedonic framework to offer data-driven insights into heterogeneity of price premiums, again focussing on the same housing market scope of Greater Manchester. Based on the individualised price premiums estimated from the meta-learner framework (X-/DR-/R-learner), *post hoc* heterogeneity analysis is applied.

The price premiums are found to be heterogeneous across housing submarkets within Greater Manchester, which is consistently found between meta-learners suggesting robustness of results in offering policy guidance.

Overall, this study confirms the effectiveness of EPCs in providing positive market incentives and the increase in premiums following the energy crisis but also its heterogeneity in housing submarkets. Importantly, the findings offer valuable insights for housing decarbonisation policy design in terms of regulatory, informational, subsidies, and financial market policies to support an efficient achievement of the net-zero goals.

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Preface

This work is an “alternative format” thesis permitted under College of Social Sciences regulations, containing three papers at different stages of journal article publication. The first paper (in Chapter 4) has been published in the peer-reviewed journal of *Energy and Buildings*. The second paper (in Chapter 6) is currently undergoing second round of review at the peer-reviewed journal of *Energy Research & Social Science*. I am the first author of both papers and played a leading role in research design, analysis, and writing up. The third paper (in Chapter 7) is a manuscript prepared for journal submission which is of publishable standard. Each paper is fully incorporated into the thesis and formatted accordingly. Repetition between papers and other chapters has been minimised, while ensuring that both the whole thesis and the individual papers are standalone works.

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others, that this thesis is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

The author retains copyright of this thesis. All information derived from this thesis should be properly acknowledged.

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Chapter 1 Introduction

1.1 Rationale and overview

Meeting climate targets for “Net-zero” by 2050 has become an urgent agenda for governments globally. At present, global domestic buildings account for around 17% of CO2 emissions and 21% of energy demand (IEA, 2023b), but the sector is largely falling behind on decarbonisation (IEA, 2022b). Reducing the environmental impact of housing (“decarbonising housing”) involves two parts: reducing energy demand and switching to renewable or zero carbon energy sources. As such, improving the energy efficiency of housing has become a key priority for governments in developed countries to reach climate goals e.g., the UK Government (GOV.UK, 2023c), the Scottish Government (GOV.SCOT, 2021), and the EU (EU/2024/1275, EPBD). Alongside contributions to achieving climate goals by reducing energy demand, housing energy efficiency improvements may also be important for cutting household energy bills (Fikru, 2019), alleviating fuel poverty (M. Liu & Gou, 2024), increasing energy security (Selvakkumaran & Limmeechokchai, 2013) and providing better indoor environments and health outcomes (Fisk et al., 2020).

The current domestic building stock in Europe is relatively old and inefficient. In the EU, 85% of buildings were built before 2000 and two thirds have poor energy performance (EU/2024/1275, EPBD). In the UK, about half of English homes are inefficient, with the proportion being higher in Northern Ireland and Wales but lower in Scotland (ONS, 2024a; UK Parliament, 2025). A key barrier to the large-scale improvement in the energy efficiency of the housing stock lies in the substantial investment required (Sorrell and O’Malley, 2004). This is likely to necessitate government support and market incentives (Bergman & Foxon, 2020). While government support represents a centralised approach with limited available resources, market incentives form a distributed approach that can scale up the investment in energy efficiency measures in a sustainable and cost-effective manner.

Energy Performance Certificates (EPC) are the building energy labels legislated in the EU and UK, to reveal building energy efficiency information to the public to foster improvement. They provide energy efficiency ratings for buildings based on both the building fabric and heating sources, covering both running costs and environmental impacts. Importantly, they serve as the tool for market incentives through the introduction of mandatory display requirements in any housing market advertisement (Directive 2010/31/EU, p.11). By quantifying and disclosing the higher operating cost in energy inefficient homes, EPCs are expected to result in a price discount for those properties (i.e., a ‘brown discount’) and a premium for more efficient ones (i.e., a ‘green premium’). Additional financial incentives may come from lower mortgage rates for energy efficient properties from lenders. The green premium may also reflect the market’s recognition of the non-financial benefits of housing energy efficiency, such as improved living comfort or reduced environmental impact. If this incentive is sufficient to drive action, it can create powerful market forces to support the shift towards an environmentally-friendly housing stock. Therefore, it is important to examine the effectiveness of EPC market incentives for housing energy efficiency.

The effectiveness of EPC market incentives has attracted a lot of attention in the literature. Given rising availability of EPC data across the EU (and the UK, as a former EU member state), there has been a significant body of research on price premiums attached to EPC ratings i.e., revealed preference of willingness-to-pay (WTP) for housing energy efficiency (Cajias et al., 2019; Fuerst et al., 2015; Galvin, 2023b; McCord, Lo, et al., 2020; J. O. Olaussen et al., 2017; Sieger, 2024). There is also a well-established methodology to examine the price premium of energy efficiency in the housing market among empirical studies i.e., the hedonic approach (Rosen, 1974).

Despite this, several major gaps and challenges exist in current knowledge and research practices. First, though the price impact of EPCs has attracted strong attention in empirical studies, the evidence is mixed: some find a positive price premium associated with energy efficient homes (e.g., Fuerst et al., 2015; Morano et al., 2020), while others suggest little effect (e.g., Olaussen et al., 2019; Wahlström, 2016). This lack of consensus creates doubt for both policymakers and investors, thereby impeding stronger policy intervention or large-scale market-led retrofit investments.

Second, there is limited understanding of the mechanisms behind housing market price premiums, which raises questions about consumers’ motivations for favouring energy-efficient homes. The knowledge of market mechanisms is fundamental to accelerate consumer behavioural change. The debate over the main mechanism centres on cost-saving motives (Aydin et al., 2020) versus environmental awareness motives (IEA, 2022c). Identifying the underlying mechanisms is challenging partly because of methodological limitations, as few approaches can examine causal drivers in revealed preference studies based on observational data.

The third major gap concerns a methodological issue inherent in the dominant hedonic approach i.e., omitted variable bias (OVB) (Guignet & Lee, 2021). It is argued that there may be confounders of housing energy efficiency e.g., housing aesthetic or functional qualities not captured in models which may be associated both with energy efficiency and with prices, weakening the causal interpretation of any association between energy efficiency and house prices (Copiello & Donati, 2021; Marmolejo-Duarte & Chen, 2022). The OVB could lead to biased estimates of price premiums, potentially misleading policymakers and investors about the true economic value of energy efficient homes.

A fourth gap is about the potential heterogeneity in price premiums for home energy efficiency, which remains insufficiently understood across housing submarkets for different housing types, locations, and market conditions, etc (Ou et al., 2025). Current approaches to investigating heterogeneous price effects are largely extensions of the typical hedonic framework which are usually estimated by OLS or other linear estimators, and therefore suffer from the restrictive linear parameter assumptions (Hainmueller et al., 2019). Moreover, though data driven approaches are available, in practice submarket selection is often theory driven, thus risking ignoring actual market dynamics (A. Hu, 2023).

Therefore, this work endeavours to address the above gaps and advance research in the field of housing energy efficiency price premiums in terms of evidence base, knowledge gaps and methodological practices. Specifically, a systematic synthesis of existing empirical studies is provided to offer a clearer summary of the quantitative evidence base. The knowledge gaps related to mechanisms, OVB and heterogeneity of price premiums are examined using innovative research frameworks. Moreover, advanced machine learning methods are explored to extend the typical hedonic modelling techniques to potentially mitigate OVB, relax linearity assumptions, and move beyond theory-driven heterogeneity analysis.

1.2 Research objectives and questions

1.2.1 Research aims and objectives

Overall, this work aims to advance understanding of the price premiums of (or willingness-to-pay for) housing energy efficiency, as represented by EPC energy labels, thus assessing the effectiveness of market incentives for energy efficiency improvements. While the empirical setting is Europe, and the UK in particular, the analytical framework and methodological approaches developed in this study are applicable to other international contexts with comparable building energy labelling systems. Based on the previous discussion, the objectives of this thesis are as follows:

- Empirical focus:
    - To conduct a systematic scoping review on European empirical studies examining price premiums associated with housing energy efficiency.
    - To contribute new empirical evidence on price premiums in the UK context, taking advantage of the exogenous shock of the energy crisis and of data-driven modelling approaches.
- Methodological focus:
    - To mitigate the potential omitted variable bias in conventional hedonic pricing models by employing multilevel hedonic specifications and causal machine learning methods, and to relieve the concern about it by assessing changes in price premiums after the exogenous shock of the energy crisis.
    - To explore the use of advanced causal machine learning techniques to investigate heterogeneous price effects across housing submarkets.

- Theoretical focus:
    - To provide insights into the mechanisms underlying house price premiums for energy efficiency, with particular attention to cost-saving versus environmental awareness motives.

1.2.2 Research questions

Three main research questions therefore motivate the thesis:

- RQ1: What is the research scope/scale, methods, and results in the quantitative evidence of the price premium of housing energy efficiency in the European literature?

- RQ2: Has the price premium for housing energy efficiency in Greater Manchester, UK increased after the “energy crisis” of 2022 and what insights does this give about omitted variable bias and the mechanisms generating the premium?

- RQ3: Is there heterogeneity in the price premium of housing energy efficiency in Greater Manchester, UK and which submarkets have a higher/lower price premium?

1.3 Structure of the thesis

This thesis is structured in eight chapters including the present Chapter.

Chapter 2 establishes the broad context for the topic of housing market impacts of energy efficiency regulations. It first establishes research importance by outlining the context of climate change and housing-related emissions, and by describing key pathways to tackling emissions, with particular emphasis on the role of energy efficiency. The Chapter then introduces the two approaches to energy efficiency improvement: market-based incentives and policy regulations. It further reviews international building energy and environmental labelling schemes and assessment approaches, with a specific focus on the Energy Performance Certificate (EPC) system developed in the EU at a time when the UK was still a member state and still operational in the UK today. Finally, it provides an overview of the UK housing stock, its current energy performance and recent government interventions related to energy efficiency.

Chapter 3 provides a narrative literature review of studies estimating green premiums in the housing market, looking more broadly than premiums related to energy efficiency and motivating the research questions in this thesis. It starts with the predominant hedonic framework and critically reviews influencing factors typically used in studies of house prices. The Chapter then discusses the empirical evidence from housing green premium studies in terms of the research areas and findings, as well as the underlying mechanisms driving green premiums. It moves to a thorough review of methodological practices, limitations, and future directions in this field. Finally, the Chapter explicitly links the knowledge gaps and methodological limitations to research questions in the thesis.

Taking up Research Question 1, Chapter 4 focuses on a systematic scoping review of empirical knowledge on the price premiums associated with housing energy efficiency as signalled by EPCs in Europe. By applying a novel review approach which integrates traditional digital databases and artificial intelligence tools for literature searching, 68 studies and 111 models are included in the review covering studies published between 2011 and 2024. The review provides a detailed summary of the literature in terms of geographical coverage, temporal scope, research design, analytical models, included variables, and broad findings. It also provides a statistical synthesis of reported price premium estimates. By offering a comprehensive and up-to-date overview of quantitative research on EPC-related house price premiums, the Chapter identifies key gaps in the existing literature, which directly inform and motivate the subsequent empirical analyses in Chapters 6 and 7. This Chapter has been published in the journal *Energy and Buildings* (Ou et al., 2025).

Chapter 5 provides an overview of the methodologies used in the subsequent empirical chapters. As those Chapters are written as standalone papers for publication in a journal, they each contain more specific details on data and methods as appropriate. Chapter 5 introduces the study area, the main data sources and the analytical approaches adopted. It begins with an overview of the Greater Manchester (UK) study area, including its administrative, geographical, socio-demographic and economic features and its housing stock, as well as justifying the study scope. The Chapter then introduces the main data sources and presents the work on data validation which underpins both empirical chapters. Lastly, it summarises the analytical methods employed in the empirical chapters. It introduces the hedonic pricing framework and offers a justification for its use, alongside a comparison between traditional hedonic models and causal machine learning approaches. Serving as a complement to the more detailed methodological discussions in the empirical chapters, this section presents the adopted methods in a coherent manner highlighting general methodological practices in the thesis.

Addressing Research Question 2, Chapter 6 presents the first empirical analysis which examines the changes in average price premiums for energy efficiency after the 2022 “energy crisis”. It begins by introducing key research gaps that motivate the study notably the issue of OVB in existing studies and the limited understanding of the mechanisms underlying energy efficiency price premiums. It then provides a narrative review of studies that explore the role of energy prices in the formation of energy efficiency price premiums. The Chapter subsequently introduces the data, model specifications and variables employed in the analysis in detail. It then presents the empirical results on average price premiums and the impact of the energy crisis on these premiums. The Chapter concludes by discussing the academic contributions of the study, as well as its practical importance and policy implications.

Turning to Research Question 3, Chapter 7 reports the second empirical analysis that explores the heterogeneity in price premiums for housing energy efficiency. It offers evidence from the causal machine learning approach of meta-learners, an advanced technique that can examine heterogeneous treatment effect in a data-driven manner. The Chapter starts with an introduction to the knowledge gap of heterogeneity in price premiums and its importance. It then outlines the detailed methodological design for the integration of meta-learners in price premiums estimation. After outlining the methodology, the Chapter introduces the data with discussion of causal assumptions and how these are satisfied, followed by a descriptive analysis. It then presents the results of the heterogeneity analysis and examines the consistency across the various meta-learner models. The Chapter finally summarises results and provides a conclusion.

Chapter 8 concludes the thesis. After summarising the overall study, it outlines key findings and contributions of this work. The Chapter further discusses policy implications. Finally, limitations of the study are acknowledged before offering recommendations for future work.

Chapter 2 Background: housing decarbonisation, energy efficiency, and labelling systems

2.1 Housing decarbonisation and energy efficiency improvement

2.1.1 Housing emissions

The impacts of climate change are worsening in recent years, with widespread climate extremes significantly threatening human lives (IPCC, 2023). Greenhouse gas (GHG) emissions are the primary driver of observed climate change (IPCC, 2023). They have continued to rise, driving global average temperatures more than 1.5°C above pre-industrial levels (IEA, 2025c). This underscores the urgent and critical need for decarbonisation. Global GHG emissions involve different sectors including energy production, transport, industry, and building (IEA, 2023b), each of which holds responsibility for decarbonisation.

Residential buildings globally are responsible for approximately 17% of GHG emissions (IEA, 2023b), while those in OECD countries are even higher with over one quarter of total emissions (Hoeller et al., 2023). In the UK, GHG emissions overall are actually falling but this is almost entirely due to the increase in renewables in the power sector (GOV.UK, 2023b). Currently, residential buildings is the second highest emitting sector accounting for one fifth of UK emissions, with very limited evidence of reductions to date so making an increasing share of the total over time (CCC, 2025a). Residential emissions mainly come from space heating and hot water through the burning of fossil fuels (IEA, 2023b). The UK has one of the highest levels of dependence on gas for home heating in Europe, with gas usage accounting for 80 percent of emissions in UK homes (CCC, 2025a).

To tackle climate change, governments worldwide have developed climate plans. The Paris Agreement (https://unfccc.int/process-and-meetings/the-paris-agreement) is the key international treaty on climate change which underpins the various national net-zero strategies. Most OECD countries have committed to achieving net-zero emissions by 2050, with some aiming for earlier targets such as the Scottish Government’s 2045 target. The UK Government’s first main climate plan was the Net Zero Strategy published in October 2021 (GOV.UK, 2021), which sets out policies and proposals for decarbonising all sectors to meet the net-zero target by 2050.

Although there has been a gradual reduction in emissions from buildings driven by policies, investments and more recently by warmer temperatures and high gas prices (CCC, 2025a), the UK's progress in housing decarbonisation is lagging significantly behind what is required. According to the Seventh Carbon Budget (CCC, 2025a), residential buildings are designated as a priority sector that must reduce emissions by 66% relative to 2023 levels by 2040. However, housing emissions are projected to reduce by just over half by 2037 (CCC, 2025a). This substantial gap between current trajectories and required outcomes emphasises the critical importance of implementing effective and rapid decarbonisation actions in the housing sector.

2.1.2 Housing energy consumption

Housing energy consumption is another key reason to enhance energy efficiency in housing. Globally, residential buildings account for around 20% of energy demand (IEA, 2025a). In the UK, residential buildings account for a quarter of total energy consumption, about two thirds of which comes from gas consumption (IEA, 2025a).

In most countries, heating and cooling make up the largest share of energy use in homes. While electricity is widely used for air conditioners, appliances, and lighting, fossil fuels are predominantly used for heating and cooking, making space heating the largest contributor to housing energy consumption. Although space cooling demand is expected to grow in the coming years due to hotter summers, it is still a minor share of total demand in the UK. In advanced economies, most energy in homes is used for space and water heating which account for about 70% (IEA, 2025a). In the UK, most of the housing energy is used for heating and hot water (80%), followed by appliance usage (15%) and then lighting and cooking (5%) (IEA, 2026). Therefore, UK residential energy intensity is largely driven by space heating, making addressing inefficient heating technologies and poorly insulated buildings important for reducing energy consumption (IEA, 2025a). In comparison, in emerging and developing economies, space and water heating energy use is less than one quarter that of advanced economies (IEA, 2025a).

There are different reasons for homes in developed countries consuming more energy and emitting more carbon than developing ones. First, there is a larger share of the population living in cooler climates among developed countries, making them rely more heavily on space heating (IEA, 2025a). Also, due to their higher disposable income, they have larger housing sizes, reduced household size and improved accessibility to affordable energy services (González-Torres et al., 2022, 2025). Moreover, developed countries have a higher proportion of older and more inefficient housing stock (more details of UK housing energy efficiency in Section 2.4.2).

2.1.3 Two routes: decarbonise heating supply and improve housing energy efficiency

As discussed above, heating makes up the largest part in both housing emissions and energy consumption in UK homes. To decarbonise homes and reduce the climate impacts of housing, the primary two routes include: (1) decarbonising heating supply and (2) demand reduction i.e., housing energy efficiency improvement (Rosenow & Hamels, 2023). On the former, adopting electric heating (heat pumps or direct electric heating) can reduce emissions as the electricity grid becomes increasingly reliant on renewables. On the latter, demand can be reduced through improvements in the efficiency of heating systems (heat pumps help here too) and through reducing heat requirements by improving energy efficiency of the building fabric which reduces heat loss from buildings.

There is an active debate about the appropriate balance between the two routes to achieving housing decarbonisation (Eyre et al., 2023). In the UK, the Climate Change Committee (CCC) has increasingly put more emphasis on low carbon heating i.e., switching to heat pumps and (renewables based) heat networks (CCC, 2025a). The pathway in the Seventh Carbon Budget (CCC, 2025a) proposed for low-carbon heating to be installed in about 70% of homes by 2040 and 100% of homes by 2050. As for energy efficiency measures, most homes are expected to receive “small” energy efficiency improvements by 2050, while “big” energy efficiency improvements are to be installed in about 15% of homes (CCC, 2025a); see CCC (2025a) for definitions of these terms. Therefore, heating electrification and small energy efficiency measures will be the central approaches in the view of CCC, with big energy efficiency measures playing a less important role.

However, this prioritisation has been criticised by those who believe improving housing fabric energy efficiency should precede decarbonising heating systems (Eyre et al., 2023), for their fundamental role in reducing energy demand as well as broader benefits. Beyond reducing emissions and energy consumption, energy efficiency measures generate multiple societal and individual co-benefits (Fawcett & Killip, 2019). These include individual benefits of lower energy cost, improved indoor environment (Fisk et al., 2020), improved comfort and health (Liddell & Guiney, 2015; Woollard & Sissons, 2024), as well as societal benefits of enhanced energy security, improved public health, and reductions in fuel poverty (C. Wang et al., 2022).

2.2 Energy efficiency improvement: housing market incentives and government intervention

The achieve energy efficiency improvement of the housing stock, housing market incentives and government intervention present the main approaches.

2.2.1 Housing market incentives and its failures

A competitive housing market mainly delivers environmentally optimal outcomes through price mechanisms (Oxley, 2004b). In those markets, if buyers demand homes with environmentally beneficial housing attributes, it would drive up house prices for those properties. These would create financial incentives to invest and ultimately shift the housing supply toward an environmentally friendly housing stock (Aydin et al., 2020), forming a main approach to housing stock sustainability transition. The positive price effect associated with housing sustainable features is referred to as a “green premium”, while a “brown discount” refers to the price discounts for properties with environmentally unfriendly or damaging features. Discussions around potential underlying drivers of green premium/brown discount are thoroughly presented in Section 3.2.2.

However, several common market failures could prevent the housing market from delivering energy and environmentally optimal outcomes. First, information on environmentally beneficial housing attributes, especially housing energy performance, presents a hard-to-observe aspect of housing construction quality, which may be known by the sellers but not revealed to the buyers (Aydin et al., 2017). This forms the well-known problem of "information asymmetry", when one party possesses more information than the other in a transaction. As a result, buyers are ineffective in recognising and purchasing energy efficient homes, generating undervalued energy efficient homes thus discouraging supply and investments.

Additionally, the existence of spillover effects (also known as externalities) on energy efficiency improvement could impede the efficiency in price mechanisms to deliver the full beneficial impact (Barile et al., 2025). In the case when housing energy efficiency is captured by energy costs savings rather than carbon savings, individual housing energy retrofit would be ineffective in aligning with social welfare if carbon emissions are not factored in energy prices.

Furthermore, the complexity of housing market structure which includes homeowners, landlords and tenants can impede the effectiveness of market incentives. One notable issue is the "split incentives" problem in the rental market, where landlords carry the cost burden for investment while tenants enjoy the benefits of cost savings and comfort (Charlier, 2015). This may lead to underinvestment in energy efficiency among rental properties although evidence from the UK (Buyuklieva et al., 2024) suggests this problem may have been over-stated.

2.2.2 Government intervention

Complementary to financial incentives in the housing market for energy efficiency improvement, government intervention is needed to mitigate market failures and further shape market incentives (Oxley, 2004b). While market incentives enable a bottom-up pathway for improvement, government intervention mainly ensures efficiency and equity. Government intervention in housing development takes various forms, primarily including planning controls, building standards, subsidies, and regulations (Oxley, 2004a). To mitigate the market failures and shape market incentives for housing energy efficiency improvements mentioned above, government can intervene through regulations, targeted subsidies and taxes. Details on how UK government interventions complement market incentives to improve housing energy efficiency are discussed in Section 2.4.3.

2.3 Building energy/environmental labelling systems

2.3.1 Why we need labelling systems

As discussed above, tackling market failures and implementing government intervention is important to ensure energy efficiency improvements. As the fundamental information tools and assessment toolkits, building energy/environmental labelling systems can both directly mitigate market failures and facilitate government intervention to indirectly mitigate further failures:

1. First, labelling systems can directly mitigate market failures on information asymmetry (Hoeller et al., 2023). Environmental labelling makes energy performance visible with the intention that the market then encourages people to act on this information, i.e., that there will be a green premium/brown discount for energy efficient/inefficient properties to reflect differences in running costs. This revelation can drive individual investment as well as mobilising financing by banks.

2. They could also indirectly tackle market failures by facilitating government interventions for improving energy efficiency by informing which properties to prioritise. For example, governments might want to regulate housing energy efficiency i.e., setting minimum energy efficiency standards for new build and existing homes in the housing market. Also, government subsidies may need to be informed about which properties to prioritise concerning energy performance levels.

2.3.2 Labelling approaches and existing systems

2.3.2.1 Labelling approaches

Building energy or environmental labelling generally considers building fabric and heating sources, and the costs and GHG emissions associated with these. Energy labelling typically provides measures of energy consumption levels while environmental labelling offers measures of carbon or GHG emissions levels. To assess building energy/environmental performance and quantify them as corresponding labels/ratings, there generally exist two approaches in practice:

asset rating and operational rating (Goldstein & Eley, 2014; D. P. Jenkins et al., 2024).

The asset rating is a modelled rating, based on the estimated energy need for heating, cooling, hot water, ventilation, and lighting under a standard set of usage conditions such as occupancy levels or climate conditions. To estimate heating energy demand, there are usually detailed measurements of building fabric (including floors, walls, windows) and then assumptions about heat losses per m2 for each. One limitation of the asset rating approach is that many building elements cannot be measured for existing properties so many assumptions go into these models (Hardy & Glew, 2019). Also, measurements of building elements rely much on the quality of training for energy performance assessors (D. P. Jenkins et al., 2024). In summary, asset rating offers information on how efficient a property is believed to be but may not correspond to energy usage in practice.

In comparison, the operational rating shows the energy performance of a building based on metered energy consumption as recorded over a defined period of time, with the baseline typically representing average energy use for residential buildings. It effectively reflects actual energy consumption and bills which could directly raise awareness on energy behavioural management (Goldstein & Eley, 2014). However, it may not be a directly useful tool to inform building retrofit as the information provided is affected by behavioural factors, i.e. the specific behaviours of current or recent occupants.

2.3.2.2 Global labelling systems

Table 2.1 summarises the building energy/environmental labelling systems in different countries and regions, in terms of the published year, authority, assessment approach, enforcement, as well as online link to the source. It shows that current labelling schemes are predominantly implemented in developed countries in the Global North, while relatively few systems have been established in developing countries or the Global South. All the labelling systems cover both residential and non-residential building sectors. Moreover, these systems were generally introduced between the early 1990s and the early 2000s. Notably, the EU EPC is the only labelling system that is generally mandatory, with legislative requirements to be displayed for any residential property advertisement. In terms of assessment approaches, some systems rely solely on asset ratings, while others apply asset ratings to new buildings and operational ratings to existing buildings, or combine both methods to derive the final rating.

Table 2.1 Global building energy/environmental labelling systems.

Building energy/environmental labelling systems	Region/Country	Year	Authority	Assessment approach	Enforcement	Building sector	Link
EPC	pre-Brexit EU countries and Norway	2002	European Commission and European Parliament through Energy Performance of Buildings Directive	Asset/operational (differs between countries)	Mandatory	Residential and non-residential	https://energy.ec.europa.eu/topics/energy-efficiency/energy-performance-buildings/energy-performance-buildings-directive_en
Green Star	Australia	2003	Green Building Council of Australia	Asset ('Design' ratings) /operational ('As Built' ratings)	Voluntary	Residential and non-residential	https://new.gbca.org.au/green-star/rating-system/design-and-built/
NABERS (National Australian Built Environment Rating System)	Australia	1999	Australia Government	Operational	Generally voluntary; mandatory in specified situations	Residential and non-residential	https://www.iea.org/policies/1448-nabers-the-national-australian-built-environment-rating-system
Green Mark/ Green Mark 2021	Singapore	2005 (Green Mark)/ 2021(Green Mark 2021)	Building and Construction Authority (Singapore)	Asset (for new building)/ operational (for existing building)	Primarily voluntary (mandatory in e.g., new building)	Residential and non-residential	https://www1.bca.gov.sg/buildsg/sustainability/green-mark-certification-scheme/green-mark-2021
ENERGY STAR	USA/Canada	1992	United States Environmental Protection Agency	Operational	Voluntary	Residential and non-residential	https://www.energystar.gov/buildings/building-recognition/building-certification

LEED (Leadership in Energy and Environmental Design)	USA/Global	2000	United States Green Building Council	Asset (for new building)/ operational (for existing building)	Voluntary	Residential and non-residential	https://www.usgbc.org/leed
BREEAM (Building Research Establishment Environmental Assessment Method)	UK/Global	1990	BRE Global Ltd	Combine asset performance and management performance	Voluntary	Residential and non-residential	https://breeam.com/
HK-BEAM/BEAM Plus (Building Environmental Assessment Method)	Hong Kong/Global	1996 (HK BEAM) /2010(BEAM Plus)	Hong Kong Green Building Council (HKGBC)	Both asset and operational rating are available	Voluntary	Residential and non-residential	https://www.hkgbc.org.hk/eng/beam-plus/introduction/
EEWH (ecology, energy saving, waste reduction and health)	Taiwan	1999	Architecture and Building Research Institute under Taiwan's Ministry of the Interior	Asset rating	Primarily voluntary (mandatory for new, large publicly owned buildings)	Residential and non-residential	https://grokipedia.com/page/eewh
CASBEE (Comprehensive Assessment System for Built Environment Efficiency)	Japan	2001	Japan Sustainable Building Consortium (JSBC) under the auspice of the Ministry of Land, Infrastructure, Transport and Tourism (MLIT)	Asset (for new building)/ operational (for existing building)	Primarily voluntary (mandatory for new, large-scale buildings)	Residential and non-residential	https://www.ibecs.or.jp/CASBEE/english/
G-SEED (Green Standard for Energy and	South Korea	2002	Korean Ministry of Environment and the Ministry of Land,	Asset rating	Primarily voluntary	Residential and	https://gseed.or.kr/

Environmental Design)			Infrastructure, and Transport		(mandatory for public buildings)	non-residential	
SBAT (Sustainable Building Assessment Tool)	South Africa	-	Council for Scientific and Industrial Research (South Africa)	Asset rating	Voluntary	Residential and non-residential	http://www.sustainablebuildingassessmenttool.com/p/contact.html

Source: The information is collected by author based on labelling systems listed in (Cespedes-Lopez et al., 2019) and (Shan & Hwang, 2018).

2.3.3 Energy Performance Certificates (EPCs)

2.3.3.1 Overview

EPCs are the building energy/environmental labels mandated in the Energy Performance of Buildings Directive (EPBD) in the European Union (EU). After Brexit in 2020, the UK continued to use this system. EPCs are widely used to evaluate and compare the energy performance of residential and non-residential properties. The assessment approaches for EPC vary across EU member states and the UK (see Chapter 4 for details).

Asset rating is used in the UK for residential EPCs. Specifically, qualified Domestic Energy Assessors (DEA) are trained to assess and determine the energy efficiency rating of residential properties. Energy assessors use the approved methodology called Standard Assessment Procedure (SAP) (GOV.UK, 2025b). For new (i.e. proposed) dwellings, design details are fed into the model from the architect's plans. For existing homes where the same level of information is not available, the Reduced Data SAP (RdSAP) is used, combining assessors' measurements of visible elements with numerous assumptions. The calculation of SAP is based on the BRE Domestic Energy Model (BREDEM), the methodology of which is compliant with the EPBD (Directive 2018/844/EU).

At present, the assessment of EPCs produces two main ratings: an energy efficiency rating (EER) and an environmental impact rating (EIR). Specifically, the EER rating is a fuel-cost-based rating, which is based on the energy costs associated with space heating, water heating, ventilation and lighting, less any cost savings from energy generation technologies. In comparison, the EIR rating is based on the annual CO2 emissions associated with space heating, water heating, ventilation and lighting, less any emissions saved by energy generation technologies. Considering energy demand and the source of energy supply, the current EPC assessment measures both routes to decarbonisation mentioned in Section 2.1.3. In the UK, current discussions around EPCs typically focus on the cost-based measure, i.e., EER. This is the rating which is given priority in public notices attached to property sales or rentals.

Both measures are adjusted for floor area and time (per square metre per year). They are expressed on a scale of 1 to 100, with higher number indicating better standards i.e., lower running cost/emissions (GOV.UK, 2025b). Scores greater than 100 are possible, however, where the building is estimated to produce more energy from renewables than it will consume. Both EPC scores are also transformed into categorical bands from A (most efficient) to G (least efficient). Table 2.2 shows the scores associated with each energy efficiency band. Additional information on EPC policy and practice can be found in Section 4.2.

Table 2.2 EPC bands and corresponding scores in the UK.

EPC band	EPC score
Band A	92 plus (most efficient)
Band B	81 to 91
Band C	69 to 80
Band D	55 to 68
Band E	39 to 54
Band F	21 to 38
Band G	1 to 20 (least efficient)

2.3.3.2 Quality of EPCs

Despite its wide and official adoption in building energy performance assessment, the quality of the ratings provided by current EPCs is under question. The most critical problem of UK asset EPC rating is about its accuracy as a credible indicator of energy efficiency (Hardy & Glew, 2019). As mentioned, EPC assessment involves many assumptions, which could flatten out hard-to-measure differences between properties, thus reducing its accuracy. Also, the dependence on energy assessors in interpretation means that the assessment involves subjective decisions from individuals. Studies suggest that there exists large inconsistencies between assessors' interpretations which undermines the reliability of EPCs (Hårsman et al., 2016).

As a result, it is also questioned whether EPCs provide a reliable indicator to represent actual energy usage. This is known as the "energy efficiency gap" between EPC asset rating and actual energy consumption, a problem criticised across countries that use the asset rating including the UK (Few et al., 2023), and Ireland (Coyne & Denny, 2021). These studies identified a similar pattern of gap between predicted and actual energy use that occupiers in lower energy efficiency buildings tend to consume less energy than expected. This may be partly due to income constrains that some households living in energy inefficient properties are probably lower-income and therefore under-heating but it also suggests an issue with the models and the assumptions they are based on.

Nonetheless, the quality of the measures provided by EPCs is less of an issue for this work. Although the credibility of labelling could influence buyers' willingness-to-pay, this work focuses empirically on how potential buyers respond to the label which is given.

2.3.3.3 Public awareness of EPCs

For EPCs to have some impact on house prices, public awareness and knowledge of EPC are pre-requisites. According to the Public Attitudes Tracker from Department for Energy Security and Net Zero (GOV.UK, 2025e), the proportion of public who claimed to be aware of the EPC was 60% in 2016, rising to 76% and 80% in winter of 2021 and 2024 respectively. However, an extremely low percentage of the public have knowledge on exact EPC rating of their homes, which was 8% in 2016 and climbed to 16% in winter 2024 (GOV.UK, 2025a). There exist different levels of awareness based on household tenure types, where owner occupiers are more likely to be aware of EPCs than renters (BEIS, 2022). As for deeper knowledge on the benefits of higher EPC ratings, a qualitative interview study suggests that the public does not fully recognise its energy saving benefits (Mugarra et al., 2025). Overall, public awareness of EPCs have been rising in the UK but the public are far from being fully aware of the relevant knowledge.

2.4 UK housing stock and government intervention

2.4.1 UK housing stock

The UK housing stock consists of approximately 30 million homes (GOV.UK, 2024b), with around 85% located in England. The UK housing stock is very diverse and represents a long history of housebuilding, local building materials and policy interventions. In terms of housing type, it is dominated by houses, while flats account for around 20%. Over half of houses are conjoined (terraced or semi-detached), leaving around 20% being detached. As for homeownership, over 60% of dwellings are owner-occupied, with the rest being private-rented, or social-rented (owned by a local authority or housing association). Additionally, over 80% of UK housing is in urban areas while the rest is in rural areas (Piddington et al., 2020).

2.4.2 Housing age and energy efficiency

Dwelling age plays a critical role in determining home energy efficiency, as construction methods, building regulations and material standards have evolved over time, in addition to the impacts of long-term wear and degradation. The UK housing stock is among the oldest in Europe (BEIS, 2020). A significant proportion (around 20%) was built before 1919, while nearly 60% date from the period between 1919 and 1980 (Piddington et al., 2020). Wales has the oldest housing stock, followed by England and Scotland, whereas Northern Ireland has the most modern dwellings (ONS, 2022).

Most UK homes (84%) rely on natural gas for space heating, with electricity primarily used for lighting and appliances. Smaller shares of dwellings are heated by electricity (8%) or by other fossil fuels or biomass (6%), while approximately 2% are connected to communal heating networks (Kavan, 2024). In terms of insulation level, an estimated 24% of homes with cavity walls lack cavity wall insulation, and around 90% of solid-wall properties have no wall insulation (UK Parliament & Bolton, 2025). These highlights the great potential in energy efficiency improvements in UK homes.

The energy efficiency of UK homes has steadily improved over time. By 2025, the median EPC score for homes in England reached 69, placing the average dwelling just above the bottom of EPC B and C. However, this figure does not fully represent the entire housing stock, as EPC coverage is incomplete across the UK where just around 70% of all residential dwellings have an EPC record in 2024 (ONS, 2024a). Flats and maisonettes tend to be more energy efficient than houses with the former reaching median EPC score of 74 (UK Parliament & Bolton, 2025), mainly due to their lower number of outside surfaces. Newer properties perform substantially better than older dwellings as building codes have regularly raised minimum standard for new builds. Specifically, 73% of homes constructed since 2002 achieved EPC bands A or B, and 93% were rated Band C or above (Ministry of Housing, Communities and Local Government, 2023).

2.4.3 UK government intervention

This section provides a summary of UK government intervention in relation to the EPCs and housing energy efficiency improvements, generally including regulations and subsidies.

The first and foremost regulation is the mandatory disclosure of EPCs in housing market advertisements, which is required by the EPBD legislation (Directive 2010/31/EU). Under the EPBD, the energy performance indicator from the EPC (e.g., the A-G rating) must be clearly stated in all advertisements in commercial media, including online portals and print, when a property is marketed for sale or rent. This mandatory market disclosure is expected to make possible and strengthen the expected market incentives for improvements bring by the EPCs.

Another regulatory approach is setting minimum energy efficiency standards for properties. There are usually improving minimum standards for new builds with building regulations steadily revised over time. As required by the EPBD, member states "shall take the necessary measures to ensure that new buildings meet the minimum energy performance requirements" (Directive 2010/31/EU, p.21). As for existing housing, England has implemented domestic minimum energy efficiency standard (MEES) regulations in relation to private rented properties with effect from April 2020 (DESNZ, 2025), which is expected to tackle the split incentives problem as discussed in Section 2.2.1. Specifically, the MEES requires private landlords to ensure rented properties meet a minimum EPC rating, currently E, with plans to raise to C by 2030 (BEIS, 2019).

Compared to regulatory approaches, subsidies represent milder intervention to foster energy efficiency improvements. At present, several subsidy schemes operate across the UK to improve the energy efficiency of privately-owned homes (including owner-occupied and private rented properties) (GOV.UK, 2025) (Table 2.3). These subsidies are mostly delivered via installers, local authorities, energy companies, and other organisations. Most of these subsidies are targeted at lower-income households living in less energy-efficient homes. They cover diverse energy efficiency measures, ranging from insulation and heating upgrades to installing smart meters and solar panels.

Table 2.3 List of UK government support schemes for private owned home energy efficiency.

Scheme	Source of funds	Time scope	Geographical coverage	Household scope	Energy efficiency measures
Energy Company Obligation (ECO)	Supported through energy company; funded by a levy on household energy bills	2013 - 2026	Great Britain	Vulnerable households and energy inefficient properties	Insulation work; heating upgrades
Boiler Upgrade Scheme (BUS)	Supported through installers (household grant up to £7,500)	Apr 2022 – Dec 2027	England and Wales	Homeowners and owners of small business properties	Replacing fossil fuel heating systems with a heat pump or biomass boiler
Warm Homes: Local Grant	Supported through local authority (£500 million in total)	2025 - 2028	England	Private owned (owner occupied/privately rented) property; EPC equal to or less then D; low income	Wall, loft and underfloor insulation, air source heat pumps, smart controls, solar panels
Great British Insulation Scheme (GBIS)	Supported through energy company	Apr 2023 - March 2026	Great Britain	Homeowners/tenants: EPC of D or below and low council tax band/at least one benefit recipient	Cavity wall insulation, loft insulation, room in roof insulation

Note: These information is publicly provided by UK government for reference (GOV.UK, 2025d).

Other than directly provide subsidies for support, the government is pushing lenders to report on the carbon emissions from their loan portfolios (Financial Conduct Authority (FCA), 2020). This is to facilitate the monitoring of risk in the banking system, specifically the risks caused by loan exposure to properties where values could be adversely affected by environmental regulations in the future. Indirectly, it encourages the development of valuation practices which reflect energy efficiency and the provision of cheaper borrowing for more efficient properties. In the UK, many lenders have been providing financial benefits for buyers purchasing a property with high energy efficiency e.g., EPC of A or B.

2.5 Summary

In summary, this Chapter sets the broader context and rationale for improving housing energy efficiency and adopting a market incentives approach. By introducing the importance of housing decarbonisation and its two routes, the role of energy efficiency improvement as one of the routes is justified. The main approaches to improve housing stock energy efficiency are further introduced, including housing market incentives and government intervention. Building energy labelling systems were discussed as essential information tools supporting these approaches, with particular focus on the EPC system in the EU. Finally, a closer examination of the UK housing stock and related government interventions is provided, highlighting the significance of improving housing energy efficiency in the UK context. Based on this broader context, the next Chapter present a narrative literature review on studies focussing on effectiveness of market incentives for transition to sustainable housing i.e., relationship between house prices and housing green features.

Chapter 3 Green premiums in the housing market: A review of the literature

3.1 Factors influencing house prices

3.1.1 Heterogeneous housing and hedonic framework

Housing is commonly treated as a heterogeneous good especially in studies of house price premiums, with each dwelling comprising a unique bundle of attributes. Research on house price premiums is therefore most often conducted within a hedonic pricing framework (Rosen, 1974). Under this framework, a dwelling is viewed as a collection of characteristics that jointly generate utility, with each characteristic contributing an implicit value to the overall price (McDonald & McMillen, 2010). Accordingly, the observed price of a property can be expressed as the sum of the marginal or implicit prices of its individual attributes, which are estimated through regression analysis (Chin & Chau, 2003). More technical details of the hedonic framework are provided in Section 5.4.1.

3.1.2 Influencing factors

To interpret the estimated coefficients from a hedonic house price model as marginal willingness-to-pay (WTP), or as the implicit price or price premium of a specific attribute, it is required to include a sufficiently rich set of control variables. In particular, attributes that are correlated with both the attribute of interest and house prices must be accounted for to avoid biased estimates i.e., omitted variable bias (OVB). Furthermore, the theoretical foundation of the hedonic model assumes that the market satisfies the “law of one price function” (Bishop et al., 2020), whereby identical houses transact at the same price within a given market. This assumption necessitates careful definition of the market and the inclusion of controls for broader market characteristics to ensure comparability across transactions.

3.1.2.1 Hedonic attributes

In the house price literature, housing-related characteristics commonly include structural, neighbourhood, and locational attributes (Chin & Chau, 2003; Ooi & Le, 2013). Structural attributes describe the physical features of the dwelling and are consistently found to be closely associated with house prices. These attributes typically including property size, number of rooms, building age, property type, structural quality, building services/facilities and, in the case of flats, floor level. Neighbourhood attributes capture characteristics that are shared across properties within the same area. Previous studies commonly group these attributes into three broad categories: (1) socio-economic variables such as average income levels and social class composition, (2) local public services such as schools and hospitals, and (3) externalities for example crime rates, traffic noise, etc (Chin & Chau, 2003; Ooi & Le, 2013; Sopranzetti, 2015).

Locational attributes refer to the location of a property within the wider geographical area and hence the access it provides to opportunities, services or facilities outside the neighbourhood (Chin & Chau, 2003). At their simplest, these attributes may be proxied by measures of transport accessibility to the Central Business District (CBD). Transport accessibility associates with the ease of commuting to and from amenities, and is commonly measured by some combination of traveling time, cost of travel, convenience, and availability of different transport modes (Adair et al., 1996). Urban location theory suggests that households trade off housing costs against transportation costs when making residential location decisions, implying a systematic relationship between locational accessibility and house prices (McDonald & McMillen, 2010).

3.1.2.2 Spatial and temporal dummies

In addition to these property-related characteristics, hedonic house price models typically incorporate spatial and temporal dummy variables to account for the price effects of unobserved factors. The inclusion of spatial dummies can absorb the influence of omitted neighbourhood and locational characteristics which are shared by properties in the same area, thereby helping to mitigate OVB and improve the accuracy of estimated price premiums (Kuminoff et al., 2010). House prices also exhibit systematic variation over time, reflecting changes in market conditions, macroeconomic factors, and policy environments. Consequently, the inclusion of temporal dummy variables is commonly used to capture time-specific effects when transaction data are pooled over a long period (Bishop et al., 2020).

However, it is challenging to adopt an appropriate resolution for spatial dummies i.e., “neighbourhoods” and temporal dummies. The choices of both spatial and temporal dummies involve a bias-variance trade-off: defining smaller neighbourhoods or shorter time spans can reduce bias by better controlling for omitted variables but increases variance by overfitting on smaller groups with less within-group variation (Bishop et al., 2020). To mitigate the issue, neighbourhoods may be defined at multiple scales or spatial regression models are used to examine effects at different levels of geography.

3.2 Green premium studies

3.2.1 Empirical evidence

Empirical studies of housing green premiums span a wide range of sustainability-related housing attributes. These include analyses of price premiums associated with solar (photo-voltaic) panels (Asproudis et al., 2024; Dastrup et al., 2012; Lan et al., 2020), low-carbon heating technologies such as heat pumps (Hahn et al., 2018; Shen et al., 2021), and electric vehicle charging infrastructure (Gao et al., 2022; Liang et al., 2023), as well as more general measures of residential building energy efficiency. Studies of building energy efficiency can be further divided into estimates of the premiums related to actual energy performance reflected in energy consumption (Foryś et al., 2020), and those related to certified energy labels which model or predict relative energy consumption (Cespedes-Lopez et al., 2019). The latter represents most of the literature, as relevant energy labels are widely implemented and readily available, as introduced in Chapter 2.

Across this literature, sustainable housing features are generally shown to command positive price premiums as expected (Asproudis et al., 2024; Liang et al., 2023; Shen et al., 2021), indicating that the market increasingly capitalises environmental performance (and the savings this can produce) into housing values. However, the empirical evidence remains inconclusive, with reported premiums exhibiting substantial variation. Regarding housing energy efficiency, some studies identified economically meaningful price effects (Bottero et al., 2017; de La Paz et al., 2019; Fuerst et al., 2015), while others find modest or statistically insignificant impacts (Fregonara et al., 2017; McCord, Davis, et al., 2020; Wahlström, 2016). Even among the studies finding significant price effects for

EPCs, the magnitude of reported premiums varies substantially. For instance, the reported premium for B and C relative to Band D ranges from approximately 1% (Gerassimenko et al., 2024; Khazal & Sønstebø, 2020; Wilhelmsson, 2023) to around 10% (Copiello & Coletto, 2023). Such heterogeneity may reflect differences in market dynamics, local climate conditions, or analytical strategies such as housing attributes included. Nevertheless, this lack of consensus on green premiums undermines the provision of robust guidance for policy and investment decisions.

3.2.2 Underlying mechanisms

While green premiums and brown discounts are generally found to exist in the housing market, the underlying mechanisms remains questionable (Li et al., 2024). The mechanisms motivating households' WTP for sustainable housing features are similar. The following aspects are discussed in existing studies, which can be broadly separated into financial and non-financial motivations. First, these sustainable features could decrease energy consumption by either reducing energy demand or shifting to more efficient usage. They are therefore expected to bring energy cost savings in operation which is found in energy benchmarking studies (Sabapathy et al., 2010). Studies suggest that high energy cost may form a key driver in incorporating green features (Ade & Rehm, 2020).

Beyond financial considerations, the direct environmental benefits brought by green housing features constitute an important additional motivation shaping households' decisions. In the context of the accelerating net-zero agenda, public awareness of carbon emissions has increased, which could lead households to value green housing as an expression of environmentally responsible behaviour (Steg & Vlek, 2009). Also, residential buildings with sustainable features often provide improved environmental quality and indoor comfort such as better thermal performance, air quality and acoustic conditions (Lee et al., 2019), which directly affect occupants' living experience and therefore play a meaningful role in housing choice. At a more individual level, households could be willing to pay for sustainable features to give the impression of being 'good environmental citizens' (regardless of actual environmental performance) which is also known as the "green signalling effect" (Y. Wang et al., 2018).

Despite this broad consensus on potential mechanisms, the relative importance of each driver remains uncertain. Customers' awareness is mainly around two aspects i.e. awareness of energy cost (Aydin et al., 2020) and environmental awareness (IEA, 2022), forming the debate on main drivers of WTP.

3.3 Methodological practices, limitations, and future directions

3.3.1 Methodological practices

Research on housing green premiums has predominantly relied on the hedonic pricing framework, which decomposes property values into contributions from individual attributes, as discussed above. Typical applications adopt ordinary least squares (OLS) regression, which provides a straightforward parametric approach to estimating green premiums. However, the OLS approach suffers from notable issues such as the assumption of linearity in parameters (Owusu-Ansah, 2013), omitted variables (Sopranzetti, 2015) and potential spatial autocorrelation/spillover effects (Vega & Elhorst, 2013). In depth discussion on the OLS approach is presented in Section 5.4.2.1.

Analytical approaches have thus become increasingly sophisticated to mitigate these problems. For example, parametric approaches such as multilevel models and spatial models are often applied to account for spatial autocorrelation in house prices (Allen et al., 2015; Glaesener & Caruso, 2015), while difference-in-differences hedonic models can exploit temporal variations in the variable of interest to remove the effect of unobserved time-invariant factors (Liang et al., 2023; Shen et al., 2021).

3.3.2 Methodological limitations

All of these approaches remain theory-driven, in that they rely on theoretical frameworks to identify patterns and relationships building upon domain knowledge (Maass et al., 2018). Despite their advantages in consistency across studies and populations as well as model interpretability (Austin et al., 2023), there could be limitations of the theory itself. Also, the assumptions of the theory may not reflect real-world data settings as introduced above. In comparison, data-driven approaches rely on exploratory approaches to reveal insights and relationships from data (Maass et al., 2018), thus relaxing data assumptions. However, these models lack theoretical explanations which undermines their applicability in price premium explainability. The recent rise of causal machine learning (ML) or causal artificial intelligence (AI) provide theoretical frameworks to integrate the use of data-driven approaches for causal effect estimation (Ness, 2025). It can both leverage advantages from data-driven approaches and enable theoretical explanations to some extent, acting as a useful tool to mitigating the long-standing problems in traditional hedonic analysis. Despite the evolving methodological practices in the field, there are three dominant methodological limitations across green premium studies using hedonic framework: (1) omitted variable bias; (2) uncertainty on the underlying mechanisms; and (3) heterogeneity in price premiums.

3.3.2.1 Omitted variable bias

A central methodological challenge in hedonic house price studies is the omitted variable bias (OVB) or endogeneity problem. To decompose house prices into contributions of individual attributes, the hedonic framework assumes all relevant factors are included in the model. This issue has two aspects. First, it is improbable that researchers can account for every attribute that influences households' decisions. In practice, many housing attributes are hard-to-measure (Osland, 2013), such as architectural quality, aesthetic appeal or neighbourhood amenities. Second, and key for this thesis, unobserved attributes which are correlated with the specific attribute of interest can introduce bias in parameter estimation (Bishop et al., 2020).

In studies of housing green premiums, it is inherently challenging to disentangle the effects of sustainable features and those from factors such as architectural quality (Marmolejo-Duarte & Chen, 2022), general appeal of modern technologies, or aesthetic quality (Parkinson et al., 2013). This is widely acknowledged in green premium studies, which note that it can undermine the robustness of findings and may lead to a risk of overstatement of green premiums, as correlated features that also would also tend to command positive price premiums are frequently uncontrolled for (Marmolejo-Duarte & Chen, 2022; J. Olaussen et al., 2019).

Traditional empirical strategies to mitigate OVB in hedonic house price studies include Difference-in-Differences (DiD) designs, matching estimators and regression discontinuity designs (RDD) (Angrist & Pischke, 2009). Unlike the standard hedonic model that uses cross-sectional data, DiD relies on longitudinal data (usually repeated sales) allowing researchers to control for unobserved, time-invariant factors (Banzhaf, 2021). Under the parallel trends assumption that treated and control properties would have followed similar temporal trend in the absence of treatment, DiD also accounts for time-variant factors (Bishop et al., 2020). The treatment effect is estimated by comparing the average change in price for treated properties to the corresponding price change for control properties. This framework therefore helps reduce OVB and strengthens the robustness of estimated parameters. However, DiD assumes a stable hedonic price function over time, an assumption that may be violated if the implicit prices of housing attributes change over time (Banzhaf, 2021). Moreover, bias may persist depending on how treatment is defined, particularly if other contemporaneous changes affect house prices, i.e. there are other time-variant factors. This method has been used, for example, to estimate the price premium associated with installing heat pumps (Shen et al., 2021).

Matching estimators provide another approach to mitigating OVB. These methods match treated properties with comparable untreated ones based on a range of observed characteristics, aiming to reduce selection bias (Bishop et al., 2020). A challenge is to determine the appropriate criteria for selecting matches. Moreover, there could still be persist OVB if the matching does not account for unobserved factors which correlate with prices. This approach has been applied in green premium studies, for examples, researchers use propensity score matched samples within a hedonic regression framework to examine how housing energy efficiency is capitalised into property prices (Walls et al., 2017).

Regression discontinuity design (RDD) offers a further quasi-experimental strategy to mitigate OVB (Wilms et al., 2021). The RDD assumes that the outcome variable would be continuous in the absence of the treatment, which is a predetermined threshold. The estimated treatment effect is identified by comparing observations just above and below this threshold. By narrowing the analysis to a specific area around the threshold, the treated and control group become highly similar in both observed and unobserved characteristics, mitigating the OVB. This strategy has been applied by researchers to examine the threshold effect/cognitive effect of EPC bands on house prices (Chareyron, 2026; Sejas-Portillo et al., 2025). There is a continuous score of EPC and categorical bands derived from it, which are associated with prices as well as other measured and unmeasured characteristics. Properties at the boundary of each band are more similar to each other on these characteristics, so any discontinuity in prices shows the effect of the banding instead of other features.

A common drawback of these empirical strategies used to mitigate OVB is that the resulting estimates are not always robustly interpretable as measures of WTP. Approaches of DiD, matching estimators and RDD improve identification by exploiting panel data, similarities across observed characteristics or discontinuities in treatment assignment. However, these methods typically rely on strong identifying assumptions such as parallel trends, local randomisation or selection on observables that may not fully hold in housing markets.

3.3.2.2 Mechanisms

Though hedonic pricing models can estimate the WTP for housing green features, their reliance on observational transaction data places them within the revealed-preference framework, making it challenging to identify underlying mechanisms driving WTP. Compared to the revealed WTP/rational WTP, estimates of stated preferences/WTP are derived from intended choices reported in surveys or interviews and therefore based on hypothetical scenarios (Zalejska-Jonsson, 2014). To better understand the motivations behind WTP, scholars often turn to stated-preference approaches.

As discussed in the previous section, the main mechanisms underlying households' WTP for green housing features remain uncertain. Researchers have attempted to identify these mechanisms by examining the factors influencing WTP for green buildings using stated-preference data (Portnov et al., 2018; Zalejska-Jonsson, 2014; L. Zhang et al., 2018). Some studies emphasise the role of environmental awareness in shaping household decision-making (Zalejska-Jonsson, 2014; L. Zhang et al., 2018), while others suggest a combination of financial and non-financial incentives influencing investment in green attributes (L. Zhang et al., 2018). Overall, however, empirical evidence on the underlying drivers of WTP remains inconclusive.

Despite their usefulness in exploring behavioural motivations, stated-preference studies are subject to important limitations. Divergences between stated and actual WTP may arise due to reporting bias or uncontrolled characteristics (Onwujekwe et al., 2005). Where the attribute has a clear implication of being socially desirable, there is a clear risk of people overstating WTP in such studies. Moreover, because such studies typically rely on surveys or interviews, sample sizes are often limited and may not be fully representative, thereby constraining the robustness and generalisability of the identified mechanisms.

3.3.2.3 Heterogeneity

Standard hedonic models primarily identify the average marginal implicit price of a green attribute at market equilibrium, reflecting an average price premium estimation across markets and buyers. However, it is widely believed that there exist housing submarkets which have important influences on determining house prices (Bourassa et al., 2003; Watkins, 2001). A submarket is commonly defined as a group of dwellings that are close substitutes for one another but relatively weak substitutes for properties outside the group (Grigsby, 1986). The criteria used to delineate submarkets are generally specified in advance, drawing on theoretical knowledge or empirical insights from data (Bourassa et al., 1999). In practice, housing submarkets are most often defined through spatial and structural factors (Watkins, 2001).

There are extensions of hedonic models designed to capture heterogeneity, including spatial regression, quantile regression, interaction terms, and varying coefficient models. These techniques have been applied in housing green premium studies. Heterogeneity in spatial submarkets are often explored using spatial regression e.g., geographically weighted regression (Soltani et al., 2026). Studies apply quantile regression to examine how price premiums differ across the price distribution (Evangelista et al., 2022; McCord, Haran, et al., 2020). Interaction terms that interact green features and other factors are also applied to capture heterogeneity in pre-defined submarkets (Marmolejo-Duarte & Chen, 2019a). Similarly, scholars apply separate regressions in different submarkets to estimate the price premium separately (Chegut et al., 2020). While these techniques are designed to estimate heterogeneity across categorical attributes, the varying coefficient models can help to identify the heterogeneity across continuous variables. For example, a study applied a partially linear varying coefficient fixed effects panel data model to carry out heterogeneity price effect analysis of heat pump installations (Shen et al., 2021).

Though several hedonic extensions are commonly used for the exploration of heterogeneity in price effects, these methods generally suffer from the limitations common to theory-driven approaches noted above. In terms of heterogeneity analysis, many require researchers to define submarkets *ex ante* based on geographic, demographic, or structural criteria. The key limitation of these models is that they can only test for differences in pre-specified submarkets. In addition, such prior segmentation may be arbitrary and relies heavily on theoretical assumptions about how markets are structured. If the chosen submarkets do not accurately reflect actual preference sorting or spatial market boundaries, the estimated heterogeneous effects may be biased or misleading. Consequently, the identification of heterogeneity may depend more on researchers' modelling choices than on true underlying differences in WTP.

3.3.3 Emerging data and approaches

The growing availability of unstructured data such as images and text alongside methodological advances in machine learning (ML), deep learning (DL) and large language models (LLMs), has offered new pathways to mitigate methodological limitations of traditional hedonic models though it remains hard if not impossible to fully solve all of them. Two main research strands around applying emerging data and approaches in hedonic house price studies have emerged. The first focuses on extracting information from new data sources to construct additional attributes that can be incorporated into traditional parametric hedonic models. The second directly integrates emerging data and AI techniques into the hedonic framework, using ML interpretability tools or causal ML methods to uncover relationships between house prices and their determinants.

In terms of variable generation, image-based proxies are particularly prominent. Though images and visual perceptions play a critical role in shaping house prices, they are difficult to quantify. Advances in computer vision, such as semantic segmentation, have enabled the extraction of environmental features from street-view imagery (e.g., green space) (Wu et al., 2022; Ying et al., 2025; Y. Zhang & Dong, 2018), satellite or aerial images (e.g., vegetation, urban forests, built-up areas, land surface temperature) (Ewane et al., 2023; Soltani et al., 2026) and interior images (M. Hu et al., 2023; Nouriani & Lemke, 2022). Beyond imagery, textual data from online listings are widely used to derive indicators of property and neighbourhood quality, often through sentiment analysis (Hebdzyński, 2024; Su et al., 2021). More recently, LLMs have been employed to extract housing-related attributes either from textual and visual inputs for inclusion in hedonic regressions (Faxvaag et al., 2025) or through prompt-based querying, indirectly leveraging a wide range of publicly available information sources on different locations (Östh et al., 2025). This strand is helpful to mitigate the OVB in hedonic models by controlling for a wider range of attributes.

The second strand applies advanced AI methods to model the relationship between house prices and property attributes within a more flexible, data-driven framework. ML and DL approaches are well suited to capturing complex, non-linear relationships and often deliver superior predictive performance. However, their limited interpretability constrains their usefulness for estimating price premiums. Recent advances in interpretability techniques, such as SHAP (SHapley Additive exPlanations) (H. Wang et al., 2024), allow researchers to assess feature importance and approximate implicit premiums (Gyger et al., 2026). Still, these methods do not fully identify the structural drivers of price differentials. Causal ML frameworks offer a more rigorous alternative by explicitly estimating treatment effects (Chernozhukov et al., 2024), which are interpreted in house price research as price premiums. Approaches such as double machine learning and meta-learners are increasingly applied in housing studies (Asproudis et al., 2024; Hull & Grodecka-Messi, 2022), providing a theoretically grounded pathway for integrating AI into premium estimation. This strand may also mitigate OVB through the ability to also integrate unstructured data directly within models. Furthermore, by enabling individualised treatment effect estimation, causal ML frameworks enables data-driven heterogeneity analysis of price premiums (Künzel et al., 2019).

3.4 Summary

In summary, the literature on housing green premiums has attracted growing research attention. Despite this progress, the field faces several knowledge gaps. Empirically, the current evidence on green premiums from energy efficiency is mixed, highlighting the need for a systematic review that synthesises and critically evaluates the existing empirical evidence. Methodologically, there are several challenges inherent in traditional hedonic house price models, including OVB, undetermined mechanisms and price premium heterogeneity. These could undermine the robustness of estimated premiums or constrain a comprehensive understanding of how green premiums are formed and distributed. Although established econometric techniques seek to mitigate these concerns, they cannot fully resolve them. At the same time, the increasing availability of emerging data and analytical approaches provide new opportunities to advance methodological practices.

Motivated by these empirical and methodological gaps, this thesis aims to address the empirical research questions already noted in Chapter 1 but reiterated here as a reminder:

- RQ1: What is the research scope/scale, methods, and results in the quantitative evidence of the price premium of housing energy efficiency in the European literature?

- RQ2: Has the price premium for housing energy efficiency in the UK increased after the “energy crisis” of 2022 and what insights does this give about omitted variable bias and the mechanisms generating the premium?

- RQ3: Is there heterogeneity in the price premium of housing energy efficiency in the UK and which submarkets have a higher/lower price premium?

These questions are answered in Chapters 4, 6 and 7 respectively.

Chapter 4 The price premium of residential energy performance certificates: A scoping review of the European literature

This Chapter is a reproduction of my open access paper published in *Energy and Buildings* (Ou et al., 2025) (https://doi.org/10.1016/j.enbuild.2025.115377). It sits well in this thesis by answering Research Question 1. The paper synthesises price premium estimations in the English-language European literature, offering a solid benchmark for the later empirical analyses in the thesis. In addition, the summary assists in the identification of key research gaps which later empirical chapters seek to address. This chapter contains three research questions, which are labelled RQ4.1 to RQ4.3 to differentiate them from the main Research Questions of the thesis.

4.1 Introduction

Residential buildings account for around 17% of CO_2 emissions and 21% of energy demand globally (IEA, 2023b). To achieve overall goals for net-zero by 2050, a significant reduction in energy demand and a decarbonisation of the energy supply is crucial (UNEP, 2023). In the residential building sector, improving building energy efficiency could help both processes. It is also vital in reducing residents' vulnerability to energy crises when shortages of energy supply led to increased prices. Moreover, the poor energy efficiency of dwellings is a major factor for low-income households experiencing fuel poverty, who have to spend a high proportion of income to keep their homes at a comfortable temperature (Boardman, 2009). Overall, the ongoing climate emergency, energy crisis due to geopolitical tensions, and social inequality highlight the urgent need to accelerate the sustainability transition of housing globally.

Mandatory building energy codes play an important role in improving the resilience of the buildings sector, by revealing energy efficiency information for governments, households, and businesses, and encouraging investment in energy efficiency. Currently, 80 countries have adopted building energy codes globally, of which 43 countries have mandatory ones (IEA, 2022a). The EU issued the Energy Performance of Buildings Directive (EBPD) in 2010 (European Parliament & Council of European Union, 2010) which initiated Energy Performance Certificates (EPCs).

EPCs are designed to reveal energy efficiency information to consumers and others, eliminating one of the main barriers to energy efficiency investment (Giraudet, 2020). Moreover, the Directive has become a significant policy in the housing market as it requires EPCs to be displayed in any sale or rental advertisement. EPCs could therefore play an important role in facilitating the capitalisation of energy efficiency in the housing market and thereby incentivise stakeholders (i.e. homeowners, landlords and tenants, investors, developers, financial institutions).

However, current evidence of the price premium of EPCs is mixed. Some studies suggest a price premium for more energy-efficient buildings, others argue that energy efficiency is not appreciated or has no influence in the housing market. While there is a relatively large body of quantitative research evidence, it varies in geographic and temporal coverage, and in the methods applied. A small number of reviews exist already. Two reviews adopt a systematic approach (Cespedes-Lopez et al., 2019; Fregonara & Rubino, 2021). The former applied a meta-analysis to review the price premium of properties having an energy certificate globally as well as those of each energy band in Europe, including journal articles, book chapters, reports and theses. The latter only reviewed the methodologies used to measure the price premium of EPCs in European studies. However, the searching and screening approach taken in these reviews is either relatively limited in scope or the information on the process is incomplete. Two other studies provide a more narrative review. One only include studies in Spain (Marmolejo-Duarte et al., 2019), and the other merely look at a limited number of studies and case study projects in Europe (Wilkinson & Sayce, 2020). Among the three review papers aiming to find the price premium of energy efficiency, the systematic review found there exists an increase in price premium with better energy efficiency - statistical synthesis showed homes with Band A have 9.9% higher sales price compared to Band D (Cespedes-Lopez et al., 2019), while the two narrative reviews suggest either no effective impact (Marmolejo-Duarte et al., 2019) or different results across studies (Wilkinson & Sayce, 2020). A comprehensive and up-to-date scoping review of existing works is therefore required.

To gain a comprehensive picture of the literature in terms of geography, time coverage and methods as well as results, the aim of this paper is to provide a scoping review (Tricco et al., 2018) of the European academic literature in English on the housing market impact of EPCs. To our knowledge, this is the first scoping review in this field. Despite the global importance of energy codes, this review concentrates on European literature for two reasons. First, it is one of the dominant economic areas contributing largely to building energy efficiency investment. Second, the EPC system is relatively well-developed and consistent across the EU. We focus on peer-reviewed academic sources (i.e. journal articles, book chapters, and PhD theses) only to improve consistency and trustworthiness of the included literature. This review is limited to literature providing quantitative evidence on the sales/rental price premium attached to EPCs in the period subject to the EBPD. Overall, this review summarises peer-reviewed academic sources of European literature in English with coverage to May 2024. To ensure comprehensive coverage of the target literature and the reproducibility of our review, we take a transparent, systematic approach to identifying and screening the literature. This also enables others to build on work by covering other literature including works in other languages or non-academic sources. Our review contributes to the current literature by providing a holistic, scientific, and up-to-date overview of quantitative price-based studies of EPC impacts on the housing market. The detailed research questions are as follows:

- RQ4.1: What is the scope and scale of the quantitative evidence of the price premium of energy efficiency under the EBPD in terms of geography? How has this literature evolved over time? Which housing sub-markets have been studied more or less, in terms of housing market contexts (i.e., tenure and price type), population (i.e. dwelling type) and intervention (i.e. EPC type)?

- RQ4.2: How are these studies conducted, i.e. what research designs and analytical models do they employ? What are the variables mostly used in modelling? Is there methodological limitation in the literature?

- RQ4.3: What price premiums are found in the literature? How do outcomes vary between different countries or regions? Is there evidence of an increasing premium being placed on energy efficiency over time? Are there differences in the price premium between housing sub-markets e.g. houses/apartments, sales/rental market?

The structure of the article is as follows. First, the *EPC Policy and Practice* section highlights the standards of EPCs as a policy intervention, details variations in how they are implemented in different European countries and provides context of relationship between EPC and price premium. The *Methods* section justifies the chosen review approach, as well as the search and screening process, data extraction, and analytical techniques. The *Results* section presents results on research scope, methods, and outcomes. The *Discussion* discusses the results in the wider policy and research context, limitation of this review, and research gaps. Finally, the *Conclusions and Policy Implications* section gives an overall summary and provides recommendations for policy design.

4.2 EPC policy and practice

4.2.1 EPC systems and standards

EPCs were initiated in the Energy Performance of Buildings Directive (EPBD) by the European Parliament and the Council of the European Union. The first version of the EPBD was published in 2002 (Directive 2002/91/EC) (European Parliament & Council of European Union, 2002), requiring member states to implement it by 2006. This was recast in 2010 (Directive 2010/31/EU) (European Parliament & Council of European Union, 2010) followed by a revision in 2018 (Directive 2018/844/EU) (European Parliament & Council of European Union, 2018) with stronger EPC assessment standards. These were required to be implemented in 2012 and 2020 respectively. In practice, all member states had implemented the EPC system in national legislation by 2013 (Aleksandra et al., 2014). The EPBD as recast made it mandatory for member states to require the EPC to be displayed in any advertisement of housing for sale or rent, stating that buildings should 'be issued an EPC when they are constructed, sold or rented out to a new tenant' (Directive 2010/31/EU, p.11).

To assess building energy performance, the European Commission has established a set of standards called the energy performance of buildings standards or "EPB standards". It allows the EPC ratings to be assessed based on calculated (i.e. "asset rating") or actual metered energy consumption (i.e. "operational rating"). While the former considers the theoretical energy needs of the building based on the building fabric and its services, the latter is based on the energy delivered to the buildings and is influenced by the way the building is maintained and used by occupants.

There are several presentation forms of EPC ratings. First, the Energy Performance Index (EPI) represents the annual energy usage per unit area (in kWh/m2/year), which is a typical starting point of calculating EPCs. The EPI can be mapped and represented in scores or bands. The EPC score typically ranges 0-100 with higher scores indicating better energy efficiency, while bands range from A (most efficient) to G/H (least).

There are two different aspects of the EPCs i.e. different ways of calculating scores/bands: Energy Efficiency Rating (EER) and Environmental Impact Rating (EIR). EER is based on the energy costs associated with energy usage, indicating how much fuel bills are likely to be and reflecting assumptions about the relative costs of different fuels. In comparison, EIR is based on the annual CO_2 emissions associated with energy use, reflecting assumptions about relative carbon emissions of different fuels. Furthermore, the EPCs also provide current and potential ratings in each case. The latter are based on recommendations for potential improvements.

4.2.2 EPC practices

In practice, there are ongoing discussions and concerns around the EPC systems, mainly including the reliability/quality of EPCs and its variation between countries.

Questions about current EPCs' quality and reliability have been raised across the EU (Concerted Action EPBD, 2015). Researchers suggested that measures may be of low quality, with significant variations between the EPC and actual energy efficiency of buildings (Coyne & Denny, 2021; D. Jenkins et al., 2017). This quality is directly related to both methodology and assessment processes. While the inaccuracy of EPC calculations could arise from using default input values to represent reality (Atanasiu & Constantinescu, 2011), there is also variation in the assessment process between individual energy assessors (Gledhill et al., 2023). This could pose a challenge to stakeholders' trust in the system, impeding housing energy efficiency investments. Moreover, there may be a low level of familiarity with EPCs by the public (DESNZ, 2023) and financial institutions (Stromback et al., 2021), limiting their impact in the housing market.

Additionally, the methodology, implementation, and data availability of EPCs are quite different across EU countries. While the EPB standards offer an internationally-accepted collection of approaches for assessing energy performance, methodologies vary widely across countries to fit with national features (Stromback et al., 2021). Among the 28 EU countries (pre-Brexit), 12 have implemented a methodology solely reliant on asset ratings, while the rest adopt both asset ratings and operational ratings depending on building type or building age (X-TENDO, 2020). Individual countries also adopt different mapping criteria between energy consumption and EPC scores/bands (European DataWarehouse, 2024), and some use a slightly more sophisticated rating schemes e.g. Italy, Ireland (European DataWarehouse, 2024). Additionally, in terms of implementing the advertisement requirements into national legislation, countries have different implementation paces (Aleksandra et al., 2014). It was not until 2015 that all EU countries required the EPCs to be listed in advertisements (Aleksandra et al., 2014). While the UK left the EU in 2020 ("Brexit"), it has maintained the EPC system since then. A more concerning issue is that the public availability of EPC databases varies between countries. While there is open access to EPC data at a national/regional level in some countries, it is restricted to selected organisations or not openly accessible at all in others(Aleksandra et al., 2014; European DataWarehouse, 2024). Table 4.1 summarises the countries (including pre-Brexit EU countries and Norway) in groups for different EPC methodology and data availability.

Table 4.1 EPC practices across countries (pre-Brexit EU and Norway).

EPC practices		Countries
EPC methodology[1]	Asset rating	Austria, Bulgaria, Greece, Hungary, Italy, Lithuania, Luxembourg, Netherlands, Portugal, Romania, Slovakia, Spain
	Asset and operational rating[2]	Belgium, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Latvia, Norway, Poland, Slovakia, Slovenia, Sweden, United Kingdom
EPC data availability[3]	Open access	Denmark, Estonia, Spain, Ireland, Italy, Lithuania, Netherlands, Norway, Portugal, Slovakia, Slovenia, Sweden, United Kingdom
	Restricted access	Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Germany, Greece, Finland, France, Hungary, Luxembourg, Latvia, Malta, Poland, Romania

Note: [1]Information retrieved from (X-TENDO, 2020). [2]Some countries apply operational rating only to specific type of buildings or building age. [3]Information retrieved from (Aleksandra et al., 2014; European DataWarehouse, 2024).

4.2.3 EPC and price premium

“Price premium” is the percentage price difference in a property with a higher energy efficiency compared to the price that would be paid for the same property if it had a lower energy efficiency. Another term widely used in literature is “Willingness-to-pay” (WTP), which is same as price premium when represented by the percentage price difference a customer willing to pay. In this review, these two terms are used interchangeably, with the latter used when explaining things from the buyer’s perspective.

The price premium of residential energy efficiency becomes more easily measurable after the introduction and mandatory implementation of EPCs. The mandatory reporting of energy efficiency in the housing market could make the higher running costs of inefficient buildings apparent, as well as higher carbon emissions. Additionally, the “green mortgages” provided by the commercial mortgage sector (e.g., low interest rates for buyers/owners of energy efficient properties) could further improve the potential benefits of owning an energy efficient house (Devine & McCollum, 2022). Therefore, potential energy savings, environmental benefits, and other financial benefits would result in a price premium from EPC ratings. In the literature, the price premium of energy efficient homes is also called the “green premium”, reflecting the expected higher price of more efficient (i.e. “greener”) homes. In comparison, “brown discount” refers to the case when buildings with poor energy efficiency suffer from reduced value.

4.3 Methods

4.3.1 Review approach

Our approach primarily falls mainly into the remit of a scoping review. We aim to map the existing literature in terms of research scope/scale, research methods and results. There is currently no scoping review on this topic, making it a valuable addition to the literature. Beyond the general conduct of scoping review, we do however move a stage further in attempting some synthesis of the major findings from the studies identified to provide an initial statement on the overall scale of price premium of EPC bands though we stop short of a formal meta-analysis.

4.3.2 Searching and screening

4.3.2.1 Process and tools

Focussing on the academic literature published in English, we develop a systematic, comprehensive, AI-supported literature searching and quality-controlled screening process (Figure 4.1). The whole process includes (1) search terms determining, (2) search commands determining, (3) database searching, (4) database results screening, (5) AI searching, and (6) AI results screening. This could be a cyclic process if we find AI results are helpful for updating the structured search strategy, though we do not implement this here. More details on each stage are explained in the remainder of this section.

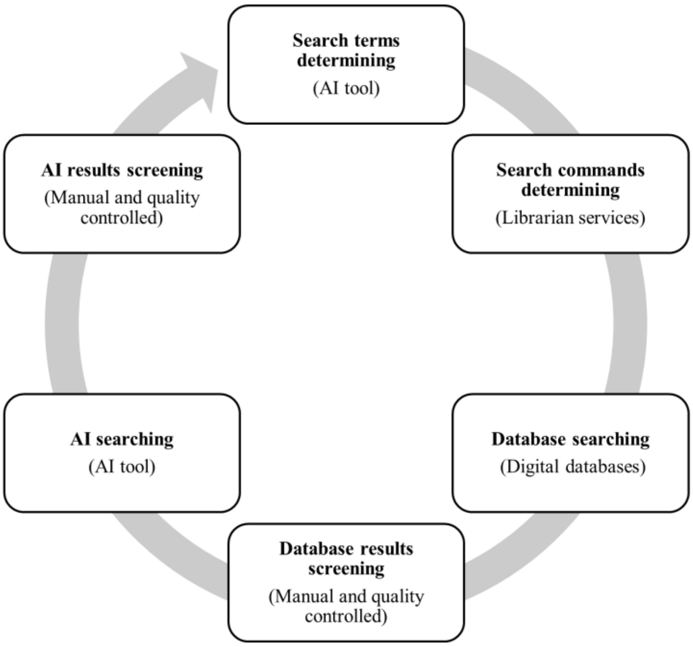


Figure 4.1 Searching and screening process with tools/services used.

We use an AI tool in two stages including initialising search terms and detecting omitted studies. To initialise search terms, we import seed papers to an AI-based literature recommendation tool to collect similar studies, from which we manually identify the search terms and synonyms used. On AI searching, the screened results from the digital databases are imported to the AI tool, which could find similar studies for missing literature detection.

The final choice of digital databases includes Scopus, Web of Science, Business Source Ultimate, Econlit, and International Bibliography of the Social Sciences. The first two are large-scale multidisciplinary databases and others are subject-specific databases relevant to this review, ensuring a comprehensive inclusion of databases. The ‘Research Rabbit’ (https://www.researchrabbit.ai/) tool is used for AI support. It is an AI-based literature recommendation engine that works based on seed papers and citations, allowing researcher to quickly find studies that are related.

4.3.2.2 Search terms and commands

To determine the search terms, we identify three seed papers in Google Scholar (Bisello et al., 2020; Copiello & Donati, 2021; deAyala et al., 2016) which are agreed to meet the aim of this review and import them into Research Rabbit, where 176 similar studies are identified. We summarise the keywords used in these studies and use these for the title/abstract search (search commands shown in

Table 4.2). Since studies use different logics to describe keywords, we employ two search commands: the first one combines ‘house’ with ‘green premium’, and the second combines ‘house price’ with ‘energy efficiency’. Details of search commands for each database is provided in Appendix C, Table C-1.

Table 4.2 Finalised search command.

Search	Search Command
Search 1	*(hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)* AND ("green value" OR "green premium")
Search 2	*(value OR cost OR price) W/3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)* OR *("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value")* AND ("energy efficiency" OR "energy rating" OR "energy performance certificates" OR “epc”)

4.3.2.3 Inclusion and exclusion criteria

We design the inclusion and exclusion criteria based on population, intervention, outcome, study design, and publication characteristics (Table 4.3). The research aim is to summarise literature investigating the relationship between EPCs and house prices. First, the literature should target the population of residential buildings, not office/commercial buildings. We exclude studies focusing on office/commercial buildings as they have different EPC regulations compared to the residential market and are affected by different investment decision-making processes. Second, we only include studies exploring the intervention of EPCs implemented in the EU under the EPBD. Additionally, the outcome of any study should include a direct measure of house prices i.e. investigating revealed preferences instead of stated preferences. Also, included literature should adopt quantitative price-based research, while reviews or qualitative research are excluded. Finally, only articles published in peer-review journals, book chapters or theses are included. Noted there existed grey literature on this topic e.g. (Bio Intelligence Service et al., 2013), but this review considers only academic sources to ensure reliability of results. Due to limited time and resources, only studies published in English are considered.

Table 4.3 Inclusion and exclusion criteria.

Criteria	Inclusion Criteria	Exclusion Criteria
Population	Residential buildings	Office/commercial buildings
Intervention	Energy Performance Certificates (EPC)	
Outcome	Include a direct measure of house price	
Study design	Quantitative price-based research	Qualitative research, reviews
Publication characteristics	Peer-reviewed journal articles or book chapters or PhD theses; Published in the English language	

4.3.2.4 Searching and screening

A summary of the searching and screening process is shown in Figure 4.2, including identification and screening of studies from both digital databases and AI tool (Research Rabbit). The digital database searching covering studies until 2nd May 2024. Overall, 68 articles are eligible for final review.

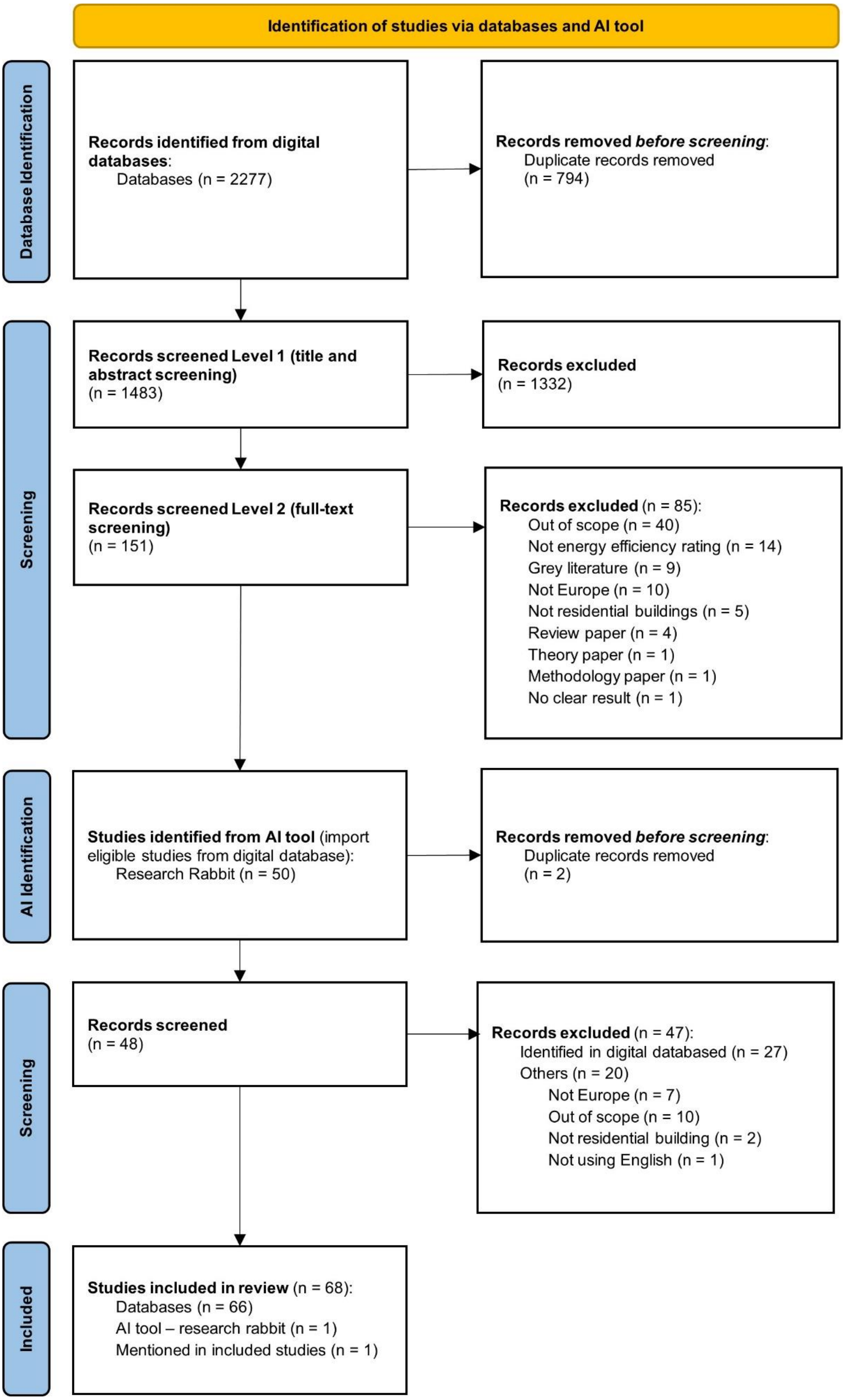


Figure 4.2 Flowchart of searching and screening process.

Note: This diagram follows the PRIMA 2020 guideline (Page et al., 2021) for reporting systematic reviews.

Firstly, digital database searching identified 2277 records (1483 records after deduplication), followed by two stages of screening. In the first stage, titles/abstracts are assessed according to the inclusion and exclusion criteria, through which 1332 (90%) records are excluded. The reasons include lack of relevance, grey literature, and non-English language. This yielded 151 articles for a further screening. In the second stage, the full text is examined through which 85 articles (56.3%) are excluded, leaving 66 articles eligible for review. In the full-text screening, there are some studies which are marginal, and where decisions need to be clarified. First, one conference paper (Dell'Anna, 2022) and one working paper (Sejas-Portillo et al., 2020) are included for their contribution to methods which rarely appear in other included studies and meaningful results. We also believe both papers have similar high quality to published articles. The conference paper is subject to stringent peer review and published in distinguished conference proceedings series while the working paper is published in a peer-reviewed journal at the time we write the review. We will refer to the published version of the working paper (Sejas-Portillo et al., 2025) in the rest of the paper. Second, studies that are unclear and from which it is hard to extract data are also excluded.

On screening, we do quality control (i.e. conduct dual review for a random sample of records to estimate if error rates are within acceptable bounds) to reduce the reporting bias. About 10% random sample of studies (135 articles for first stage and 13 for second stage) are checked by one of the co-authors. The agreement rate is 96% (113+17 out of 135; Table 4.4) in the first stage and 100% in the second. It is noted that within all the disagreements, the person suggesting inclusion had doubts, indicating all the five articles are likely to be dropped at the next stage. We agree that error rates are within acceptable bounds for this review.

Table 4.4 Confusion matrix of sample screening at first stage of database results screening.

		Author 2		Grand total
		Yes	No	
Author 1	Yes	17	1	18
	No	4	113	117
Grand total		21	114	135

After the digital database searching, the AI tool is used to detect omitted studies not retrieved through the structured search. By importing the 66 post-screening results from the database searches into Research Rabbit, much similar research is recommended. We choose the top 50 “most relevant” studies returned by Research Rabbit as potential studies for review. To screen these, first we remove duplicated studies (n = 2) and then compared the rest with the studies already identified from digital database, which leads to the removal of 27 studies. The remaining 21 studies are screened according to the inclusion and exclusion criteria, finally detecting just one additional article (Cajias & Piazolo, 2012) to be eligible for this review. Most of the other 20 studies were removed because of their focus on commercial/office buildings. Lastly, one more study is added (N. Liu et al., 2018) which was mentioned in the literature review of one of our included studies.

On checking, we find that both of the two additional studies were included in our chosen databases but their specific terms do not fit with our structured search commands. This finding provides further insights to update our search commands. However, the fact that there were just two additions at this stage suggests changing search commands would yield very limited benefits. Finally, therefore, we conclude the literature search and screening process with a set of 68 articles.

4.3.2.5 Summary

In summary, the adopted search and screening process follows a systematic workflow to ensure the integrity and quality of evidence base at every stage. Based on our experience for this review, digital databases and AI tools are complimentary in literature searching. While database searches are transparent and replicable, the retrieved results are limited by the adopted search strategy. In comparison, AI literature recommendation tools do not rely on structured search commands, despite the drawback on reduced transparency. Therefore, compared to traditional literature searching process, we find combining digital database and AI tools could improve the efficiency and accuracy of searching.

4.3.3 Data extraction

Data extraction captures factors of research scope, methods and outcomes from included studies (Table 4.5). We initially record data of all categories in the model level and most categories are aggregated to study level when reporting. A few factors need to be explained here. First, the factors in “Time coverage” category are based on the time of data used. Next, there are two factors to extract for research outcome, including “Broad finding” and “Price premium”. The former is a qualitative assessment of the overall finding on price premium (e.g. positive or negative) with one result recorded for each study. The latter refers to model coefficients for EPC scores or bands, which are recorded by model. If different models are applied to the same dataset, only the authors’ preferred model is recorded. Multiple models are included if they used different data that would result in distinct outcomes. When recording the price premium, if the study used grouped EPC ratings, the coefficients would be recorded as the same for each rating in one group.

Table 4.5 Data extraction form.

Category	Sub-category	Factors	Report level
Research scope and scale	General information	Authors	Study
		Published year	Study
		Journals	Study
	Geography coverage	Research country	Study
		Geographical scale	Study
	Time coverage	Start time	Study
		End time	Study
		Time span	Study
	Research design	Comparative/Noncomparative	Study
		Cross-sectional/Longitudinal	Study
	Context	Tenure (sales/rent)	Study
		Price type (transaction/listing)	Study
	Population	Dwelling type (house/apartment)	Study
	Sample size	Sample size	Study
	Intervention	EPC aspect (EER/EIR)	Study
		EPC time (current/potential)	Study
		EPC scale (band/score/EPI)	Study
Research method	Research model	Research model	Model
	Variables	Variables	Model
		Location fixed effect	Model
		Temporal fixed effect	Model
		Spatial effect	Model
Research outcome	Research outcome	Broad finding	Study
		Price premium	Model

4.3.4 Analytical techniques

4.3.4.1 Descriptive analysis and narrative summary

First, we mainly map the results descriptively according to research scope/scale, methods, and outcome, e.g. present simple frequency counts. Narrative summary (Aromataris & Munn, 2020) of overview/trends are also presented to supplement the frequency tables, figures, etc.

4.3.4.2 Statistical synthesis

Statistical synthesis of models' coefficients is applied to summarise an overall statement of price premium. Since the models and variables may differ from one another, they need to meet the following conditions to be included for synthesis: (1) use regression methods, (2) use the categorical EER bands as the variable of interest, (3) use log transformed house price as the dependent variable. Studies which group EER bands into a smaller set of categories or transform EER bands to numerical variables are not included. To make model coefficients comparable, the coefficients of each EER Band are first subtracted from the coefficient of Band D (i.e. we make Band D the reference point).

There are a few caveats with this approach, including the fact that models use different controls and may have different specifications despite the conditions we impose on selection, and that there are different EPC calculation methodologies in each country, as discussed previously. In addition, and also discussed above, each country uses different cut-points in terms of energy efficiency to produce the bands (European DataWarehouse, 2024). Nevertheless, we feel these bands are the most useful basis for comparison since they will have been set to reflect the relative situation of each country's housing stock, i.e. they are appropriate to the national context and housing market in each case. Critically for our review, model coefficients capture the relative value of more or less efficient properties across housing markets with widely-varying underlying housing and energy costs so the absolute energy efficiency rating is not the important factor. As for different step ups between bands across countries (e.g. some countries might have bigger step up from C to B), this could potentially matter but only if consumers pay close attention to the efficiency values of different levels. In our knowledge of people's awareness of EPC ratings, most consumers make a broad judgement based on the grades. Therefore, we believe the energy bands used in each country form the best basis for comparing the price premium of energy efficiency across countries.

4.4 Results

The final literature inventory is made up of 68 studies covering 111 models. We provide the full results of our data extraction in Appendix A (literature inventory) and B (model inventory).

4.4.1 Research scope and scale

4.4.1.1 Journals, geographic and temporal coverage

Table 4.6 summarises the timing and geographic coverage of the studies. The earliest publication was 2011 (Brounen & Kok, 2011). Studies found in this review range from 2011 to 2024. The number of publications increased over time, with over 67% of studies published from 2019-2024. The literature is dispersed across a wide range of journals with about 40% of studies published in a journal where it is the only study from that journal meeting our criteria.

Table 4.6 Summary statistics for journals, geography, and temporal coverage.

Characteristics	n	Characteristics	n
Published Year	68	Research country	68
2024 (from Jan to May)	3 (4.4%)	*Italy*	14 (20.6%)
2023	8 (11.8%)	*Germany*	12 (17.6%)
2022	10 (14.7%)	*United Kingdom*	9 (13.2%)
2021	4 (5.9%)	*Sweden*	8 (11.8%)
2020	12 (17.6%)	*Spain*	7 (10.3%)
2019	9 (13.2%)	*Norway*	4 (5.9%)
2018	3 (4.4%)	*Netherlands*	3 (4.4%)
2017	4 (5.9%)	*Portugal*	3 (4.4%)
2016	7 (10.3%)	*Belgium*	2 (2.9%)
2015	2 (2.9%)	*Ireland*	2 (2.9%)
2014	2 (2.9%)	*Finland*	1 (1.5%)
2013	3 (4.4%)	*Denmark*	1 (1.5%)
2012	0 (0.0%)	*United Kingdom and Netherlands*	1 (1.5%)
2011	1 (1.5%)	*Italy and Spain*	1 (1.5%)
Journals	68	Geographical Scale	68
Energy Policy	*6 (8.8%)*	*National*	*26 (38.2%)*
Energy Economics	*6 (8.8%)*	*Regional*	*12 (17.6%)*
Energy and Buildings	4 (5.9%)	*City*	28 (41.2%)
Journal of European Real Estate Research	4 (5.9%)	*Neighbourhood*	1 (1.5%)
Buildings	4 (5.9%)	*City and neighbourhood*	1 (1.5%)
Sustainability (Switzerland)	4 (5.9%)	Data Time Span	68
International Journal of Housing Markets and Analysis	3 (4.4%)	*<= 1 year*	10 (14.7%)
Energy Research and Social Science	3 (4.4%)	*1-3 years*	13 (19.1%)
Energies	2 (2.9%)	*3-5 years*	14 (20.6%)
Journal of Real Estate Finance and Economics	2 (2.9%)	*5-10 years*	15 (22.1%))
Journal of Sustainable Real Estate	2 (2.9%)	*> 10 years*	7 (10.3%)
Other (one study each)	28 (41.2%)	*Not mentioned*	9 (13.2%)

The studies spread across Europe geographically from north to south but cover just 12 out of the 29 countries implementing EPCs (including pre-Brexit 28 member states plus Norway) (Figure 3), while 17 member states having no studies. Despite the focus on publications in English, Italy and Germany are the most popular settings for studies, followed by the United Kingdom, Sweden and Spain. Only two studies have covered more than one country. There are no studies identified for central or eastern Europe (regions defined in (Publications Office of the European Union, 2015)), nor for France or Austria. One factor here may certainly be the limiting of our search to studies published in English, but another may be data availability. As mentioned previously, the EPC data are not publicly accessible in some countries. As shown in Figure 4.3, there is a strong relationship between public accessibility of data (Aleksandra et al., 2014; European DataWarehouse, 2024) and the volume of published evidence. Specifically, 13 countries have publicly available EPC data (links available in Appendix C, Table C-2) and they account for about 80% of the identified studies. Among the 18 countries with no publicly available data, there are just 15 studies concentrated in three countries – Germany, Belgium, and Finland. Studies in these countries use EPC data provided indirectly from either website listings or real estate agencies. Overall, we find studies in this field are much more prevalent in countries where EPC data is publicly available. Therefore, we conclude that research evidence in this field is being limited by EPC availability and call for governments to accelerate the process of publishing open EPC data.

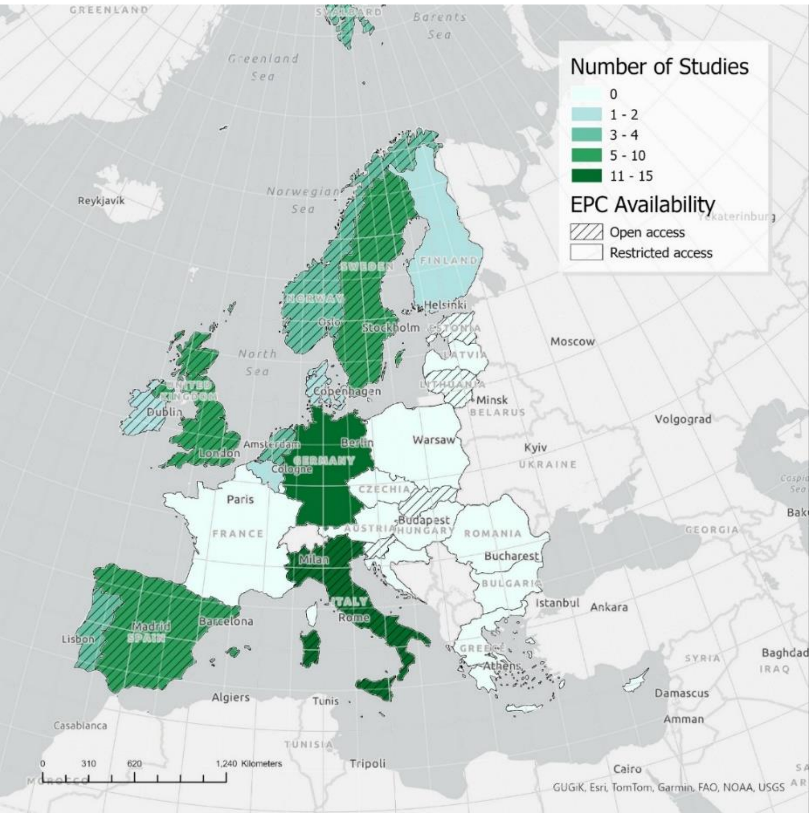


Figure 4.3 Geographical coverage of studies and EPC data availability (pre-Brexit 28 EU member states and Norway).

Most studies use data at a city or national level, followed by those at regional scales (Table 4.6). This may be related to EPC data availability, as we find there are no national level studies conducted in Italy/Portugal where EPC data is only publicly accessible in certain regions (Aleksandra et al., 2014). While studies at a neighbourhood scale (part of a city) are rare, many studies have suggested differentiating housing market impacts across spatial sub-markets (Barreca et al., 2021; Dell'Anna, 2022; McCord, Lo, et al., 2020). As for boundaries to define market areas, most of the included studies applied administrative boundaries, while past studies have suggested that administrative boundaries do not necessarily delineate consistent housing sub-markets (Helbich et al., 2013).

The time coverage of data is shown in Figure 4.4. The data of interest include both EPC and house prices data. Though these are matched with each other to study the housing market impact of energy ratings, they may stem from different times. Most papers used data later than 2006 when the EU member states were required to transpose EPC regulations into national laws as stated in first version of EPBD. However, there is a clear time lag between the implementation deadline and time of data used as found here. And all the data adopted are before 2024. The time span of data ranges from less than one year to more than ten (Table

4.6). Few studies include house price data from periods before EPCs were available. These are mostly comparative or longitudinal studies that include house prices data from an earlier time. Specifically, some includes earlier data to do a longitudinal/repeated sales analysis and find the EPCs' impact on price change (Fuerst et al., 2015; Fuerst, McAllister, et al., 2016), while others separate pre/post EPC labelled transactions to investigate if the price premium is related to the energy label itself or other features (J. Olaussen et al., 2019; J. O. Olaussen et al., 2021).

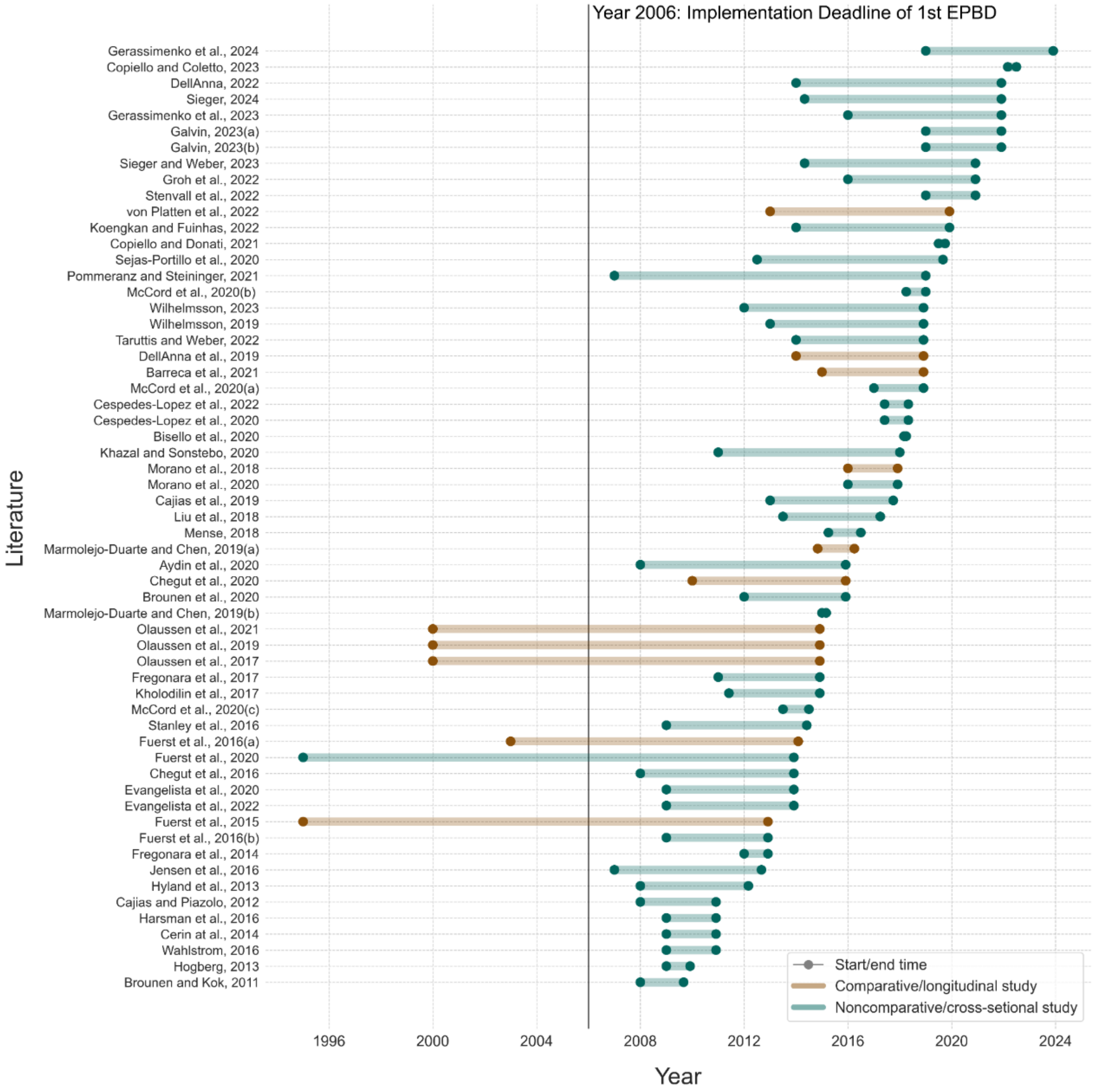


Figure 4.4 Time scope and scale of data adopted in literature.

Note: In this figure, the studies can be referred to the 'Reference' field in the data extraction results in Supplementary material. Only one start and end date are used for each study. For studies with different data start times or end times in different models, only the earliest start time and latest end time are chosen to visualise. Six studies are not included in the figure as there is incomplete information on the time span of the data.

4.4.1.2 Housing market contexts, population, intervention

Table 4.7 provides a summary of housing market contexts (i.e., tenure and price type), population (i.e., dwelling type) and intervention (i.e., EPC type). On tenure type, most studies analyse sales market. Nine examine only rental markets with seven more exploring both (Fuerst et al., 2020; Fuerst, McAllister, et al., 2016; Galvin, 2023b; Gerassimenko et al., 2023, 2024; Hyland et al., 2013; Kholodilin et al., 2017). To reflect the revealed preference of homeowners/tenants, transaction price is usually preferred but not always available, in which case a listing price (also known as "asking price") is used as a substitute. It is worth noting that listing price reflects more the sellers' expectations instead of residents' WTP, although no doubt the former is informed by the latter. It is important for researchers to assess any differences between the two before using listing price as a substitute but, for our work, it would only bias results if the differences were affected by energy efficiency in some way and this seems unlikely. Among included models, over 40% apply transaction prices (n=29). Meanwhile, slightly more studies (n=35) adopted listing prices, mostly due to the fact that official transaction information is not available in some countries such as Spain (Marmolejo-Duarte & Chen, 2019a) and Italy. Again, it highlights that the availability of data forms a main limitation in this field.

Table 4.7 Summary statistics for housing markets.

Characteristics	n	Characteristics	n
Context - tenure type	68	Intervention - EPC aspect	68
Sales	52 (76.5%)	*EER*	67 (98.5%)
Rents	9 (13.2%)	*EER and EIR*	1 (1.5%)
Sales and rents	7 (10.3%)	Intervention - EPC presentation	68
Context - price type	68	*Band*	46 (67.6%)
Transaction price	29 (42.6%)	*Score*	2 (2.9%)
Listing price	35 (51.5%)	*Band and score*	6 (8.8%)
Appraisal price	3 (4.4%)	*Energy Performance Index (EPI)*	13 (19.1%)
Transaction and listing price	1 (1.5%)	*Band and EPI*	1 (1.5%)
Population - dwelling Type	68	Intervention - EPC time	68
House and apartment	38 (55.9%)	*Current*	66 (97.1%)
House	10 (14.7%)	*Current and potential*	2 (2.9%)
Apartment	20 (29.4%)		

Though most studies include all types of housing, a number focus on submarkets in terms of dwelling type. Several studies suggest that the price premium varies by dwelling type (e.g. (McCord, Davis, et al., 2020)). Many studies (n = 20) explore the housing market of only apartments (i.e. multi-family housings) (details in Supplementary material). A smaller number of studies focus merely on houses (i.e. single-family housings, n = 10). Others explore a wide range of submarkets in different models, by separating models for existing/new apartments/houses (Evangelista et al., 2020, 2022).

As noted in the discussion of EPC systems and standards above, EPCs provide a range of information on energy efficiency which might be thought to influence prices and hence be used in models. First, different aspects of EPC include: the EER reflecting relative energy costs; and the EIR, reflecting relative emissions. Every study but one used the cost-based measure (EER) rather than the EIR measure of environmental impacts; the exception used both EER and EIR (de La Paz et al., 2019). Secondly, as introduced previously, there are different EPC presentation forms which could potentially affect residents' perceptions. While continuous scores provide more detailed information on energy efficiency, bands offer an aggregated judgement and would produce threshold effect in price premium (more discussion in Section 4.4.2) (Aydin et al., 2020). Most use the EPC bands but two models used scores while six report results for both, and 13 use only the EPI. By simply sorting the results according to countries, there is a sign that studies in each country tend to use the same EPC presentation. Specifically, only certain studies in Germany, Sweden, and Netherlands adopt the EPI and only certain studies in the UK use EPC scores, while other studies in these countries and all those in the remaining countries use EPC bands. This further suggests that, among those countries where EPC data is available, there exist obstacles to comparative analysis as the EPC presentation provided in data is different though it may be possible to transform EPC presentation based on given reference e.g. band to score transformation. Thirdly, concerning EPC time, two studies use information on the potential ratings of properties (Hårsman et al., 2016; McCord, Lo, et al., 2020).

4.4.1.3 Research design and sample sizes

Table 4.8 summarises information on study designs and sample sizes. Six studies adopted a comparative perspective, comparing price premiums across different geographical regions within the study area (Barreca et al., 2021; Chegut et al., 2020; Dell'Anna et al., 2019; Marmolejo-Duarte & Chen, 2022; Micelli et al., 2024; Morano et al., 2018). While most studies considered the price premium cross-sectionally, eight studies are considered longitudinal studies either for adopting repeated samples or aiming to measure the change of price premium over time with techniques (e.g., pooled regression). For example, (von Platten et al., 2022) explored the relationship between energy efficiency improvements and rent increases in Sweden while (Fuerst et al., 2015; Fuerst, McAllister, et al., 2016) studied the impact of energy efficiency ratings on price change in England/Wales using repeated sales transactions from 1995 to 2012 and 2003 to 2014 respectively. (Chegut et al., 2020) applied separate regressions on the same appraised rental properties in different years (2012 and 2015 in England; 2010 and 2015 in Netherlands), exploring the change of relationship between energy efficiency rating and appraisal prices over time. (Marmolejo-Duarte & Chen, 2019a) included an interaction term between year and EPC rating with spatial pooled regression to assess whether any price premium changed from 2014 to 2016 in Spain. By including sales data before the implementation of EPC, researchers compare the "post-label" and "pre-label" model to see if the impact of energy efficiency was already priced in before the display of EPCs in Norway, using fixed-effects models on repeated observations (J. Olaussen et al., 2019; J. O. Olaussen et al., 2021). Some studies use repeated samples only for robustness check alongside the estimate using all samples (e.g. (Aydin et al., 2020)) and are thus not included as longitudinal study.

While most studies adopt property-level data as the analytical unit, (Koengkan & Fuinhas, 2022) undertook the study at the aggregated level of municipalities in the Portuguese real estate market. This exploration is meaningful for supporting large-scale housing renovations (e.g., municipality level). Though most studies are interested in buyers/tenants' WTP, a few others utilise appraisal price to explore the attitude of real estate agents on energy efficiency (Table 4.7) (Cajias & Piazolo, 2012; Chegut et al., 2020; J. O. Olaussen et al., 2021) as this may play an important role in housing market price formation.

Table 4.8 Summary statistics for research design and sample size.

Characteristics	n	Characteristics	n
Comparative/non-comparative	68	Sample Size (number of properties)	68
Non-comparative	62 (91.2%)	*<= 1,000*	10 (14.7%)
Comparative	6 (8.8%)	*1,001 - 10,000*	25 (36.8%)
Cross-sectional/Longitudinal	68	*10,001 - 100,000*	17 (25.0%)
Cross-sectional	60 (88.2%)	*100,001 - 1,000,000*	11 (16.2%)
Longitudinal	8 (11.8%)	*> 1,000,000*	4 (5.9%)
		Not applicable	1 (1.5%)

Note: One study apply data at aggregated municipality-level (Koengkan & Fuinhas, 2022) and record as "Not applicable" in the "Sample Size" category.

Sample sizes vary across a large range from less than one thousand to more than one million. Table 8 shows that most studies have sample size of 10^3-10^4, followed by sample sizes of 10^4-10^5, <10^3 and 10^5-10^6. Few studies have a sample over one million, all of which are conducted at national level in the UK (Sejas-Portillo et al., 2025), Portugal (Evangelista et al., 2022) and Germany (Cajias et al., 2019; Sieger, 2024).

4.4.2 Research methods

4.4.2.1 Analytical models

In the field of estimating price premiums for housing attributes, hedonic regression (Rosen, 1974) is a technique being widely used, where house price is the dependent variable and attributes influencing buyers' utility are independent variables. Based on the hedonic framework, specification of the functional form varies, as well as estimation methods (including parametric, semi-parametric and non-parametric estimations) (Owusu-Ansah, 2013; Taylor, 2008). In addition, some scholars use techniques out of hedonic regression to identify the price premium. In this review, we define those models regressing house price on housing attributes as hedonic regression. All analytical models found are summarised in Table 4.9.

Table 4.9 Summary statistics for analytical models.

Analytical model		n = 111
Linear regression (LR)		68 (61.3%)
Spatial regression (SR)	Spatial Lag Model (SLM)	4 (3.6%)
	Spatial Error Model (SEM)	7 (6.3%)
	Geographically Weighted Regression (GWR)	3 (2.7%)
	Spatial Autoregressive Model (SAR)	3 (2.7%)
Extensions of linear correlation	Quantile Regression (QR)	13 (11.7%)
	Regression Discontinuity Design (RDD)	2 (1.8%)
	Multilevel Regression (MLR)	2 (1.8%)
	Evolutionary Polynomial Regression (EPR)	4 (3.6%)
Generalised Linear Model (GLM)	Generalised Additive Model (GAM)	2 (1.8%)
	Ordinal Logistic Regression (OLR)*	1 (0.9%)
	Analysis of Variance (ANOVA)*	1 (0.9%)
Machine learning	Random Forest (RF)	1 (0.9%)

Note: *These approaches do not align with hedonic regression.

The most common approach (found in 61.3% of models) is classic linear regression (LR). Most LR use the semi-log model specification (use log transformed house price) with ordinary least squares (OLS) estimation technique. This parametric approach fits well with the purpose of estimating price premium by assuming a uniform percentage increase in price associated with the unitary increase of the housing attributes.

We separate those regression models including spatial interactions as spatial regression (SR). Many scholars apply some form of spatial regression to capture the spatial impacts of price premiums, including Spatial Lag Models (Bisello et al., 2020; Dell'Anna et al., 2019; McCord, Lo, et al., 2020), Spatial Error Models (Barreca et al., 2021; Dell'Anna et al., 2019; Marmolejo-Duarte & Chen, 2019a, 2022), Geographically Weighted Regression (Dell'Anna, 2022; Marmolejo-Duarte & Chen, 2022; McCord, Lo, et al., 2020) and Spatial Autoregressive Models (Bottero et al., 2017; Copiello & Coletto, 2023; Copiello & Donati, 2021). Several studies recommend taking into account spatial effects (Bottero et al., 2017; Copiello & Donati, 2021) and temporal heterogeneity (Bottero et al., 2017; Dell'Anna, 2022). Of these, (Barreca et al., 2021) indicate that local models have better unbiasedness. (Copiello & Donati, 2021) suggest spatial autocorrelation should be considered in models to lessen an overestimation of the price premium.

Various extensions of linear regression are used, most of which are applied to investigate more than a single mean conditional estimate of price premiums. Basic linear regression models adding interaction terms mentioned later could also capture different estimates of the price premium. Firstly, some scholars applied Quantile Regression (QR) to examine the different effects of EPCs across the price spectrum (Cajias & Piazolo, 2012; Evangelista et al., 2022; Koengkan & Fuinhas, 2022; McCord, Haran, et al., 2020; Wilhelmsson, 2019). Secondly, two studies adopted a Regression Discontinuity Design (RDD) approach to measure the threshold effect of EPC ratings (Aydin et al., 2020; Sejas-Portillo et al., 2025). The main idea behind this method is that houses with EPC scores just below the threshold (i.e. each EPC band) are comparable to those just above the threshold, but there might be a sharp discontinuity at the EPC band to estimate the price premium of energy efficiency. This might occur in the context of discussion about regulatory requirements, minimum energy efficiency standards or green mortgage applications, for example. It might also indicate that consumers focus on bands and not on scores, as noted previously. Thirdly, Multilevel Regression (MLR) have been used to correct model bias when a hierarchical structure is assumed to exist in the observational data. Two studies apply MLR, with (Cespedes-Lopez et al., 2022) separating housing/district level in the model and(Khazal & Sønstebø, 2020) applying hierarchical geographical areas. Furthermore, the technique of Evolutionary Polynomial Regression (EPR), a data mining tool to solve feature engineering problems, is used in three studies (Massimo et al., 2022; Morano et al., 2018, 2020) to find the features that could best explain house prices in a concise way. However, this approach uses a genetic algorithm to search for model structures (Giustolisi & Savic, 2009) thus not including all commonly-used independent variables. It maintains the hedonic framework by regressing house prices on housing attributes but offer less interpretability compared to the general hedonic approach.

Generalised linear model (GLM) is applied in several studies. Brounen et al. (Brounen et al., 2020) and Groh et al. (Groh et al., 2022) apply Generalised Additive Models (GAM) to include nonlinear relationships within the model while keeping the hedonic framework. The Analysis of Variance (ANOVA) has been employed in (von Platten et al., 2022), to measure if rent increases with energy performance improvements differ among renovation categories (e.g. no renovation, light renovation, and extensive renovation depending on investment percentage). Other than adopting regression methods with house price as the dependent variable, (McCord, Davis, et al., 2020) use an Ordinal Logistic Regression (OLR) approach taking EPC Band as the dependent variable and property characteristics/house prices as independent variables, determining the price premium by examining if there is increased probability in higher sales price with a higher EPC rating.

While superior in predictive performance, machine learning (ML) techniques' results are difficult to interpret, making them less adopted in the field of estimation of housing attributes' value (Potrawa & Tetereva, 2022). Though not as explicit as coefficient from linear regressions, the interpretability of ML is gaining more attention among scholars to estimate price premium. One study (Ruggeri et al., 2023) applied a non-parametric machine learning technique of Random Forest (RF), using feature importance coefficients to measure the impact of energy ratings on sales prices.

Overall, it is found that all analytical approaches used are regression models of some form. Most studies follow the hedonic regression approach by estimating attribute-specific effects on house prices. While two exceptional cases include the use of ANOVA and OLR, neither approach could generate an isolated price premium. The prevalence of hedonic regression highlights its theoretical robustness and empirical flexibility. By sorting the studies based on the year they were published, we find that classic LR approaches are predominant in earlier years but are less prevalent in later years. Conversely, increasingly sophisticated models such as spatial regressions and extensions of linear regression are gaining prevalence over time. Regression with advanced machine learning methods first appear in this field in 2023.

4.4.2.2 Variables

To give a causal interpretation of the parameter estimate, models should control for all variables correlated with energy efficiency and house prices (Taylor, 2008) though of course this is never possible in practice. The set of characteristics determining house prices generally fall into three categories: structural, neighbourhood-related, and locational attributes (Chin & Chau, 2003). We summarise the variables found in studies and group them into those three categories plus temporal variables (Table 4.10). While structural variables control for features of the individual property, neighbourhood-related variables control for those of the neighbourhood context. The remaining two categories typically include dummy variables for geography and time, controlling for which could get rid of variations between properties in terms of geography and time and thus improve the performance of models. Here we only include the fixed geographical attributes (i.e., the sub-area with respect to the whole study area) in the locational category, while some attributes related to location e.g., accessibility are grouped into the neighbourhood-related category. Spatial effects are also included in the locational category, which includes spatial heterogeneity and spatial dependence (Florax & Nijkamp, 2003), accounting for which contributes to spatial regression models.

Table 4.10 Summarised core set of included variables.

Category	Variables
Structural	EPC (variable of interest)
	Property size
	Dwelling type
	Building age
	Number of rooms, bedrooms, bathrooms
	Number of floors*
	Built-in kitchen, basement, garage, terrace/balcony, garden
	Structural quality (e.g., 'luxury'/'good'/'normal'/'simple')
	Building services (e.g., parking, lift, air conditioning, etc.)
	Facilities (e.g., swimming pool, gym, etc.)
	Heating type (e.g., gas, central heating, etc.)
Neighbourhood-related	Accessibility (e.g., distance to CBD/highway/subway/park/sea, etc.)
	Socio-economic characteristics (e.g., population density, income level, unemployment rate, etc.)
Locational	Geographical location (e.g., district, postal town, latitude and longitude, etc.)
	Spatial effects
Temporal	Time-period of transaction (e.g., year, quarter, etc.)

Note: * means the variable is only considered as a feature of an apartment.

We summarise the inclusion of variables in each model in Table 4.10, by further separating "Quality variable" from the "Structural variable" category and "Spatial effects" from the "Location" category. The dwelling's structural quality (e.g., "luxury"/ "sophisticated"/ "normal"/ "simple") is also referred to as "property condition", "maintenance level", etc. It is considered a significant variable which is likely to correlate with energy efficiency features (Copiello & Donati, 2021; Marmolejo-Duarte & Chen, 2022; Mense, 2018), as investment in improving energy efficiency is likely to be accompanied by investment in aspects such as fittings and fixtures or decoration. Therefore, it is important to control for this variable to generate an unbiased estimate of price premium for energy efficiency. As shown in Table 4.11, nearly all models consider structural variables (99.1%) except for one study applying aggregated-level analysis. In comparison, fewer than half of models include neighbourhood-related variables (45.0%). Results also show that about 78.4% of models include location variables while temporal variables are considered in around 53.2% of models. As introduced previously, 17 out of 111 models apply spatial regressions with spatial effects included. We find that 38.7% of models consider structural quality to some degree.

Table 4.11 Summary statistics for included variables per model.

Model characteristics	n	Model characteristics	n
Structural variable	111	Neighbourhood-related variable	111
Yes	*110 (99.1%)*	*Yes*	*50 (45.0%)*
No	*1 (0.9%)*	*No*	*61 (55.0%)*
Location variable	111	Temporal variable	111
Yes	87 (78.4%)	*Yes*	59 (53.2%)
No	24 (21.6%)	*No*	52 (46.8%)
Spatial effects	111	Quality variable	111
Yes	17 (15.3%)	*Yes*	*43 (38.7%)*
No	94 (84.7%)	*No*	*68 (61.3%)*

Overall, it could be inferred that more than half of models are at high risk of omitted variable bias (OVB) for limited control of housing attributes. OVB is the bias occurs in estimating parameters in regression, appearing when an independent variable related to the dependent variable and one or more of the included independent variables is omitted. On price premium estimation, omitting variables correlated with energy efficiency and house prices would lead to inaccurate estimates. Specifically, omitting variables positively correlated with energy efficiency (e.g. structural quality) would overestimate price premium, while omitting those negatively correlated with energy efficiency results in underestimation.

Among all variables, the quality variable is of particular concern for OVB, which is difficult to measure objectively and precisely (Chin & Chau, 2003). Existing studies including quality variables mostly obtained the variables indirectly from online real-estate listings (e.g., (Cespedes-Lopez et al., 2020; Pommeranz Carolin & Steininger, 2021)), real-estate agent association (Brounen & Kok, 2011; Morano et al., 2018) or real-estate research centre (e.g., (Fregonara et al., 2017)). We further find that these models are highly aggregated in several countries including Italy, Germany, Netherlands, and Spain. Online listings with quality variables are available in Germany (immobilienscout24.de) and Spain (idealista.com), while the agent association in Netherlands (Dutch Association of Realtors) and research centre in Italy (The Real Estate Observatory of the City of Turin) provide relevant data. Traditionally, these variables are mostly measured by real-estate appraisers requiring on-site visits or assigned by sellers (Cespedes-Lopez et al., 2020) which could involve bias. Two studies applied advanced methods (semantic analysis) to extract dwelling quality variable from descriptive text (Marmolejo-Duarte & Chen, 2019b, 2022). The measurements and sources of these quality variables are summarised in Appendix C, Table C-3.

Generally, the availability of housing-related data forms a main obstacle to tackling OVB. Other than obtaining data directly, there exist several techniques to address endogeneity introduced by OVB. One common approach is using an instrumental variable, a variable correlated with the endogenous independent variable (i.e., driver) while independent of the omitted variables. It could be a substitute variable for the driver as it affects the outcome only through its effect on the driver (Ekeland et al., 2004). One study (de La Paz et al., 2019) finds instruments for independent variables in a statistical way (using instruments with higher correlation to the independent variable), choosing EIR Band as the instrumental variable for EER band. The logic is that buyers might not consider emissions when buying or renting a property, while environmental impact (EIR) and energy cost savings (EER) of a property are highly correlated. Another study chooses an instrumental variable for energy efficiency (here EPI) theoretically (Aydin et al., 2020). By assuming the improvement of energy efficiency is the combined result of demand for energy efficient housing and the revision of building codes after the 1973-74 oil crisis, the EPI is instrumented by the logarithm of the oil price two years before the construction of the dwelling. Another way to try to address OVB is adopting longitudinal designs with repeated measures as some quality features remain constant over time (e.g., (Fuerst, McAllister, et al., 2016)). However, it is worth noting that some qualities may have changed along with energy efficiency levels.

Other than including individual variables, some researchers add interaction variables to explore whether EPCs have different effects on house prices depending on other independent variables. Examples include: EPC score and several structural variables (e.g., dwelling age) or spatial autocorrelation of property prices (in spatial lag model) (McCord, Lo, et al., 2020); EPC rating and area type (Taruttis & Weber, 2022), climate area (de La Paz et al., 2019; Mense, 2018), property type (Fuerst et al., 2020), property age (Dell'Anna, 2022; Mense, 2018), sales year (Marmolejo-Duarte & Chen, 2019a), heating type (Mense, 2018), and environmental awareness/purchasing power (Pommeranz Carolin & Steininger, 2021). A similar effect would be achieved by estimating different models for different groups e.g., property types (Evangelista et al., 2020).

Furthermore, to see if any WTP is general to public or specific to groups of buyers rather than others, some studies consider heterogeneity in buyers. Two studies include the household's green attitude in their models (Hårsman et al., 2016; Pommeranz Carolin & Steininger, 2021). In addition, researchers explore households' characteristics by including number of children and elderly of household in the model (Aydin et al., 2020). As buyers' WTP for housing energy efficiency is partly driven by green awareness (could be related to households' demographic characteristics (Vardopoulos et al., 2023), socio-economic status), it is meaningful to consider these variables in the model.

4.4.3 Research outcome

4.4.3.1 Broad findings

We define three types of broad findings summarising from the conclusions of studies: "positive", "no impact" and "depends". No study found that higher energy efficiency leads to lower values. Most studies conclude that energy efficiency has a positive impact on house prices (75.0%; n=51) while twelve (17.6%) found no impact. Five (7.4%) conclude that the price premium depends on different housing market segments (Cerin et al., 2014; Sieger, 2024), the intensity of renovation (von Platten et al., 2022), spatial features (McCord, Lo, et al., 2020) or geographical location (Galvin, 2023b).

Other than the price premium, we take a further step to summarise whether the price premium is growing over time in those longitudinal studies (n=5). Two studies found the price premium increases over time (Chegut et al., 2020; Marmolejo-Duarte & Chen, 2019a) while one suggests no clear growth premium is found (Fuerst et al., 2015). The remaining ones suggest the results are mixed according to intensity of retrofitting (von Platten et al., 2022) and different EPC bands (Fuerst, McAllister, et al., 2016).

4.4.3.2 Price premium

We provide an impression of the scale of the price premium by aggregating results from different models in a form of simple meta-analysis. Following the conditions for model filtering mentioned previously, 38 models (within 28 studies) are included for statistical synthesis.

Figure 4.5 shows the distribution of estimates for the relative price in each band from these 38 models, summarised as a box plot where the central bar represents the median. The mean is also shown in each case. Overall, there is clear evidence of a positive price premium. Relative to Band D, the median coefficients of EER bands are: A (0.061), B (0.045), C (0.014), E (-0.010), F (-0.026), and G (-0.035). In general, the coefficient increases by 0.01-0.03 for each band increase. As house price is log-transformed, the coefficients can be interpreted in terms of house prices percentage change (Owusu-Ansah, 2013). For example, the coefficient is 0.1 means the dependent variable increase by about $e^{0.1} = 1.11$ which is 11% (Clay, 2018). Therefore, the median price premium of EER bands relative to Band D are: A (6.3%), B (4.6%), C (1.4%), E (-1.0%), F (-2.6%), G (-3.4%). Each additional band worth about 1%-3% in price increase. The additional price increase for Band A/B is more substantial than others. This might be caused by OVB where dwelling quality is not included in the model, as homes with Band A/B are likely to be new builds with high quality. It also shows that the estimate of the price premium varies across studies, suggesting the price premium may vary in different housing submarkets (e.g. in terms of geography, time, dwelling types, etc) though there might be sampling variation in studies even given the same population. The varying results could also be caused by different model settings such as the breadth of variables.

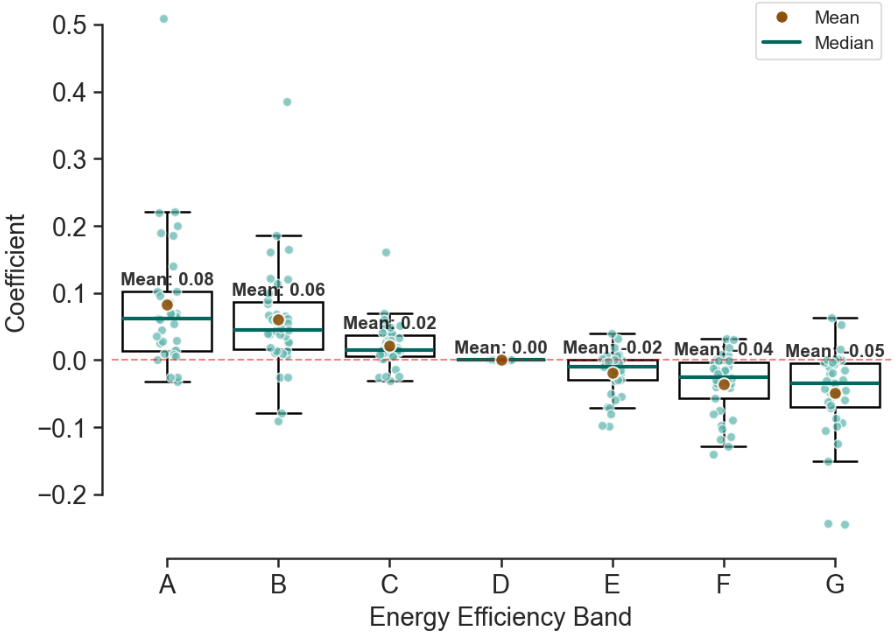


Figure 4.5 Distribution of coefficients of categorical EER bands.

Note: models in 28 studies are used to generate this figure. Models with sales and rents are both included as the hedonic approach estimates the relative impact of the variables, which are comparable in terms of coefficients. All the models have results for EPC C/D/E/F/G, but five models have no information on Band A and coefficients for Band B and Band G are missing in two models. And one model has no information on Band D which is incomparable with other models and cannot be included in the figure.

While the great majority of models are based on bands, three others (from two studies; both in the UK) (Davis et al., 2015; McCord, Lo, et al., 2020) are based on the EER score (scaled 0-100). On average, these models suggest a price premium of 0.25% for each unit improvement on the energy efficiency measure (range 0.1 to 0.4%). In the UK, moving from medium score point of Band D (= 61.5) to Band B (= 86) would represent an increase of 24.5 points, suggesting a price premium of 6.13% (= 24.5*0.25%) which is similar to the previous synthesis.

4.4.3.3 Outcomes in different housing markets

Apart from an overall summary of research outcomes, we are also interested in the variation of research outcomes by submarkets. To explore the geographical differences among outcomes, we group the studies into two broad areas using the EU’s geographical subregions (Publications Office of the European Union, 2015). We contrast the colder and wetter climates of Northern/Western Europe with the warmer and drier climates of Southern Europe. In addition, to investigate if the price premium is increasing over time given people’s awareness of energy efficiency is expected to improve, we split the research outcomes into two groups, depending on whether the data end time is before 2016 or not. This year is chosen for several reasons. First, as mentioned above, it was not until 2015 that all EU countries mandated the listing of EPCs in commercial media. Second, this dividing line ensures a good balance of data between the two groups. Thirdly, the Paris Agreement on climate change entered into force in 2016, which stated the 1.5°C temperature increasing threshold and have drawn people's attention to climate change since then.

First, broad outcomes are compared in terms of geographical regions and time period. In both northern/western and southern subregions, most studies find positive impacts of energy efficiency with a slightly higher proportion in the northern/western subregions (Table 4.12). Similarly, most studies found positive effects but a higher proportion of later ones (Table 4.13). Given relatively small numbers in each case, it is difficult to identify a clear trend here. We further apply the Fisher-Freeman-Halton test (Freeman & Halton, 1951) which is used to find statistical relationship between categorical variables with small sample size in a 2×3 table. The results of test (for geography: $p = .15$; for time: $p = .14$) do not indicate a significant association between geography/time and broad outcomes.

Table 4.12 Contingency table for research outcome and geography.

	'Positive'	'No impact'	'Depends'	Total
Northern/Western Europe	32	6	5	43
Southern Europe	19	6	0	25
Total	51	12	5	68

Table 4.13 Contingency table for research outcome and time.

	'Positive'	'No impact'	'Depends'	Total
After 2016	29	3	3	35
Before 2016	22	9	2	33
Total	51	12	5	68

The coefficients for energy efficiency bands are compared in terms of geographical subregions, time period, dwelling type and tenure (Figure 4.6). Generally, the price premiums in northern/western Europe are similar to those in southern Europe. Considering the time period of the data used, the green premium appears slightly higher before 2016, while the brown discount seems greater after 2016. Also, the price premium for energy efficient houses is greater than that for apartments, including the green premium and brown discount. As for tenure type, we find that dwellings with high energy efficiency e.g. Band A/B are more appreciated in the sales market. Noted the data in many studies suffer from the problem of small sample size since there are limited number of buildings with very high/very low energy efficiency e.g. Band A/G, and the small number of models make definitive statements difficult.

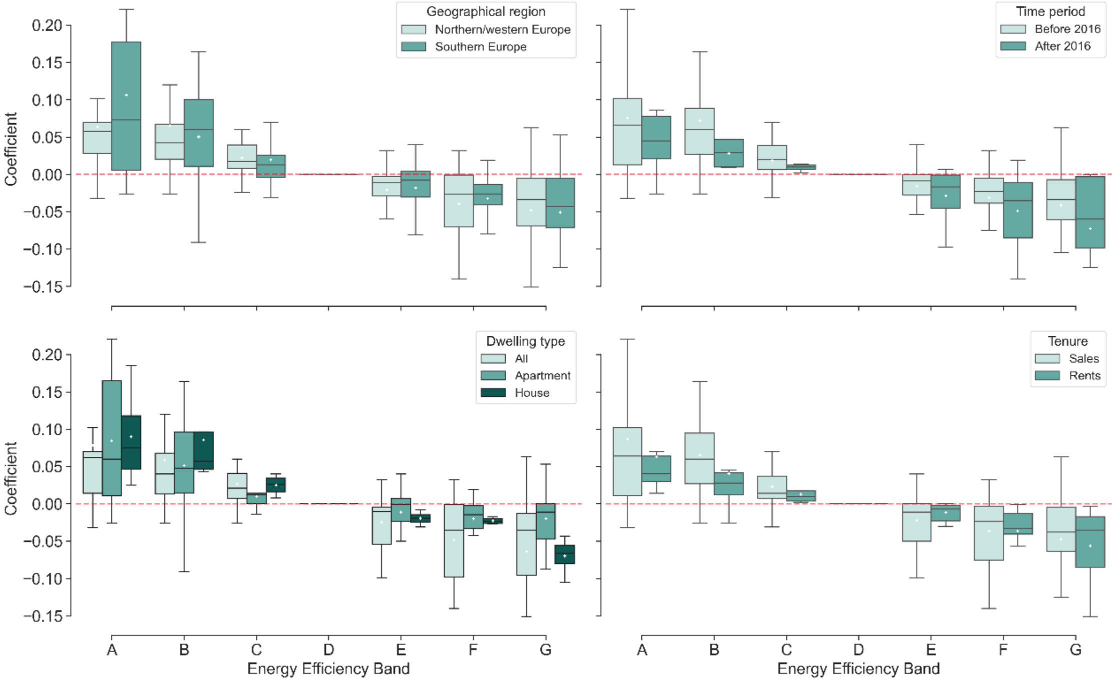


Figure 4.6 Distribution of coefficients of EER bands in different subregions/time period/dwelling types/tenure.

Note: Totally 38 models are used to generate these figures. There are 22 models in northern/western Europe and 16 models in southern/eastern Europe. And 26 models only apply data before 2016, while 12 models include data after 2016. Also, 13 models consider only apartments while 4 focus on the houses and 21 ignore dwelling type. Lastly, there are 30 models for sales market and 8 for rental market.

4.5 Discussion

4.5.1 Discussion of results

In terms of research scope and scale (research question 4.1), we find a relatively modest literature comprising 68 studies over a 14-year period, almost all providing evidence for a single country, for a region comprising 29 countries (pre-Brexit EU plus Norway). There are signs that the pace of publication is picking up but studies remain geographically concentrated. The lack of evidence from countries in central and eastern Europe is of particular concern. If we are to see the development of a more substantial European evidence base to support the net-zero target for housing, much more needs to be done at EU level to mandate the provision of open access to property-level EPC data. Researchers will also need access to other linkable property-level data on house prices and property characteristics. Ethical concerns could be one of the main barriers to open access property-level data, which ties to specific properties and may indirectly disclose residents' information. Open EPC data could potentially reveal residents' energy usage and socioeconomic status. While restricted access prioritises privacy concerns, open access supports climate goals, market competitiveness, and social equity. Therefore, to promote the open access of EPC and other property-level data, governments should invest in data governance and protection regulations to protect privacy and responsible use of information.

Regarding study designs and methods (research question 4.2), we find a great deal of variety, although variations on hedonic regression form the core, reflecting its widely accepted theoretical base and high interpretability of models. We find the model sophistication increases over time, with classic linear regression becoming less common while spatial regression and extensions of linear regression become more popular. Having had a period of experimentation with different approaches, however, it would be helpful to have multiple national studies conducted on a consistent basis, providing greater comparability into the state of attitudes to energy efficiency in each country.

With most studies using the hedonic model, OVB is a major methodological limitation leading to inaccurate estimate of price premium. Again, this is mainly a result of limited availability of property-level data. Several studies tried to tackle OVB by using longitudinal study designs or instrumental variable approaches. However, the former could incur selection bias as properties that sell more than once may not be representative of the whole housing stock (Melser, 2023). On both studies including instrumental variable, their choice of variables may not be effective. While the variable of oil price two years before the construction of the dwelling (Aydin et al., 2020) is not necessarily related to housing energy efficiency, the variable of EIR could have a direct impact on house prices. The direct way to address OVB is to include the omitted variable in the model if it is observable and measurable. On estimating the price premium of energy efficiency, potential omitted variables which are possibly correlated with both energy efficiency and house prices include building age, dwelling quality, etc. Dwelling quality is perhaps the critical challenge as it is usually hard to measure but also likely to be correlated with energy efficiency: people making improvements in energy efficiency are likely to make other functional and cosmetic improvements at the same time.

On the research question 4.3, the overwhelming majority report a positive effect overall and, for the group where more direct comparisons were possible, a clear gradient across the bands exists. These suggest a market preference for more energy-efficient homes. Although we noted risks of OVB in some models, we focus on median values on results synthesis to minimise the reporting bias. Comparing to the results of an earlier meta-analysis (Cespedes-Lopez et al., 2019), this review finds a smaller effect size for both green premium and brown discount. In terms of applying more systematic searching process and including up to date studies, this review represents an important addition to this field. It is worth noting that although the percentage premium remains the same, in contexts with high house price inflation (e.g., in the UK) the absolute value of the premium would likely be increasing faster than other prices. Presumably this means it is also increasing relative to the cost of improvements. It is also noted that this review mainly focuses on the cost-based EER rating (only one study is found to include EIR rating), where the carbon impact of heating sources is not priced. If the market continues to emphasise the EER rating, unit cost of heating sources would need to be adjusted to reflect their carbon impact to better suit the net-zero goals.

The geographical coverage of included studies could introduce bias in research findings especially price premium. Included studies are highly concentrated in western, southern, and northern Europe, while missing in central and eastern Europe. As socioeconomic and housing market conditions are significantly different between European countries/regions, the findings of this review could skew towards specific conditions. Additionally, the sample size and time span of data used in each study could affect the robustness of price premium findings. Increasing sample size could increase the precision of effect size estimation (Egger et al., 1997) and longer time span would improve the robustness and generalisability of results. All these factors should be noted when discussing the price premium findings.

That said, we do not find much variation between northern/western and southern European countries despite very different climates. This could be due to the fact that a good EPC rating is important in both regions for either winter heating or summer cooling. Nor did we find evidence that the gradient is increasing over time. Although our conclusions here are limited by the small scale of the literature, this last finding is particularly concerning. Despite the increasing awareness of environmental issues and rising energy costs, there is no clear trend of increasing price premium. This indicates that continuing efforts are needed to improve residents' awareness and EPCs' effectiveness. This could also be the result of more government support, lower investment cost due to technology advancements, and that studies are applying more robust data/models, etc. Among the several longitudinal studies investigating whether the price premium changes over time, the results are also mixed. Given these studies are limited in quantity and not up-to-date, future research should make further efforts to explore impact of EPCs on price change.

We do find that the price premium varies between rental/sales markets as well as apartments/houses markets. The finding of a price premium for both sales and rents is important in the context of debates about the 'split incentive' in the rental market. The argument made by some is that landlords do not have the same incentive to carry out energy efficiency improvements since the benefits of lower running costs are enjoyed by the tenant while the landlord carries the investment costs (Weber & Wolff, 2018). This review suggests that at least some of the reduction in running costs can be captured in rent while the landlord will presumably also enjoy the same capital gain as others when they come to sell. A recent analysis of energy efficiency levels in the UK found that landlords did not in fact tend to own less efficient properties, once basic property characteristics were taken into account (Buyuklieva et al., 2024).

As mentioned previously, the reliability of EPCs is a concerning issue. In the long term, people's WTP for energy efficiency depends on whether homes with better EPC actually bring energy savings and better living conditions. The overall market incentive would be more effective with better EPC systems. Therefore, it remains fundamental to improve the methodology/quality of EPCs to make it a useful facilitator in housing decarbonisation.

Other than environmental awareness, the mechanism of price premium is influenced by energy cost savings (Fuerst, Oikarinen, et al., 2016; Galvin, 2023b; Sieger, 2024) and the cost of retrofitting (Galvin, 2023b) as well as other financial benefits. The ongoing energy crisis in Europe could influence consumers' WTP as the potential energy cost savings becomes more attractive. However, the fact that only two studies found in this review cover data after 2022 makes it difficult to draw conclusions here. This calls for future researchers to apply price premium analysis on more recent data and explore changes in WTP. Furthermore, mortgage lenders are increasingly recognising the value of energy-efficient homes, which can lead to better financing options for consumers, thereby raising benefits of purchasing energy-efficient properties.

The finding of a positive price premium could raise broader concerns in terms of the ultimate realisation of housing stock decarbonisation. On the positive side, the premium could encourage homeowners and builders who can afford the investment to prioritise energy efficiency. This could be further supported by policies offering tax incentives (BPIE (Buildings Performance Institute Europe), 2021) and other financial benefits to promote energy-efficient investments. However, there are also disadvantages to consider. Lower-income households and tenants may be pushed towards less efficient homes and might not have the financial means to cover retrofitting costs. In addition, the ongoing housing and cost of living crises in many countries make it challenging to rely solely on market incentives to achieve decarbonisation. Government support such as subsidies should therefore be complementary measures to reach the net-zero goals. Furthermore, the price premium should be weighed against the potential carbon savings to ensure that energy-efficient homes contribute effectively to net-zero goals.

Some other interesting findings from the literature point towards additional future areas of work on the wider housing market impacts of energy efficiency. (Bisello et al., 2020) suggested the presence of a spillover effect to nearby properties from retrofitting investment. However, no study examined whether there might be more general spillover effects of housing energy efficiency. Also, (Copiello & Donati, 2021) suggested comparing the price premium with the cost of energy efficiency investments, which could aid interpretation of the strength of the market signal which the price premium provides. Researchers are also concerned about the so-called rebound effect of price premium for energy efficiency (Galvin, 2023a), where households with more energy efficient homes overconsume heating energy while those living in energy inefficient homes use less energy to save money (Galvin, 2023a).

As data availability and OVB are both found to be major limitations, using new forms of data and methods could make important improvement. New data such as listings text/images would be easily accessible given permission from owner, and include rich information about property quality and features such as location, decoration, facilities, etc. It may be possible to obtain measures of the traditionally hard-to-measure variable of dwelling quality, potentially reducing problems of OVB. While hedonic regression can only include structured data, machine learning (ML) and deep learning (DL) methods are widely used to process unstructured data e.g. text/images. Therefore, price premium modelling could start from using ML/DL to extract attributes from text/images, followed by inclusion of attributes in the hedonic regression. Alternatively, both structured and unstructured data could be put in a ML/DL model to estimate house price in one attempt. However, this approach could not give an estimate of price premium, but only feature importance values e.g. ‘SHapley Additive exPlanations’ (SHAP) values. This again highlights the importance of the hedonic regression in this field with its high interpretability.

4.5.2 Limitations

There are several limitations of this review. An important one is stated clearly from the outset: that we only include English-language studies in the review, mainly due to shortage of time and resources. This limitation should be noted when discussing the findings, especially on geographical coverage of studies. Though we conclude that a group of countries have a research gap, there are very likely studies published in other languages missing from this review. Important work also exists in the grey literature which we have not tried to cover for the same reasons. Nonetheless, we develop a comprehensive, systematic, and innovative searching approach as well as quality-control screening approach, to allow reproducibility of results and minimise bias in findings. In addition to language limitation, access to EPC data (Aleksandra et al., 2014) appears to be a very significant influence on the geographic coverage of the literature which puts our limitations in context, limiting the applicability of findings across Europe.

Further limitation concerns the trustworthiness of research outcomes (especially price premium synthesis) related to quality of research, which are not controlled for in this review. We try to ensure a minimum standard of studies by limiting the search to articles which have appeared in peer-reviewed journals. Even so, studies may still vary in relation to the scale and quality of data, as well as research design and other features. Frameworks have been proposed for assessing the quality of studies on the basis of these features (Gorard, 2024), but we have not applied them here, partly because of the relatively small scale of the literature and partly because of the limitations of time.

4.5.3 Research gaps

In addition to the general comment about the restricted geographical coverage of the current literature, we identify the following knowledge gaps:

(1) Towards new forms of data and methods

To tackle the methodological limitations of OVB and obtain a more accurate estimate of the price premium, prospective research could either extract features from new forms of data (e.g. unstructured images/texts data) to include in the hedonic approach or apply advanced methods (e.g. ML/DL) directly to measure price premium accounting for these features.

(2) Towards sub-market studies

To fit with and inform housing policies on different submarkets (e.g. dwelling types, tenures, geography, years, group of buyers, etc.), it is recommended that future studies look at the impact on submarkets and tailored the research question and method to the specific setting of the submarket.

(3) Towards wider housing market impact of energy efficiency

Upon exploring WTP for housing energy efficiency, it would be valuable to look at wider housing market impact for example the comparison of price premium across multiple countries, the spillover effect of energy efficient dwellings, the cost premium of energy efficiency investments, tenants' energy cost savings, etc. This would help policy makers to form a more comprehensive understanding of incentives, obstacles, and impact of housing energy efficiency.

Additionally, we have following comments for future conduct of scoping and systematic review in the same area of interest. To address the limitations of this review, future scoping review could improve in: (1) incorporate multilingual searching strategies, (2) include wider types of sources of evidence. Future systematic reviews are needed to provide more robust result synthesis. For quality control on included studies, we recommend systematic reviews to assess the risk of OVB in regression models. We find the primary research in this area is the impact of current EER bands on sales prices considering all dwelling types and using hedonic regression methods, which can be considered as the focus of a systematic review.

4.6 Conclusions and policy implications

In conclusion, this scoping review provides an overall picture of the European literature studying price premium of EPCs, from research scope/scale to methods applied and research outcomes. This review is the first to apply a transparent, systematic searching and screening process to the academic literature in English. Drawing upon 68 studies reporting 111 models, this review highlights several major findings among the many. First, the studies are geographically concentrated in limited number of countries in western, northern, and southern Europe. Additionally, we find hedonic models are predominant in this field with more sophisticated models gaining popularity. Two modelling challenges are identified, including data availability and OVB. Beyond EPC data, there is a lack of comprehensive property-level data, leading to the methodological challenge of OVB, rendering difficulties in isolating the impact of energy efficiency. Finally, this review confirms the presence of a positive price premium associated with higher EPC ratings with each additional EPC band worth about 1%-3% in house price increase, suggesting market preference for energy efficient homes. It also finds varying price premium across different sub-markets but no evidence of an increase over time.

For policy makers, the following recommendations need to be considered to support market incentives for housing energy efficiency improvements. First, there is a clear call for the EPBD/governments to accelerate open access to property-level EPC data across EU. It is especially important for EPBD to mandate the open access of EPC data in central and eastern Europe. Harmonisation of the data system would also enable cross-country price premium analyses. It remains crucial for EU regulations to promote other property-level data availability. Second, the market preference for energy efficiency encourages wider implementation of EPBD as well as the promotion of equivalent measures in other dominant economic areas such as the US and China. Furthermore, it is important for governments to acknowledge difference in market incentives between housing submarkets and to adopt submarket-specific policies. Tailoring policies for submarkets would address market-specific barriers and allow wider adoption and greater equity. Specifically, findings from this review suggests flats and rental markets should be given priority in government support.

4.7 Summary and reflection

After its publication in the Energy and Buildings journal, the paper has gain 13 citations at the time of thesis submission. Most of the citing papers (seven papers) are exactly examining price premiums of energy efficiency labels, with one PhD thesis on meta-analysis building largely on the literature inventory from this scoping review (Benyák, 2025). A few other citing papers focus on related topics such as energy efficiency evaluation method (Kaczmarczyk, 2025), drivers of energy efficiency (C. Zhang et al., 2026), and housing decarbonisation policies (Anastasiadou et al., 2026; Duraković, 2026; García-Lamarca, 2026; MAKAREVIČIENĖ et al., 2025). In reflection, the transparent and systematic approach taken in this paper to identify and screen papers with the public available data sources have largely facilitated future review studies. Also, the comprehensive and rigor analysis provides solid conclusions for reference in both price premium analysis and wider literature.

Chapter 5 Methodology overview

5.1 Study area and scope

The empirical analyses of this thesis explicitly focus on the second-hand house sales market in Greater Manchester, UK.

5.1.1 An overview of Greater Manchester

This study focuses on the housing market of Greater Manchester (GM), the second largest metropolitan region in the UK. The focus on one metropolitan area over a few years is a common practice in hedonic price studies to align with the law of one price function, as introduced in Chapter 3. Within metropolitan areas, the physical and financial costs of moving are generally similar, while social and psychological moving costs tend to be lower as such moves often enable households to preserve social, familial and neighbourhood connections (Bishop et al., 2020). Also, economic conditions will be the same as it is a single labour market area. Consequently, limiting moving costs and similar economic conditions within a single metropolitan area supports the applicability of the law of one price function, improving the internal validity of the hedonic model. Nevertheless, it is recognised that the focus on a single city-region could potentially limit generalisability of results.

Greater Manchester (GM) is the second largest metropolitan region in the UK, located in the northwest of England with central coordinates of approximately 53°29’ N and 2°14’ W. As is shown in Figure 5.1, it is a highly urbanised, interconnected area covering 1,276 km^2, comprising ten local authorities including Bolton, Bury, Manchester, Oldham, Rochdale, Salford, Stockport, Tameside, Trafford, and Wigan as well as an upper tier level of governance, Greater Manchester, with a directly-elected mayor. The main transport network is a circular radial network, which focuses on radial routes connecting Manchester city centre to multiple town centres and circular connections to improve orbital travel around the city region.

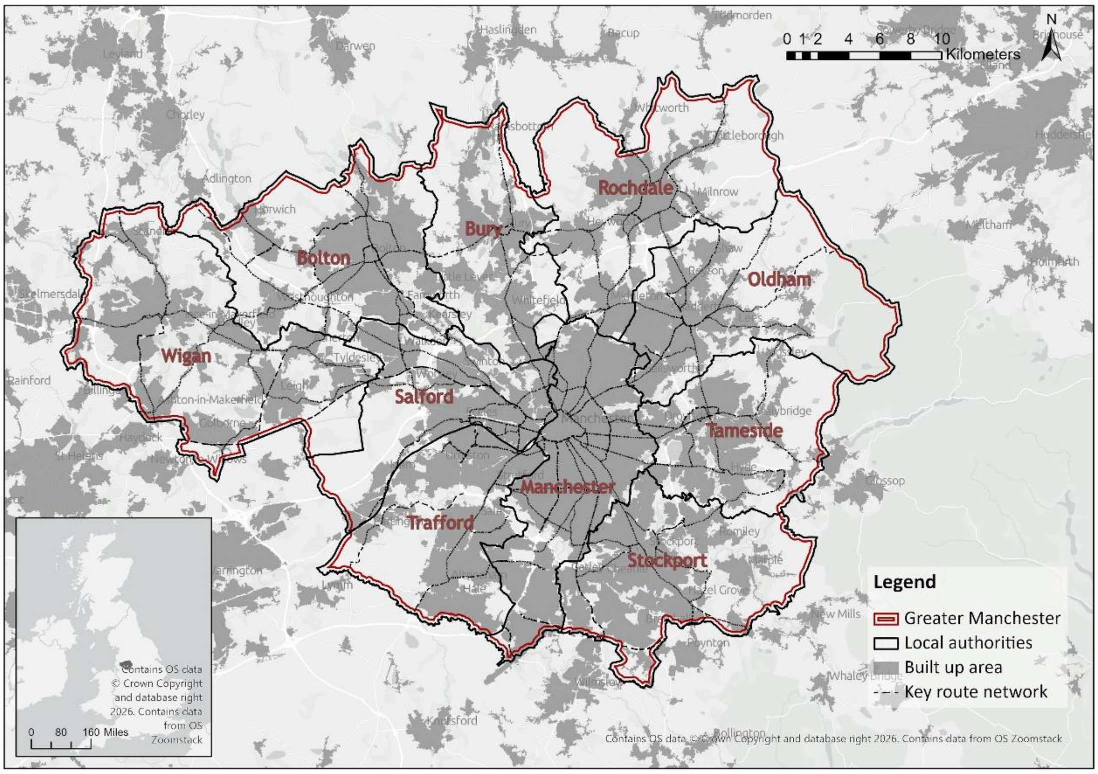


Figure 5.1 Greater Manchester in the regional context.

Source: Author's compilation based on data from Great Britain built up area (Ordnance Survey, 2026) and GM key route network (Transport for Greater Manchester, 2025).

According to the 2021 Census, Greater Manchester's resident population was 2.8 million in 2021, with an average age of 38.2 years in 2024 (ONS, 2024c). The population density was 2360/km² in 2024, which was among the most densely populated metropolitan areas in Europe (Eurostat, 2024b). Economically, Greater Manchester has been at the forefront of the UK economy since the industrial revolution. It is currently the largest city region economy outside London with a gross value added of close to £75 billion (GMCA, 2025). The region hosts several world-leading businesses and exhibits strong activity across key sectors, including advanced manufacturing, health innovation, clean growth, and the creative, digital, and technology industries (GOV.UK, 2023a).

5.1.2 Housing in GM

According to the 2021 Census, GM contained nearly 1.2 million households. Among all households, 58% were owner-occupied while private rented and social rented households each accounted for 21% (ONS, 2023a). The owner-occupied percentage is slightly lower than England and Wales as a whole and social renting slightly higher (Office for National Statistics, 2023). The tenure patterns vary substantially across local authorities: Manchester recorded the lowest proportion of owner-occupied households (37%) and the highest share of private rentals (32%), whereas Stockport (71% owner-occupied; 14% private rented) and Trafford (69%; 15%) showed the opposite pattern (GOV.UK, 2024c).

In terms of housing stock, GM was estimated to contain approximately 1.29 million dwellings in 2024. Of all dwellings, 80% are houses while flats comprise 16% of them (ONS, 2023a); the house share is slightly higher than the England as a whole (Office for National Statistics, 2023). Furthermore, annual rates of new building are relatively low so the majority of buildings are older (GOV.UK, 2026b).

5.1.3 Study scope

Given the diversity of tenure structures and dwelling types across the GM housing stock as well as the potential differences in EPC market incentives/regulations in different segments (as introduced in Chapter 2), this study focuses on a more concentrated and dominant market segment, which is the existing or second-hand house sales market, to ensure analytical consistency in examining energy efficiency-related price premiums. This study focuses on houses rather than flats partly because of the issues with linkage of address-based data with flats (Chi et al., 2022) and partly because the price premium for houses is generally found to be greater than for flats from the previous scoping review (Chapter 4).

Though we avoid variations in economic circumstances which impact on prices by focussing on a single metropolitan region, there may still have submarkets within GM (the definition of submarket can be found in Section 3.3.2.3). These submarkets may exhibit differing market behaviours and potentially varying energy efficiency price premiums. One key source of differentiation is property type: among houses in GM, 17.5% are detached, 47.5% are semi-detached, and 36.25% are terraced (ONS, 2023a). These housing types differ in their building envelopes, particularly in wall exposure, which can lead to variations in energy performance (ONS, 2023b). Housing market values also display substantial spatial variation, with the average house price in GM at approximately £241,000, peaking in Trafford (£377,000) and Stockport (£307,000), and reaching their lowest levels in Wigan (£191,000) and Bolton (£200,000) (HM Land Registry, 2026a). Consequently, beyond estimating the average price premium across the second-hand housing market, this study is motivated to examine the heterogeneity of energy-efficiency price premiums across submarkets within the GM second-hand house sales market.

5.2 Data

5.2.1 Data overview

Data collection begins after we define the specific market for this study. In hedonic property value studies, the preferred standard is applying a cross-sectional random sample or ideally, the full population of housing transaction prices along with property characteristics within the defined market (Bishop et al., 2020). The transaction prices reflect revealed market behaviour, which meets the aim of hedonic models to estimate the implicit prices of housing attributes.

Although property transaction price data is available in the study area (Land Registry Price Paid Data as mentioned below), the dataset fails to include the standard UK property identifier, the Unique Property Reference Number (UPRN), which limits its linkage to wider property datasets. This study therefore adopts the property listing price. The main critique of using listing prices in hedonic analysis is that there could be bias as they reflect more of sellers' expectations instead of negotiated sales prices. This may lead to bias in parameter estimates in the hedonic price models (Bishop et al., 2020). For the current study, this would only be a problem if there was a systematic relationship between any bias and energy efficiency. To support the use of listing prices for analysis, we validate the listing prices by comparing them to the transaction prices in a limited period within our study area where we are able to link a subset of the data. We show that listing price is a very reliable indicator of the recorded transaction price (details in the following section 5.3).

Following the preferred standard of hedonic price analysis, this study applies analysis at the unit of properties. We mainly draw on three property level datasets: Zoopla property listings, Price Paid Data from Land Registry, and Energy Performance Certificates. A summary of each is provided below. Other aggregated data sources are also used in this study, mainly to capture neighbourhood or locational characteristics. Further information about all the datasets applied along with data preprocessing procedures are detailed in the following empirical chapters.

5.2.2 Zoopla property listings

Zoopla plc is one of the UK's leading property listings services, providing comprehensive domestic property listings for both rentals and sales. The company provides historical property listing data for the UK back to 2010. The Zoopla dataset includes a wide range of structured property characteristics including location, property type and property size as well as other features, alongside listing prices and the dates for which the listing was live. Additionally, open textual and image fields contain further unstructured information on property attributes and amenities.

The Zoopla dataset is held under licence by the Urban Big Data Centre (UBDC), which is accessible for UK-based non-commercial academic research. Generation 1 of the dataset covers the period 1 January 2010 to 31 December 2021 (Zoopla et al., 2025), while Generation 2 covers listings from the 1 of October 2016 until 2025 at present (Zoopla HomeTrack, 2023). However, the version of the dataset available through UBDC does not include the UPRN which is required for linkage with other property-level datasets. With additional support from Zoopla/Hometrack, this study has been granted access to the dataset with UPRNs included which enables such data linkage.

A key challenge in using listing prices for housing market analysis is about data representativeness including (1) whether listing price reflects the actual transaction price, and (2) whether the listing market represent the broader transaction market. Both points are addressed by data validation in Section 5.3.

5.2.3 Price Paid Data

To validate the Zoopla listing price as a reliable guide to actual transaction price, the Price Paid Data (PPD) from Land Registry (HM Land Registry, 2026b) is used in this study. PPD tracks all property sales in England and Wales submitted to HM

Land Registry for registration from 1995 onwards. The data is licensed under the Open Government License, openly available for both commercial and non-commercial usage. The data provide property transaction prices, property type, freehold/leasehold, existing/new build status, date of transfer, as well as transaction type and address data (HM Land Registry, 2016). However, it contains no further information on property characteristics such as size or energy efficiency rating, nor is there a UPRN included in the dataset, limiting its application in studies requiring linkage to additional datasets.

With a limited period of time (from 1995-2023), however, we obtained a PPD-UPRN dataset covering the PPD data with an estimated UPRN which is openly available in UK Data Service (Chi et al., 2025). This allows us to match with Zoopla listing price and validate the use of listing prices as reliable indicators of transaction prices. The technical validation note is detailed in Section 5.3.

5.2.4 Energy Performance Certificates

The Energy Performance Certificates (EPC) data is published by Department for Levelling Up, Housing & Communities (DLUHC) (OpenDataCommunities, 2026a), including EPCs issued for domestic and non-domestic buildings constructed, sold or let in England and Wales since 1 October 2008. It is an open dataset available for data analysis to enable independent research into energy efficiency issues. As noted above, energy assessors carry out the energy assessment inspections, inputting data to a standard model which creates the EPCs, with additional validation checks ensuring data quality (OpenDataCommunities, 2026b). This study focuses on the domestic EPCs. They offer the UPRN and various property characteristics including energy efficiency ratings, property type, built form, total floor area, building age as well as other features, along with inspection and lodgement dates.

5.3 Validation of Zoopla listing prices

To validate Zoopla listing prices, we adopt a limited period of PPD data with estimated UPRN for linkage and comparison. Here we match Zoopla listing records with PPD registered sales transaction records, with the matched dataset covering Greater Manchester in the period from September 2017 to October 2023.

5.3.1 Data preparation

5.3.1.1 Data preprocessing

The original Zoopla listings data for Greater Manchester with UPRNs cover the period 1 Sept 2017 to 31 May 2024. The PPD-UPRN data cover the period 1 Jan 1995 to 31 Oct 2023. We therefore restrict both datasets to the intersection of these two date ranges, i.e. 1 Sept 2017 to 31 Oct 2023, and to the area of Greater Manchester. For this analysis, we include all property types whereas our own empirical work focuses on house sales. In Section 5.3.3 below, we discuss how matching rates vary by property type.

The initial Zoopla dataset has N=1,007,351 rows for the relevant period. Records are for listings, i.e., occasions where a property is advertised for sale. There are 333,097 unique values for the listing ID. Each listing may have multiple records if details such as asking price are updated during the life of the listing. Listings also include a flag to identify selling status (‘for sale’, ‘under offer’ and ‘sold’). We keep only ‘sold’ listings (N = 327,911). We then de-duplicate leaving N=157,571 records. Lastly, we retain only ‘sold’ listings with a valid UPRN (N=145,181). These cover N=124,380 unique UPRNs. Some properties may have been sold more than once within this period but a small number record an improbably high number of listings (Table 5.1). We retain these for now as they will effectively be removed at the next stage when we match with PPD data.

Table 5.1 Number of UPRNs with N sales listings.

Count of sales listings	Number of UPRNs
1	106,214
2	15,902
3	2,006
4	222
5	30
6	5
7	1

The initial PPD dataset has N=301,530 records for the relevant period. We exclude records which the Land Registry identifies as ‘Type = B’, which covers transfers under a variety of transactions where values are unlikely to represent open market prices (power of sale/repossessions, transfers to non-private individuals and sales where the property type is classed as 'Other', for example). This leaves N=243,610 records. A valid UPRN is available for N=218,029 of these. These cover N=198,522 unique UPRNs. As with the Zoopla listings, some properties are recorded with multiple transactions (Table 5.2).

Table 5.2 Number of UPRNs with N transactions in registered sales.

Count of transactions	Number of UPRNs
1	179,855
2	17,980
3	756
4	39
5	2

5.3.1.2 Time gap analysis

Since a property can be listed or sold more than once, we need criteria to match each listing with its corresponding transaction. To understand the typical time gap between listing end date and transaction date, we use listings that can be linked to only one transaction to analyse the time gap in those cases. We start with the N=106,214 Zoopla listings and the N=179,855 PPD transactions where the UPRN appears only once in each dataset. We join transactions to listings using UPRN, giving N=71,972 records with a match.

Almost one third (32.2%) of these listings have no corresponding transaction. These unmatched listings are much more common in the last six months of our period (Figure 5.2), and this is likely because there can be a gap between a listing being closed and the corresponding transaction being registered. The Zoopla website also states that the transaction record normally occurs within six months of the end of a listing (https://www.zoopla.co.uk/house-prices/).

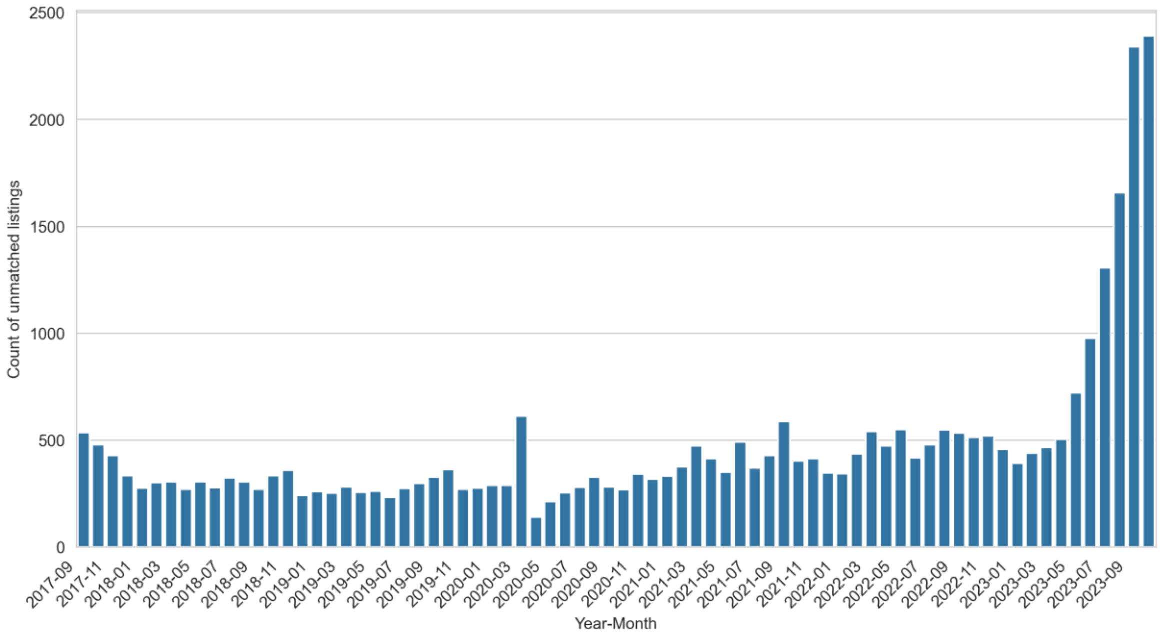


Figure 5.2 Number of unmatched listings by month.

Using the matched records, Figure 5.3 shows the distribution of the time gap (transaction date – listing end date) with and without outliers (left and right panes respectively). It shows that most of the date gap is between -20 to 20 days. A negative gap will occur if listings are kept ‘live’ on Zoopla until the transaction is completed. Combining this information, we use the range [-20, 183] days to determine when a sales listing may be matched with a recorded transaction.

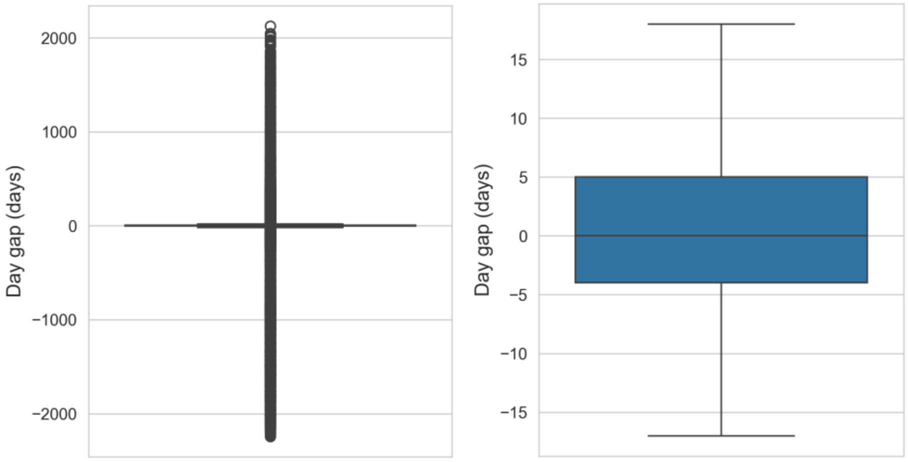


Figure 5.3 Distribution of time gap (transaction date – listing end date) without outliers.

5.3.1.3 Data linkage, matching, and cleaning

The whole data linkage, matching and cleaning process is shown in Figure 5.4. We start with the Zoopla dataset and left-join the PPD data so each Zoopla listing may be linked to more than one potential transaction (a one-to-many join). We then restrict matches to those where the transaction is with the range [-20,183] days of the listing end date. Where one listing has multiple transactions matched to it within this period, we keep the closest time match. And where one transaction matches to multiple listings, we again keep the closest time match.

The matched dataset has 80,519 rows, where each row represents a unique listing with one unique transaction record linked. Of the 145,181 'sold' Zoopla listings with a valid UPRN, we have matched 55.5% to a PPD transaction. Of the 218,029 PPD transactions with a valid UPRN, we have matched 36.9% to a Zoopla listing. Some unmatched listings will have matched with a corresponding transaction which fell outside our study period, and vice versa, so these matching rates should be seen as lower bounds. A small number of properties still appear more than once in this final dataset, indicating repeated sales (Table 5.3). Some unmatched transactions may have had a Zoopla listing but failed to match because one or other address was given the incorrect UPRN, or failed to generate a UPRN. There is considerable uncertainty in the process of converting free-text address information into a UPRN (Chi et al., 2022).

Table 5.3 Number of UPRNs with N observations in matched dataset.

Count of observations	Number of UPRNs
1	72,724
2	3,765
3	87
4	1

The price data cleaning step aims to check and filter abnormal cases, which also needs to be done in any other analysis of price data. First, checking missing data of listing and transaction prices shows there is no missing value in either column. Next, the range of values is checked by making a boxplot, showing there are a few observations with very high prices (greater than £5,000,000) and very low prices (less than £10,000). These do not normally appear at the housing market and are considered as extreme outliers. So, listing/transaction prices greater than £5,000,000 or smaller than £10,000 are dropped (6 cases). The final cleaned dataset of 80,513 rows is used for following analysis.

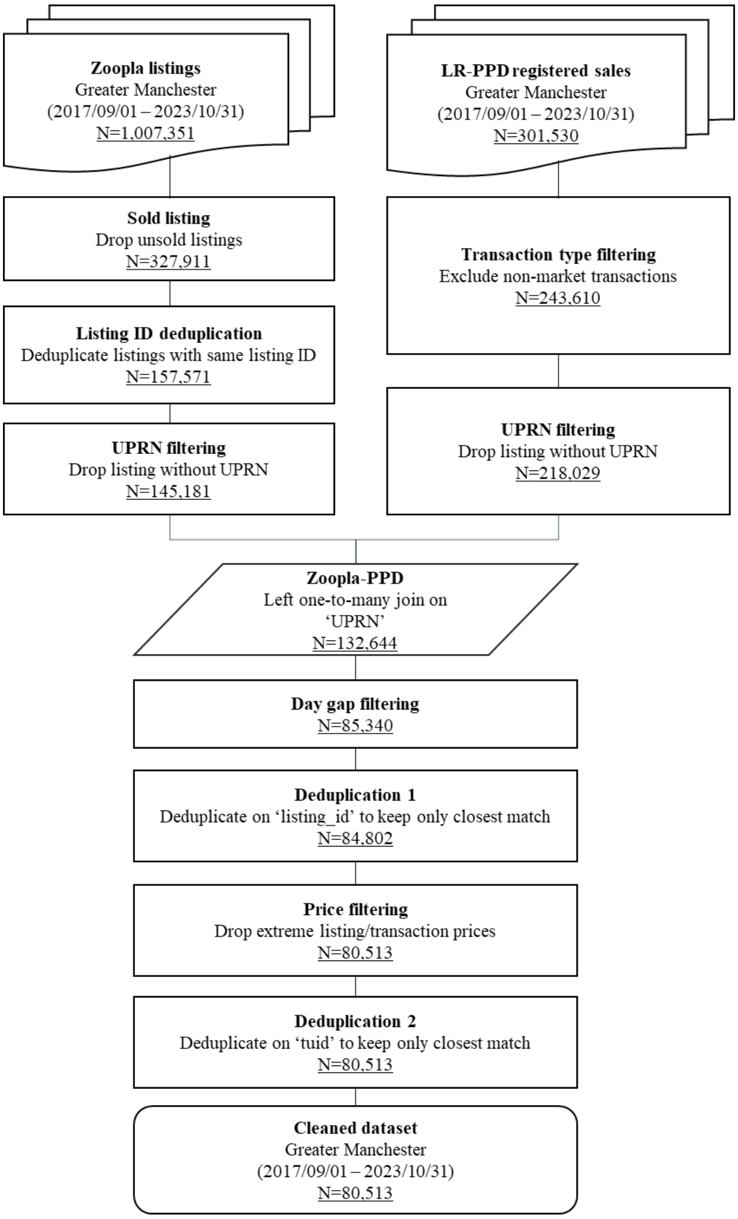


Figure 5.4 Data preparation overview.

5.3.2 Prices comparison

We examine the relationship between the prices recorded in the Zoopla sales listings and those in the corresponding registered sales transaction. The analysis here focuses on the 80,513 matched records. The summary statistics of listing and transaction prices (Table 5.4) shows strong similarities between them. On the distribution of both prices, Figure 5.5 shows while the two prices have similar distribution within interquartile range, the spread of listing prices is slightly greater than for transaction prices.

Table 5.4 Summary statistics of listing and transaction prices (£).

	Listing price	Transaction price
Mean	210,094	209,093
Std	124,066	122,169
Min	15,000	30,000
Median	180,000	180,000
Max	2,795,000	2,700,000

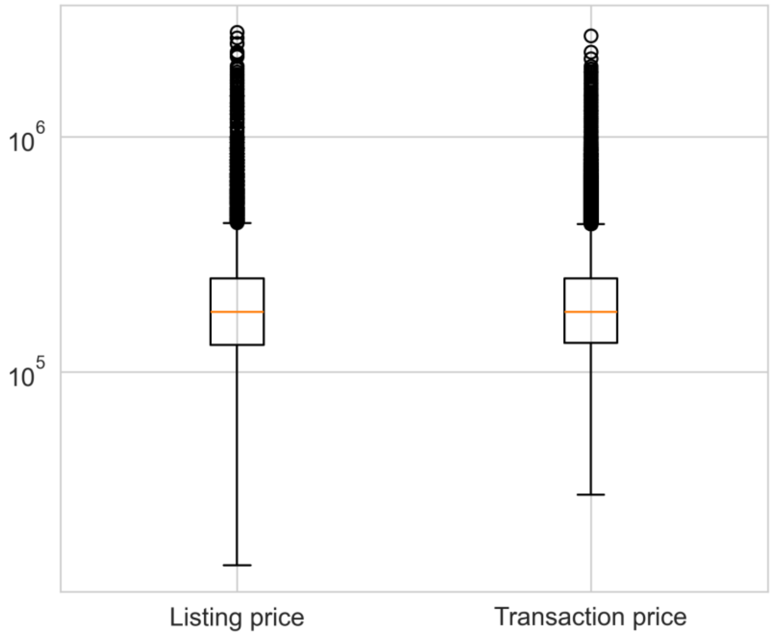


Figure 5.5 Boxplots of listing and transaction prices (£) – log scale.

Figure 5.6 shows the scatterplot between listing and transaction price. On average, listing prices are almost identical to transaction prices: the smoother (lowess) line is very close to the y = x line across the entire range. This suggests that listing prices can be used as a reliable (unbiased) guide to the registered transaction price even if there are likely to be some variations at the individual level. For the most expensive properties, listing prices tend to be a bit above the registered transaction price while for the very cheapest properties, we see the opposite. A very small number of cases have a transaction price much greater than their listing price (points well above the line). Looking at the text description of these listings, we find a significant proportion are properties listed for public auction or shared homeownership. We therefore decide to exclude records above £1.5 million (corresponding to the highest property transaction tax rate in England (GOV.UK, 2026a)) and those identified as for public auction or shared ownership sales. This results in a dataset of 79,273 rows which is used for the remainder of the analysis. For the records where we can link a listing with a registered transaction, listing price is a very strong guide to transaction price. The correlation between (log) listing and (log) transaction price is r = .994 (Pearson correlation coefficient) so listing price would explain 99.8% of the variation in transaction prices in a simple linear model.

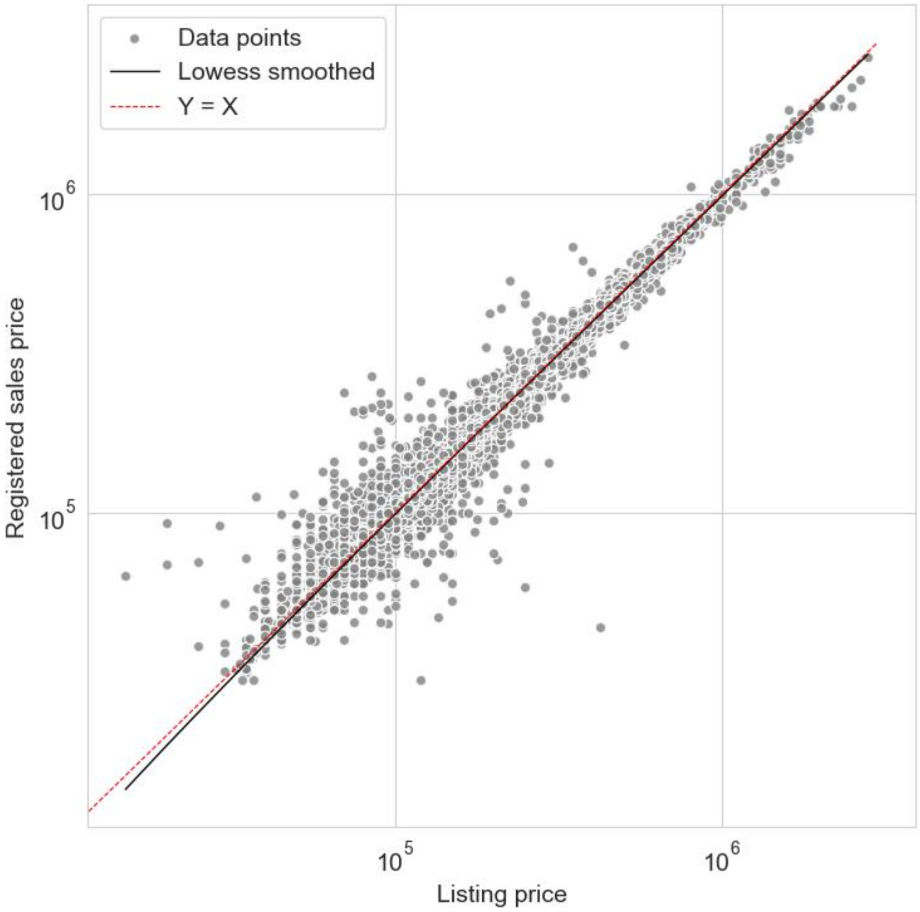


Figure 5.6 Scatterplot of transaction prices vs. listing prices (£) with regression smoother.

Furthermore, two values are calculated to compare listing and transaction price (Table 5.5), the ‘Price difference’ is the absolute difference (listing price minus transaction price), while ‘Price difference percentage’ is the percentage difference (difference as a proportion of the transaction price). The median price difference is zero, and half of the differences are between -1.6% and 3.1%. Two standard deviations above/below the mean (which would correspond to approximately 95% of the sample if price differences were normally distributed) gives a range -11.7% to +13.3%. There are a small number of extreme differences which are likely due to inevitable errors in the matching process. A paired t-test shows the mean difference is statistically significantly different from zero (p-value: 1.51e-175) but the sample is very large. As the Table shows, it is less than 1% on average.

Table 5.5 Summary statistics of price difference.

	Price difference (£)	Price difference percentage (%)
Mean	1140	0.79%
Standard Deviation	11,339	6.26%
Min	-335,000	-76.38%
25%	-3000	-1.57%
Median	0	0.0%
75%	5000	3.12%
Max	381,000	865.90%

Note: N = 79,273 cases.

Table 5.6 reports Pearson correlation coefficients by year of listing. The data include the period of the COVID-19 pandemic when the housing market was disrupted by social distancing measures and the subsequent recovery. Nevertheless, the relationship between listing and transaction prices remains remarkably stable, with the lowest correlation of r = 0.992 in 2022.

Table 5.6 Pearson correlation between listing and transaction prices (logs) by year.

Year of listing	Pearson correlation (r)
2017 (part)	0.994
2018	0.995
2019	0.997
2020	0.994
2021	0.994
2022	0.992
2023 (part)	0.994

Note: N = 79,273 cases.

Overall, the results indicate that, for the records where we obtained a UPRN match, listing price is very highly correlated with transaction price, meaning that we can use listing price as a very reliable guide to transaction price in other analyses.

5.3.3 Data representativeness

To assess representativeness of Zoopla listings on actual transaction market, we explore the matching rates of both listing records and transaction records and investigate how matching rates vary by property type, year and local authorities.

5.3.3.1 Listings records

Here we explore the match rate for Zoopla listings, i.e., the proportion of Zoopla listings which can be matched to an appropriate registered sale transaction. We note above that transactions may not be recorded for up to six months after listings end. In Figure 1 above, we see a notable rise in unmatched listings in the last six months of our date range because the corresponding recorded transaction falls outside this period. We therefore restrict our analysis to the N=127,986 listings which end at least six months before the end of the study period. Of these listings, 60.5% can be matched with a registered sale transaction.

There could be two situations where a listing cannot be matched with a transaction. First, it could indicate that listings have not resulted in a sale. We have filtered out records not identified by Zoopla as ‘sold’ but their information may be inaccurate. Second, we may fail to make a match with the actual transaction record. We failed to put a UPRN on around 10% of PPD transactions but there may also be errors in the identification of UPRNs from the address text on both datasets which lead to missed matches. There may also be missed matches which fall outside the time gap criteria we set.

Match rates are higher for houses than for flats (which includes maisonettes) (Figure 5.7a). This is to be expected given the difficulties in matching flatted properties, reflecting the varied ways in which flat locations can be described (Chi et al., 2022). Match rates are relatively stable across years, with a slight decline in 2022 and 2023 (Figure 5.7b). Manchester and Trafford have slightly lower match rates than other local authorities, at least partly reflecting the higher proportion of flats in these locations (Figure 5.7c).

Figure 5.7 Match rates for listings by housing submarkets.

Note: N = 127,986 listings.

5.3.3.2 Transactions records

To explore match rates for transactions, we restrict the data to transactions at least six months after the start of the study period, following the same logic as previously. Overall, 37.0% of these registered transactions have a corresponding Zoopla listing (N = 80,519). As previously, there are generally two cases when price paid record cannot be matched with a Zoopla listing. First, the transaction may not have been listed on the Zoopla website. Second, it may have been listed but not matched to the relevant transaction because of a failure to identify the correct UPRN on one or another dataset.

Similar to that for listings, match rates on transactions are much lower for flats than for houses (Figure 5.8a). It increases steadily year by year (Figure 5.8b). Manchester, Oldham, and Trafford have much lower match rates than other local authorities, of which Manchester and Trafford suffer from higher proportion of flats while Oldham homes may be underrepresented in Zoopla listings (Figure 5.8c).

Figure 5.8 Match rates for transactions by housing submarkets.

5.3.4 Summary

More than half of Zoopla listings with a UPRN in this period (55.5%) can be matched to a corresponding registered transaction on the PPD. Over one third of registered transactions with a valid UPRN in this period (36.9%) can be matched with a corresponding Zoopla listing. Some unmatched listings may have matched with a corresponding transaction which fell outside our study period, and vice versa, so these matching rates should be seen as lower bounds.

Overall, the listing price appears to be a very reliable indicator of the agreed transaction price. For our sample of matched records, the correlation between listing and transaction price is r=0.994 (using logs for both), and this correlation is very consistent across each of the years 2017-23. Matching rates are lower for flats than for houses due to the challenges of identifying UPRNs for the former. Local authorities with a higher proportion of flats therefore tend to have slightly lower match rates. Otherwise, match rates are fairly consistent over time and across geographies.

The analysis provides strong support for studies using Zoopla sales listings data in analyses of the UK housing market, particularly where the focus is on houses. We do recommend removing the most and least expensive listings (above £1.5m or below £10,000) and those noted to be auctions or shared ownership sales since the differences between listing and transaction prices appear greater in these cases. However, these categories cover only a small fraction of the total (less than 0.1%) so their inclusion is very unlikely to have a material impact on results.

5.4 Analytical methods

5.4.1 Hedonic framework

To estimate the price premium of energy-efficient homes, we adopt the hedonic framework as the methodological framework for empirical modelling. The theoretical foundation of hedonic framework is that the utility of a good is simply the aggregated utility of each of its characteristics (Lancaster, 1966). In the context of housing, it assumes people make home purchase decisions based upon number of bedrooms, number of bathrooms, etc. Accordingly, hedonic model is developed (Rosen, 1974): an item's price is a function of its characteristics:

$$Price = f(X_1, X_2, \dots, X_n)$$

where f represents the envelope regression function which can take various functional forms and $X_1, X_2, \dots, X_n$ represent the characteristics. Importantly, this model can be used to determine the contribution of each characteristic to the total price. Specifically, it can determine how much buyers would pay for a property with an extra unit of a particular housing related characteristic, which is known as the implicit price of a property characteristic. Therefore, the hedonic model is appropriate for this study which aims to estimate the implicit price of housing energy efficiency.

Regression analysis is typically used to estimate the hedonic model. The hedonic housing price model (HPM) generally regresses house price on its structural, neighbourhood, and locational attributes (Chin & Chau, 2003; Taylor, 2008). The outcome variable of house price is often natural logarithm transformed, which is implemented here. The log transformation is applied for several reasons. First, the distribution of house prices is typically right skewed, so logarithmic transformation can move the distribution of the residuals of regression closer to a normal distribution which mitigate heteroskedasticity (Malpezzi, 1999). Second, this introduces a degree of nonlinearity in the house price function which is generally assumed in the equilibrium house price function, improving the estimation accuracy (Kuminoff et al., 2010). Moreover, the log transformation facilitates an economically intuitive interpretation of coefficients for linear parameter models (more details in the following section). Therefore, the hedonic house price model across all models in this work can be written as:

$$\ln(Price_{ij}) = f(S_{ij}, N_j, L_j) + \epsilon_{ij}$$

where $Price_{ij}$ is the observed value of house i in neighbourhood j which is natural log-transformed; S_{ij} is the structural attributes of house i ; N_j is the neighbourhood attributes of neighbourhood j ; L_j represents the locational attributes of the neighbourhood j; and ϵ_{ij} is the error term. The housing energy efficiency is one of the structural attributes to be included in the HPM. The empirical challenge lies in approximating the unknown function f and interpreting estimated coefficients as marginal implicit prices/marginal willingness-to-pay (WTP) under appropriate assumptions.

5.4.2 Estimation methods

5.4.2.1 OLS

The OLS is a parameter estimation method used in linear regression model, which estimates parameters by minimising the sum of the squared differences between the observed outcome and the fitted or estimated outcome. As a foundational linear regression estimation technique, OLS has been widely applied for estimation of a single level, semi-log hedonic model:

$$\ln(Price_{ij}) = \beta_0 + \beta_S X_{ij} + \beta_N N_j + \beta_L L_j + \epsilon_{ij},$$

$$\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$$

where X_{ij}, N_j, L_j are the vectors of structural, neighbourhood, and locational attributes respectively; $\beta_S, \beta_N, \beta_L$ are the vectors of coefficients for these attributes; and the ϵ_{ij} is the error term. The OLS assumes the errors are independent and follow a normal distribution.

As introduced before, the semi-log specification facilitates economically intuitive interpretation of coefficients in linear models. Specifically, coefficients on covariates can be interpreted as approximate percentage changes in price, at least while they are relatively small in absolute size (Jan van Garderen & Shah, 2002). For larger coefficients, the exact percentage change is given by $\exp(\beta) - 1$. Among the empirical analyses in this thesis, coefficients are sufficiently small so that the linear approximation provides an accurate and transparent interpretation.

Notably, the OLS is based on several assumptions (Burton, 2021). The most important ones include, first, that the relationships between the outcome and the independent variables are linear in parameters i.e., linearity. Second, all independent variables are uncorrelated with the error term, which confounding variables/omitted variables can violate i.e., no omitted variables. This relates to the well-known omitted variable bias (OVB) in house green premium studies (see Section 3.3.2.1). Third, error terms of the observations are uncorrelated with each other, violating which is known as autocorrelation. Fourth, the error term has a constant variance i.e., no heteroscedasticity. Moreover, the independent variables are not highly correlated with each other i.e., no multicollinearity.

While OLS is the most prevalent estimation for hedonic models, house prices often violate its assumptions of no autocorrelation and no omitted variables. In terms of autocorrelation, studies generally suggest that autocorrelation is likely to be common in hedonic house price analyses both spatially and temporally (Bishop et al., 2020). Spatially, properties in the same neighbourhood are likely to be more similar and share neighbourhood and locational features (i.e., within-neighbourhood correlation) and nearby properties are likely to affect each other through externalities or spillover effects (i.e., spatial correlation) (Basu & Thibodeau, 1998; Dubin, 1998; Zhao & Shen, 2011). The spillover effects can be at property level (between-property correlation) or neighbourhood level (between-neighbourhood correlation). Regarding omitted variables, given that housing is extremely heterogeneous, there are known to be unobserved variables both at property level and neighbourhood level (i.e., neighbourhood effects) (Osland, 2013). The neighbourhood effects represent unobserved neighbourhood characteristics that affect house prices, which leads to correlation between house prices for individual properties from the same neighbourhood. The existence of omitted variables would influence the estimation of the standard errors of regression coefficients, leading to inaccurate coefficient estimations or statistical significance levels (Rasbash et al., 2000).

5.4.2.2 Multilevel model

Housing data typically have hierarchical structure as properties are nested within neighbourhoods within a city, presenting strong within-neighbourhood correlation and neighbourhood effects which violate assumptions in OLS, as noted above. Though neighbourhood characteristics are typically controlled for in single-level OLS model, there are likely to be omitted neighbourhood characteristics rendering parameter estimates inefficient. In comparison, multilevel regression models (MLM) account for unobserved neighbourhood characteristics as well as within-neighbourhood correlation by allowing for neighbourhood random effects at the upper level, adjusting for autocorrelation within neighbourhoods. MLM has thus been widely applied to hedonic house price studies (Djurdjevic et al., 2008; Glaesener & Caruso, 2015; Jones & Bullen, 1993).

As a multilevel linear regression model, MLM allows for residual components at each level of the nested structure, and is thus able to partition residual variance into between-neighbourhood and within-neighbourhood component (Rasbash et al., 2000). There are a few reasons to use MLM. For this study, the main advantage of using MLM over OLS is that it improves the efficiency of coefficient estimates. Compared to OLS which assumes the error terms are independent, MLM acknowledges the dependence of observations within the same group and treats the observations in different groups differently. It helps to correct for within-neighbourhood correlation among house prices, thus adjusting for standard errors and improving the efficiency of parameter estimates for both property- and neighbourhood-level predictors (Rasbash et al., 2000). More technical details and specification of the MLMs used in this study can be found in Chapter 6.

As with the linear parameter models in OLS regression, the coefficients in MLM can be easily interpreted as implicit prices. Moreover, MLM holds the same assumptions as OLS, and may therefore still suffer from linearity limitations and further autocorrelation/omitted variables problems.

5.4.2.3 Spatial multilevel model

While within-neighbourhood correlation is captured in MLM, further spatial correlation in house prices is ignored in both OLS and MLM models (Xu, 2014). Ignoring potential spatial correlation between neighbourhoods may lead to overstatement of the statistical significance of neighbourhood effects (Chaix et al., 2005). To account for between-neighbourhood correlation, spatial multilevel models have been applied to hedonic house price studies (Habib & Miller, 2008; T. Liu et al., 2020; Soltani et al., 2026). As for attributing spatial correlation between properties, more granular spatial regression models are typically applied such as geographically weighted regression (Cellmer et al., 2020) and spatial lag/spatial error models (Allen et al., 2015). This study however did not apply the spatial models at property level due to computational cost in building a property level spatial weights matrix and estimating the resulting models.

Spatial MLM extend MLM by incorporating spatial autocorrelation between neighbourhoods with a neighbourhood spatial matrix. While MLM assume independence of neighbourhoods, spatial MLM account for the fact that nearby neighbourhoods may be more similar to each other or may influence each other through externalities, potentially improving estimation of random effects.

To examine if there is substantial spatial correlation between neighbourhoods in our data, spatial diagnostics are applied to the neighbourhood random effects modelled from the MLM in Chapter 6. Details are in Appendix D, Figure D-2 but, in summary, while results show that the neighbourhood residuals are significantly spatially correlated, the spatial MLM models do not improve overall fit to any substantial degree as shown in Appendix D, Figure D-1. We therefore focus on the use of MLM as our main theory-driven, parametric model in this study.

5.4.2.4 Causal machine learning and meta-learners

Causal machine learning (ML) refers to methods that estimate treatment effects by quantifying changes in outcome due to interventions (Feuerriegel et al., 2024). Meta-learners are a class of causal ML methods that construct treatment effect estimates by combining outcome prediction models with causal identification logic. First, they are highly flexible methods which can incorporate any ML methods for prediction, offering data-driven methods for predicting outcomes which often require sufficiently large sample sizes. Second, being able to estimate individualised treatment effects, they support the heterogeneity analysis in WTP. Third, with the use of flexible ML methods, it can integrate both structured and unstructured data such as images and texts, offering potential to mitigate the omitted variable bias. Nevertheless, a key challenge in using causal ML approaches including meta-learners lies in model interpretation. Though causal ML provide frameworks to quantify the treatment effects, there is no ground truth for validation hindering trust in informing decision-making.

To draw causal inference, strong data assumptions are needed including those also required in linear parametric regression on (1) unconfoundedness, (2) no autocorrelation, and (3) independent and identically distributed data as well as (4) counterfactual observability/positivity regression (Feuerriegel et al., 2024). Positivity means that for each combination of characteristics, both treated and untreated group can be observed. On confoundedness, if hidden, unmeasured factors influence both the treatment and the outcome, the model may fail to isolate the true causal effect. Therefore, though meta-learners could capture more complex relationship between variables, it does not relax the assumption on no confounders.

The motivation for adopting meta-learners in hedonic pricing framework arises from well-known limitations of parametric linear regression models. Tradition hedonic models such as OLS and (spatial) MLM impose linearity and additivity assumptions. While these assumptions yield interpretable coefficients, they may be overly restrictive in housing markets, where price responses to attributes are often nonlinear and characterised by complex interactions. Moreover, the traditional hedonic models typically focus on estimating average implicit prices, while house prices effects are often heterogeneous among submarkets. The use of meta-learners in hedonic pricing framework can help in addressing both issues, which combine the strengths of hedonic regression on inference and those of machine learning on its predictive performance (Pérez-Rave et al., 2019).

The conventional concepts used in causal ML and hedonic framework are different, while most of them are interchangeable. Table 5.7 provides a mapping between conventional terms from the two frameworks. Within the hedonic framework, the treatment variable corresponds to a housing attribute of interest, while the outcome variable is the observed transaction price. The resulting treatment effect represents the causal change in house price induced by a marginal change in the attribute, conditional on other housing and neighbourhood characteristics. This treatment effect is interpreted as the implicit price of the attribute and forms the basis for estimating WTP. Though implicit prices are generally considered correlational rather than strictly causal, it can be interpreted causally if all relevant variables that influence both house price and housing energy efficiency are included.

Table 5.7 Mapping between concepts from causal inference and hedonic framework.

Causal inference concept	Hedonic framework concept
Treatment	Housing attribute of interest
Outcome	House price
Covariates	Other structural, locational, and neighbourhood attributes
Treatment effect	Implicit price

Overall, the use of meta-learners enables the estimation of causal, heterogeneous implicit prices within the hedonic framework, combining hedonic theory with the flexibility of modern machine learning methods to capture more complex relationship as well as enabling heterogeneity analysis. This study applies meta-learners of X-learner, DR-learner, and R-learner to explore the heterogeneity in price premium of housing energy efficiency. More methodological details of meta-learners models are available in Chapter 7.

5.5 Ethics and research integrity

5.5.1 Ethics

There are few ethical issues associated with this study. All the data used are about properties or neighbourhoods, with no personal data involved. Most datasets are publicly available including EPC, PPD, and all neighbourhood level datasets. The Zoopla listings data are commercial property of Zoopla plc, which is at one time publicly accessible on the website and the historical listings is available under licence. This study is responsible for protecting that commercial interest by keeping the data safe and not sharing.

5.5.2 Research integrity

Grounded in the principles of Open Science, the following research integrity considerations are adopted in this work. First, most software and programming languages involved is free and open-source, including Python (Python Software Foundation, 2026)/R (R Core Team, 2021) for programming, Visual Studio Code/JupyterLab for integrated development environment (IDE) as well as Zotero for reference management. ArcGIS Pro is used under university licences for mapping production, where there are open-source alternatives such as QGIS for reproducibility. Second, systematic and reproducible workflows are outlined in the scoping review and both empirical chapters. Finally, all the research data (where possible) and code are shared in public GitHub repositories, organised by chapters as follows (the code for Chapter 7 will be made available once the paper is published):

- Ch.4: https://github.com/YunbeiOu/ScopingReview_EPC_PricePremium
- Ch.6: https://github.com/YunbeiOu/WTP_EPC_EnergyCrisis

5.6 Summary

Overall, this Chapter provides an overview of the methodology for the following empirical chapters, with more detailed methodology outlined in those chapters separately. This Chapter first presents Greater Manchester (GM) as the study area and justifies the focus in the empirical work on the second-hand house sales market. It further outlines the main data sources for empirical modelling including Zoopla listings, PPD and EPC data. Additionally, the validation of Zoopla listing prices through a comparison with PPD is presented to show its reliability. Following the data overview, the Chapter introduces the hedonic research framework and discusses the various estimation methods including OLS, multilevel models, spatial multilevel models and causal ML models. The next Chapter will empirically apply multilevel and spatial multilevel models to examine the price premium of energy efficiency in GM, utilising the 2022 energy crisis as a natural experiment. The following Chapter applies multilevel and causal ML models to explore heterogeneity in price premiums from energy efficiency.

Chapter 6 Willingness-to-pay for energy-efficient homes: new insights from the energy crisis in Greater Manchester, UK

This Chapter is a reproduction of a submitted paper which currently under second round of peer-review in the journal of *Energy Research & Social Science* (the preprint is available as (Ou et al., 2026)). To make the flow of the argument in the thesis clearer, the supplementary materials from the submitted paper have been moved partially to Section 5.3 (“Validation of Zoopla listing prices”) and partially to Appendix D. The paper answers Research Question 2 of the thesis, modelling the change of price premium after the energy crisis which sheds light on omitted variable issues and the drivers of willingness-to-pay.

6.1 Introduction

The improvement of housing energy efficiency is vital for mitigating global environmental, economic and social challenges. Residential buildings account for around 17% of CO_2 emissions globally (IEA, 2023b), representing a substantial and detrimental driver of the worsening climate crisis. They also account for 21% of global energy demand (IEA, 2023b), making housing one of the most energy intensive sectors (Solà et al., 2020) with significant pressure on energy markets. Also, high energy costs disproportionately burden poorer households in energy inefficient homes, posing socioeconomic challenges of fuel poverty (C. Wang et al., 2022). Moreover, the increasing frequency of unforeseen challenges including extreme climate events and energy price volatility highlights the need for a more resilient housing stock.

Given the importance of housing energy efficiency, investment in improving efficiency fall far short of the requirements of net-zero goals (IEA, 2023a). A substantial share of the housing stock is still highly inefficient, as is the case in the UK (ONS, 2024a), making public spending insufficient to renovate all inefficient buildings (IEA, 2025a). Therefore, private investment must grow, with market incentives playing a key role in fostering such investment. If energy efficiency is capitalised into house prices, homeowners, investors and other stakeholders would have stronger financial incentives to undertake energy efficiency retrofits. A positive willingness-to-pay (WTP) for more energy-efficient dwellings can therefore help foster private investment, offering a cost-effective pathway to accelerate improvements across the housing stock. In Europe, the market incentive mechanism has been strengthened by the introduction of Energy Performance Certificates (EPCs), which are mandated to appear in housing advertisements throughout the EU and the UK as a former EU member state (Directive 2010/31/EU, p.11). EPC ratings provide information on building energy performance and its impact on potential running costs using EPC bands or scores.

Extensive studies have examined the price premium of housing energy efficiency as indicated by EPC ratings, generally finding a positive WTP for more energy-efficient homes (Cespedes-Lopez et al., 2019; Ou et al., 2025). However, there are two key gaps in the literature that this paper aims to address. First, while numerous studies show a positive correlation between energy efficiency and house prices, a causal interpretation of this relationship is weakened by methodological issues of omitted variables bias (OVB) (Ou et al., 2025). It is typically argued that there may be some unmeasured housing features which are positively associated with both energy efficiency and house prices; the obvious example would be higher aesthetic or functional quality in internal spaces (Copiello & Donati, 2021; Marmolejo-Duarte & Chen, 2022). These could confound the estimation of the causal relationship between energy efficiency and house prices, weakening the empirical validity of existing estimates and limiting their usefulness for policy design. Second, identifying the mechanism(s) is also methodologically challenging, as there exist few approaches to examine causal mechanisms in revealed-preference studies based on observational data. Understanding these mechanisms is nevertheless crucial for interpreting estimated WTP and for designing policies that effectively target the drivers of household decision-making. The debate on mechanisms of WTP for energy-efficient homes mainly falls into two sides, awareness of energy costs (Aydin et al., 2020) and awareness of environmental issues (IEA, 2022c).

This study proposes to address these research gaps by examining the changes in WTP following the recent “energy crisis”. This crisis began around summer 2021 and intensified due to the conflict in Ukraine in February 2022, which resulted in sharp increases in energy prices that have affected households globally (IEA, 2025b). As a key way to tackle energy cost challenges (IEA, 2018), energy efficiency improvement is likely to draw growing public attention. Given higher energy prices, operating costs should become more important in housing decisions; long-term cost savings of retrofits could outweigh the upfront costs (IEA, 2025a), potentially reshaping buyers' WTP for housing energy efficiency. It is expected that WTP for more energy-efficient homes may rise following the energy crisis, but empirical evidence capturing this behavioural response remains limited. Furthermore, evidence of a change in WTP after the crisis can shed light on both mentioned gaps. First, as the energy crisis is unlikely to be related to commonly discussed confounders of housing energy efficiency, such as housing aesthetic and functional quality, any observed increase in WTP can be more confidently attributed to energy efficiency itself, reducing concerns about OVB and strengthening causal inference. Second, since the crisis primarily and directly triggered higher energy costs, an increased WTP would support the argument that households are, at least partly, motivated by energy cost savings when investing in energy-efficient housing.

Therefore, this study attempts to answer the following research question: Has WTP for housing energy efficiency in the UK increased after the energy crisis? Our focus is on the effect of energy efficiency signalled by EPCs on sales prices in the second-hand house market in Greater Manchester (GM), UK. We draw on a dataset containing rich information on more than 170,000 existing homes listed for sale in GM between 2017 and 2024. Methodologically, we follow best practices in hedonic house price models (Bishop et al., 2020). To mitigate OVB, we include a wide set of control variables commonly included in hedonic models (Ou et al., 2025) and specify a multilevel hedonic model. To capture potential changes in the price premium after the crisis, the model includes interactions between EPCs and a proxy variable for the energy crisis i.e., listings appearing 2022 onwards.

This study contributes to existing literature in four ways. First, it offers new empirical evidence on the responsiveness of housing markets to large-scale energy price shocks, an area where empirical research remains limited. Second, by using a rich multi-year dataset and a robust multilevel hedonic modelling framework, the study advances methodological practices in estimating energy efficiency premiums. Third, by examining the change of WTP after the crisis, this study addresses long-standing concerns regarding OVB and confirm causal interpretation of WTP. Finally, by examining whether higher energy costs translate into increased market valuation of energy-efficient homes, it offers new insights into the underlying mechanisms behind energy-efficiency premiums.

6.2 Background

6.2.1 Energy crisis and the UK housing market

The 2022 energy crisis led to sharp price increases in major energy sources, impacting economies and societies worldwide (IEA, 2025b). The crisis began around the summer of 2021 amid the post-COVID-19 pandemic economic rebound and intensified following the outbreak of the conflict in Ukraine in February 2022, which significantly reduced fuel supplies from key producers. Influenced by global wholesale energy markets, UK domestic gas and electricity prices experienced substantial disruption. In April 2022, gas and electricity prices recorded their steepest monthly rises since 1988, while by October 2022, the year-on-year price rises reached the highest level since 1970 (Stewart & Bolton, 2025). Although energy prices began to decline from mid-2023, they remained significantly higher than pre-2022 levels for the remainder of our study period (Bolton, 2025).

With residential energy use making up over a quarter of total consumption, households faced substantial financial burdens from the energy crisis (Eurostat, 2024a; Guan et al., 2023). In the UK, the Office of Gas and Electricity Markets (Ofgem) regulate domestic energy prices through an energy price cap. This cap increased by 12% in October 2021 and by a further 54% in April 2022, marking a significant pass-through of wholesale energy increases to UK households. In response, the UK Government introduced several support measures. The Government's initial measure was an Energy Bills Rebate support package, providing £9.1 billion support through a £200 discount on bills for all households in autumn 2022. The Government also launched the Energy Bills Support Scheme (EBSS), which delivered a £400 grant to every household throughout the 2022-23 winter period to alleviate higher energy costs.

However, these measures did not eliminate the significant vulnerability of UK homes to energy cost volatility. Despite a gradual improvement in home energy efficiency, the UK housing stock remains inefficient overall with a median EPC rating of Band D (ONS, 2024a), placing it among the least energy-efficient in Europe (tado, 2020). Additionally, domestic heating in the UK relies predominantly on gas and, while electricity is also a major energy source, its prices are largely determined by gas prices (ECC, 2024). The challenges of inefficient homes and gas-reliant energy infrastructure left UK households particularly at risk from the energy price shock.

6.2.2 Literature review

6.2.2.1 The value of housing energy efficiency

The price effect of residential building energy efficiency has been widely examined in hedonic pricing studies. A systematic scoping review (Ou et al., 2025) identifies nearly 70 empirical studies conducted cross Europe from 2011 to 2024, covering diverse housing submarkets including sales (Cerin et al., 2014; McCord, Lo, et al., 2020) and rental markets (Khazal & Sønstebø, 2020; N. Liu et al., 2018), as well as houses (Hårsman et al., 2016; Mense, 2018) and flats (Galvin, 2023b; Kholodilin et al., 2017). While the review reports that most studies identify a positive EPC price premium at around 1–3% for each improvement in band, there are few studies providing evidence on temporal trends. Despite frequent claims of robustness on estimated results, many studies raise concerns regarding OVB (Marmolejo-Duarte & Chen, 2022) and the risk of overestimated price premiums (Galvin, 2023a).

Focussing on the UK context, the existing evidence base is both relatively sparse and uneven. Early work by (Fuerst et al., 2015) found a 1.8% sales price premium between Band D and C using data for England and Wales up to 2012, while subsequent studies largely targeted rental markets (Chegut et al., 2020; Fuerst et al., 2020) or specific EPC threshold effects (Sejas-Portillo et al., 2025). Research on Northern Ireland (McCord, Haran, et al., 2020; McCord, Lo, et al., 2020) and Wales (Fuerst, McAllister, et al., 2016) generally finds premiums between 2-3%, but these analyses focus on pre-2019 conditions. Importantly, there is almost no evidence on the English sales market post-2013, despite major policy shifts and market changes. While results from existing UK studies broadly align with

European findings, the empirical evidence does not reflect any changes due to the energy crisis.

6.2.2.2 Energy prices and WTP for energy-efficient homes

The role of energy prices in the capitalisation of energy efficiency into house prices has been discussed in some previous studies e.g., (Aydin et al., 2020; J. Olaussen et al., 2019). This work falls into two categories: studies comparing the price premium and the actual energy cost savings (Kholodilin et al., 2017; J. Olaussen et al., 2019; Taruttis & Weber, 2022); and studies testing whether energy prices affect the WTP for home energy efficiency (Aydin et al., 2020; Mense, 2018; J. Olaussen et al., 2019).

This study aligns with the latter category. Empirical evidence in this area is mixed and inconclusive. (J. Olaussen et al., 2019) find no relationship between energy costs and EPC premiums using data in Oslo, suggesting that EPC price premium may be driven by factors unrelated to energy efficiency (i.e. the omitted variables problem). Similarly, (Mense, 2018) finds that local energy price variation in Germany has little influence on the capitalisation of home energy efficiency. From these findings, both studies argue that energy cost saving is not a major consideration for investment. In contrast, others use a more direct proxy for energy efficiency i.e., actual energy consumption per square metre for analysis in the Netherlands (Aydin et al., 2020), observing a positive correlation between energy prices and capitalisation.

Despite these useful findings, limited attention has been given to examining the impact of the recent energy crisis on WTP for energy efficiency. This represents a substantial gap as the crisis provides a natural experiment with unprecedented and sharp price increase, allowing for stronger causal inference regarding the role of energy costs in shaping housing market behaviour. One notable exception is the study which explicitly investigates the relationship between energy crisis and demand for energy-efficient housing in the UK (Braakmann et al., 2026). Although this study employs a sophisticated difference-in-difference hedonic framework, its analysis is limited to a short time window surrounding the crisis. To extend the evidence base, this study examines changes in WTP for energy efficiency in the post-crisis period using data from 2017-2024, thereby contributing to the ongoing debates on causal interpretation of WTP and the underlying behavioural mechanisms.

6.3 Study area and data

6.3.1 Study area

The study area is Greater Manchester (GM), UK. Located in the northwest of England, GM is a metropolitan county of approximately 493 square miles which includes ten local authorities (Figure 6.1). It has a population around 2.8 million, covering a wide range of settlements and a highly varied housing stock.

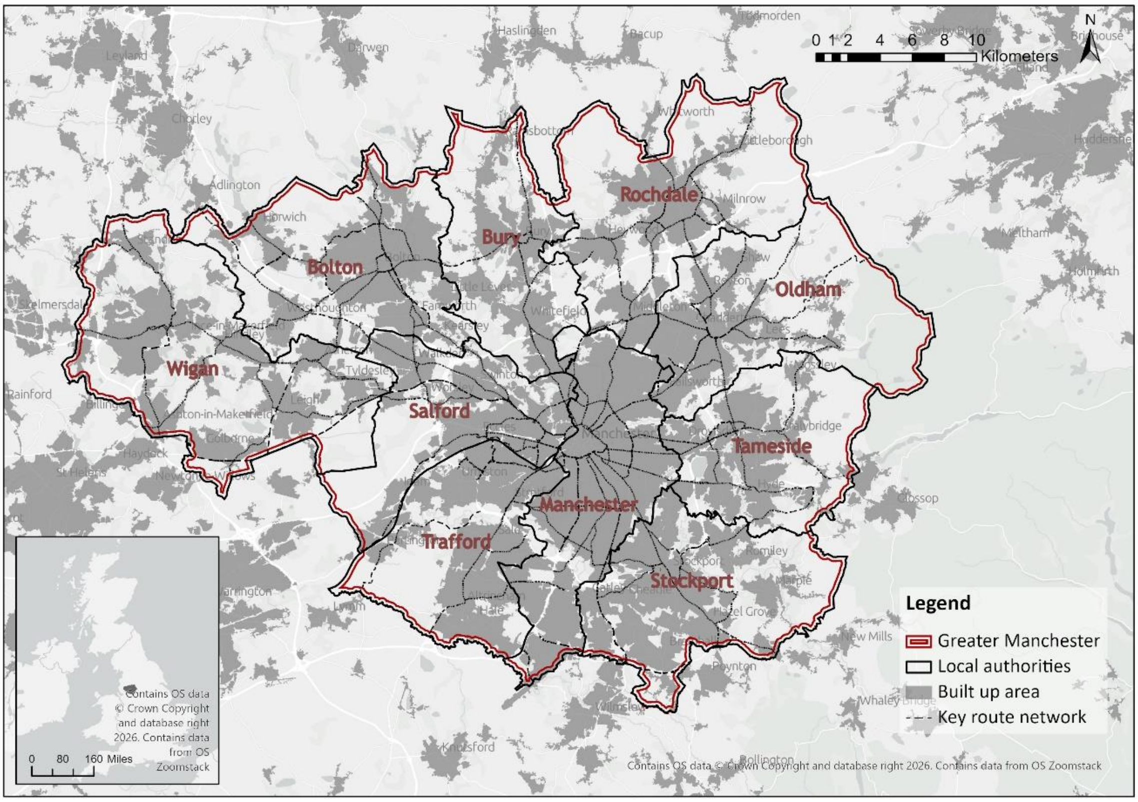


Figure 6.1 Study area: Greater Manchester.

Source: Author's compilation based on data from Great Britain built up area (Ordnance Survey, 2026) and GM key route network (Transport for Greater Manchester, 2025).

6.3.2 Data sources

We draw data from three main sources: Zoopla property listings, Energy Performance Certificates and neighbourhood datasets.

6.3.2.1 Zoopla property listings

We use Zoopla property listing data (Zoopla HomeTrack, 2023) covering period from 2017-09-01 to 2024-05-31 in GM, accessed under a licence held by the Urban Big Data Centre, University of Glasgow. This time range is chosen as it includes listings both before and after the energy crisis, enabling an examination of temporal changes in WTP. The Zoopla data offer property-level information including an official indexing variable, the Unique Property Reference Number (UPRN), listing price, tenure (freehold/leasehold), number of bedrooms and bathrooms, floor area, listing end date, and description text that potentially includes information on property facilities.

As our analysis relies on listing prices as the main price measure, it is important to establish how well Zoopla listing prices reflect the actual transaction prices. Actual sales prices are recorded in the official Land Registry Price Paid Data (PPD). However, these records lack UPRNs and therefore cannot be linked to EPC information. For a more limited period, however, we obtained a lookup file that provides estimated UPRNs for PPD transactions. Using this linkage, we show that Zoopla listing prices closely approximate transaction prices, with a consistently high correlation coefficient (r = 0.99) across all years from 2017 to 2023 (see Section 5.3), supporting the use of listing price as a valid proxy in our analysis.

6.3.2.2 Energy Performance Certificates (EPC) Data

In England, EPC data (OpenDataCommunities, 2024) are openly available. To ensure temporal alignment, we use the version including all certificates issued up to 2024-05-31. The EPC dataset includes UPRN identifiers as well as detailed property features including EPC ratings, property type, total floor area, number of habitable rooms, built form, and building age. EPCs provide energy performance measures based on modelled energy costs per square metre, which consider multiple inputs including the building envelope and heating system. Energy performance is reported both as a categorical band (A to G, where EPC A indicates the most energy-efficient properties and EPC G the least) and as a continuous score ranging from 0 to 100, with higher scores reflecting better energy performance.

6.3.2.3 Neighbourhood datasets

We incorporate four datasets to account for neighbourhood characteristics, the justification of inclusion of these characteristics are provided later in Section 6.4.2. The neighbourhood datasets are mainly defined at the Census geographical unit of Lower-layer Super Output Areas based on the 2011 UK Census boundaries for England and Wales (LSOA11). LSOA11s contain approximately 400–1,200 households and 1,000–3,000 residents, providing an appropriate level of spatial resolution for capturing neighbourhood characteristics.

We first apply the Public Transport Accessibility Index (PTAI) (Verduzco Torres & McArthur, 2024), which provides various measures of public transport accessibility to services including city centres, employment centres, healthcare, schools, and retail centres at the LSOA11 level. We adopt the measures of “cumulative service counts” which shows the number of specific service accessible within different time ranges and “minimum travel-time” that presents the travel time to the nearest specific service.

We also include the 2019 Income Deprivation score from the English Indices of Deprivation (OpenDataCommunities, 2019), which measures the proportion of the population experiencing deprivation relating to low income in each LSOA11. Additionally, population density at mid-2020 is provided by Office for National Statistics (ONS) (ONS, 2024b), offering population density of LSOA11s based on estimates of the usual resident population. Finally, the State-funded Schools Inspections data (Ofsted, 2024) is obtained, which includes rating for each school based on the rating system from Office for Standards in Education, Children's Services and Skills (Ofsted).

6.3.3 Data preprocessing

An overview of data preprocessing as well as each data source’s geographical and temporal coverage, sample sizes, level of aggregation and features is provided in Figure 6.2. Data preprocessing involves three key steps: data preparation, linkage, and cleaning. The first step involves filtering Zoopla listings and EPC data. We start with second-hand residential sales listings in Greater Manchester covering 2017-09-01 to 2024-05-31. Using keyword matching in Zoopla description text (with specifics in Appendix D, Table D-1), we remove listings for auctions as listed prices were less likely to reflect registered sale price and shared-homeownership and rent-to-buy schemes, as these do not represent the typical housing market. We remove listings without UPRNs and eliminate duplicates where the same UPRN appears multiple times within one week. For the EPC data, we start with the version covering all EPC records issued up to the end date of our Zoopla dataset. We remove entries where the same UPRN value and inspection date appear multiple times, possibly representing lodgement errors (Hardy & Glew, 2019).

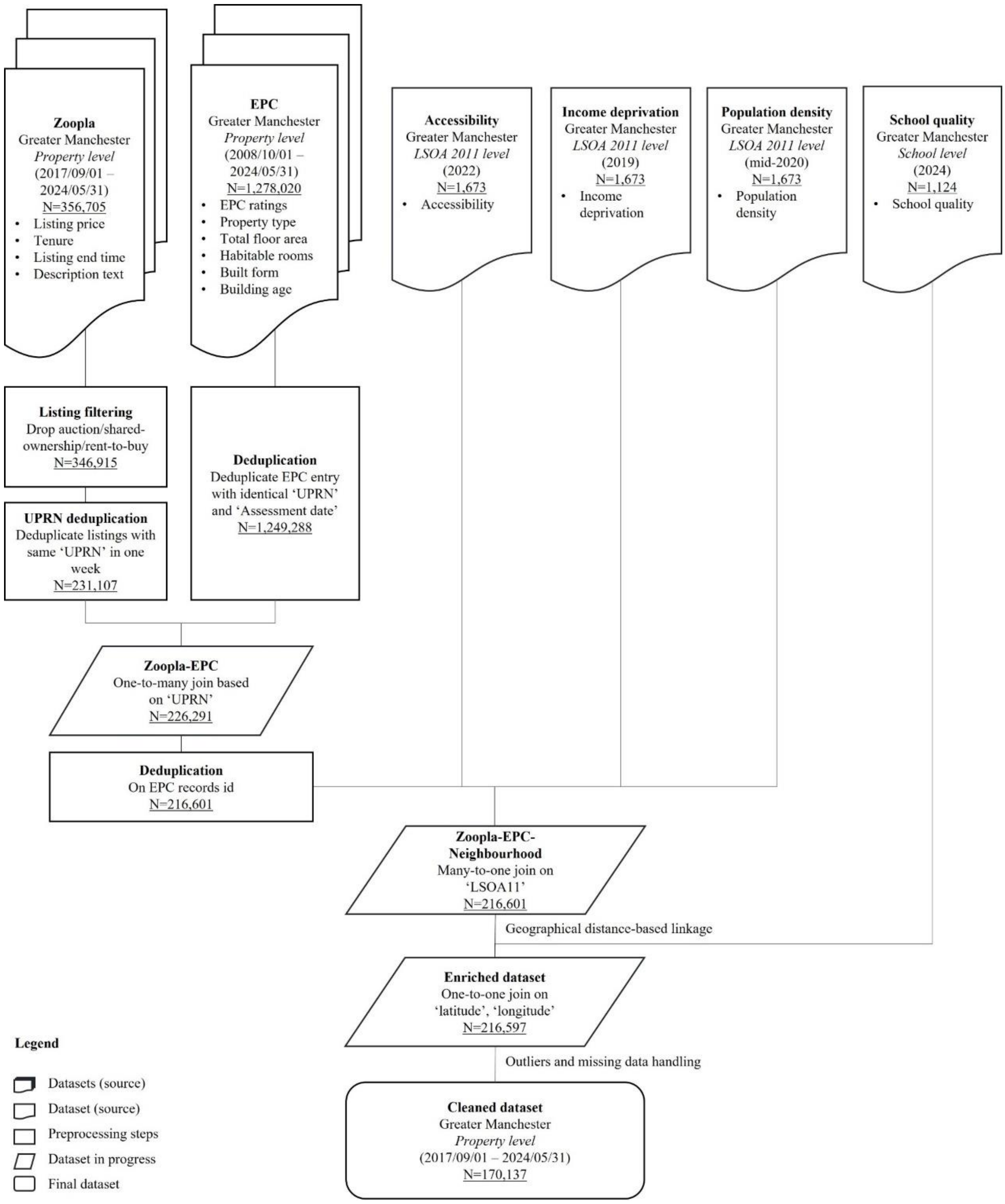


Figure 6.2 Data preprocessing.

Zoopla and EPC datasets are linked via a one-to-many join based on the UPRN, where 98.13% of listings can be linked with at least one EPC record. To deduplicate Zoopla-EPC matches, the following steps are applied: (1) EPCs issued more than ten years prior to the listing end date are excluded as their validity in the UK expires after ten years; (2) EPCs with an assessment date later than the listing end date are removed; (3) for each listing, only the EPC record with the assessment date closest to the listing end date is retained. It should be noted that certain information such as floor area and number of rooms is available from both Zoopla listings and EPC data. In these cases, we use the EPC data as it represents a more reliable source with standardised assessment procedures.

At neighbourhood level, the combined Zoopla-EPC dataset is linked to three of the neighbourhood datasets using a lookup for UPRN to LSOA11. All neighbourhood datasets fully cover LSOAs in GM, resulting in 100% linkage rate with the Zoopla-EPC data. The exception is on school quality data which is available at the school level. In this case, each property is linked to the nearest primary and secondary schools within the same local authority, based on the Euclidean distance between their latitude and longitude coordinates, with the average of the two scores used.

Data cleaning involves checking for consistency, handling outliers and addressing missing values. First, coding inconsistencies among categorical variables are identified and corrected. Second, outliers are addressed using a trimming approach, where extreme values are removed based on both domain knowledge and the data’s distribution (see Appendix D, Table D-2). Low-end outliers likely represent errors or non-primary residences, while high-end outliers may reflect data entry issues or unusually large properties beyond the scope of this analysis. Regarding prices, listings with prices greater than £1.5 million or less than £30k are removed. The upper threshold of £1.5 million is chosen because it corresponds to the highest price Band among the UK land tax rates, above which properties are subject to the maximum tax rate and typically represent a distinct high-value segment of the housing market. The lower threshold follows the convention used within the PPD to exclude non-market transactions. Third, for missing data, since the proportion is low and appears to be missing at random, affected observations are excluded. The final dataset consists of 170,137 observations. The observations cover 1671 out of 1673 neighbourhoods (LSOA11s) in GM, with an average of 101 observations each (range 1-403).

6.4 Methods

6.4.1 Hedonic pricing model

6.4.1.1 Hedonic framework

We apply the hedonic model (Rosen, 1974) which is a well-established approach for revealed preference studies to estimate the implicit price of attributes within the overall price of heterogeneous goods. Typically, the hedonic model regresses product price against its utility-bearing attributes. In housing market modelling, house prices are usually expressed as a function of structural, neighbourhood and locational attributes (Chin & Chau, 2003):

$$Price_{ij} = f(s_{ij}, n_j, l_j) \tag{6.1}$$

Where $Price_{ij}$ is the observed price of property i in neighbourhood j; s_{ij} are the structural attributes of property i in neighbourhood j; n_j are the neighbourhood attributes of neighbourhood j ; and l_j represents locational attributes of neighbourhood $\boldsymbol{j}$.

It is widely noted that the hedonic approach is prone to the methodological issue of OVB. This occurs when a relevant variable correlated with both the predictor and outcome is missing from the regression, which may lead to biased estimates of coefficients (Wilms et al., 2021). When estimating the price premium for energy efficiency, for example, one may argue that other hard-to-measure property characteristics (e.g., property condition) may be correlated with both energy efficiency and price. It may also be argued that both housing energy efficiency and house prices are spatially clustered or clustered at neighbourhood levels, so that energy efficiency might be correlated with unmeasured neighbourhood features.

6.4.1.2 Multilevel hedonic model

This study employs the multilevel hedonic model (MLM) to estimate WTP for home energy efficiency. This has methodological advantages over the traditional ordinary least squares (OLS) models when the response variable varies across higher-level units (Peugh, 2010). The OLS assumption that observations are independent is often violated in nested data structures. In comparison, multilevel models explicitly account for this dependence by allowing random intercepts and/or random slopes for clusters i.e., upper levels. Moreover, by allowing random intercepts at clusters, it can partition the total variance in an outcome into components at different hierarchical levels (e.g., within-group and between-group variance), thereby providing insights into the heterogeneity of outcomes across/within clusters.

The MLM is well suited to this study. First, housing data naturally exhibit a hierarchical structure with nearby properties sharing neighbourhoods or locational attributes. This approach has been increasingly applied in studies examining house price premiums e.g., of green space (Glaesener & Caruso, 2015) or accessibility (Deboosere et al., 2019). Second, by capturing neighbourhood heterogeneity, MLM helps mitigate bias from unobserved, time-invariant neighbourhood factors (Gelman & Hill, 2006). Empirically, we conducted robustness checks comparing the performance of OLS, MLM, and spatial MLM models where the spatial relationship between neighbourhoods is also accounted for in the model (details in Appendix D, Figure D-1). The results show that MLM produces lower residual variance than OLS, indicating a better model fit. While MLM results show that the neighbourhood residuals are significantly spatially correlated (see Appendix D, Figure D-2), spatial MLM offered limited improvements in price premium estimations over the standard MLM, suggesting that the basic multilevel structure captures most of the spatial dependence present in the data.

We therefore adopt a two-level random intercept hedonic model, with property listings in the lower level and neighbourhoods indicated by LSOA11 in the upper level. We follow the standard practice of semi-log model specification, using natural log of price as the dependent variable. Leaving aside the energy crisis to begin with, the basic two-level model is:

Level 1 (Listing Level) model:

$$Log\left(Price_{ij}\right) = \beta_j + \beta_S X_{ij} + \beta_t Time_{ij} + \beta_k EPC_{ij} + \epsilon_{ij}$$

$$\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$$

(6.2)

Level 2 (Neighbourhood Level) model:

$$\beta_j = \gamma_0 + \gamma_N Z_{jN} + u_j$$

$$u_j \sim N(0, \sigma_u^2)$$

(6.3)

Where $Price_{ij}$ is the listing price of listing i in neighbourhood j; X_{ij} represents a vector of property level attributes, including tenure, property type, floor area, number of habitable rooms, built form, building age, property facilities and school quality; EPC_{ij} is the energy efficiency measure for the listing; Z_j is a vector of neighbourhood-level attributes including population density, public transport accessibility, and income deprivation; $Time_{ij}$ is the year-quarter period of the listing end date (dummy terms); β_j denotes the random intercept for each neighbourhood j; γ_0 is the fixed intercept at neighbourhood level; u_j is the random effects at neighbourhood level while ϵ_{ij} is the one at listing level. Separate models are estimated using dummy terms for EPC bands (Model 1) and using a single continuous measure for the EPC score (Model 2). We assume normal distributions for both random effects ($u_j \sim N(0, \sigma_u^2)$, $\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$), where σ_u^2 is the residual component of variation due to neighbourhood variability and σ_ϵ^2 is the component of variation due to listing level variability. We also assume these two random effects are independent of each other.

6.4.1.3 Impact of the energy crisis

We estimate the impact of the energy crisis on WTP for energy efficiency by adding an interaction term between EPC and an energy crisis dummy term into the model. The full MLM specification is:

Level 1 (Listing Level) model:

$$Log(Price_{ij}) = \beta_j + \beta_S X_{ij} + \beta_t Time_{ij} + \beta_k EPC_{ij} + \beta_l EPC_{ij} * EnergyCrisis_{ij} + \epsilon_{ij}$$

$$\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$$

(6.4)

Level 2 (Neighbourhood Level) model:

$$\beta_j = \gamma_0 + \gamma_N Z_{jN} + u_j$$

$$u_j \sim N(0, \sigma_u^2),$$

(6.5)

where *“EnergyCrisis”* distinguishes listings before or after the start of 2022. This model is again estimated using both EPC bands (Model 3) and EPC score (Model 4).

Additional assumptions are needed to interpret results as showing the impact of the energy crisis on the price premium for energy efficiency. First, the proxy variable for the energy crisis effectively identifies the period for which consumers were aware of higher energy costs. Second, there are no confounders of the energy crisis affecting the WTP for energy efficiency. Third, the energy crisis has little impact on the price premium of unmeasured confounders of housing energy efficiency.

On the first assumption, it is challenging to identify a precise point at which the crisis began to materially affect household energy bills or attract widespread public attention. Here we construct a dummy variable which is “1” if the property listing end date is 2022 onwards and “0” otherwise. This point of time is supported by the timing of the Government response (Section 6.2.1) and data on household energy bills (Appendix D, Figure D-3). On the second assumption, as we use the dummy variable of post-2022 to define the energy crisis, potential confounders include both underlying temporal trends and events contemporary with the crisis. For the temporal trends, it is possible that WTP was already rising over time regardless of the crisis. To address this, we run interaction models using alternative cut-off years and compare results with our 2022 cutoff. As for simultaneous events, although it is inherently difficult to separate them completely, we argue that other relevant events will not have led to changes in WTP related to energy efficiency (with detailed discussion provided in Section 6.6). On the third assumption about potential unobserved confounders, we think it is highly unlikely that household valuation of these items will have changed at the same time as the energy crisis so they cannot explain any change in WTP for energy efficiency.

6.4.2 Variables

We include a wide set of structural, neighbourhood, locational, and temporal controls, classified into listing-level and neighbourhood-level variables (Table 6.1). These capture key dwelling characteristics (such as type, size, and age), neighbourhood characteristics (such as population density and accessibility), and market conditions that are commonly shown to influence house prices in hedonic studies (Chin & Chau, 2003; Ou et al., 2025).

Table 6.1 All variables for modelling.

Level	Variable		Measurement	Variable definition
Dependant variable	Listing Price		Ratio	Natural log of total price, GBP
Listing-level variables	EPC band	AB/C/D (ref)/E/FG	Ordinal	
	EPC score		Ratio	Energy efficiency score (0-100 with higher score more energy efficient)
	Tenure	Freehold (ref) /leasehold	Nominal	
	Property Type	House (ref)/bungalow	Nominal	
	Total Floor Area		Ratio	Natural log of sqm

	Habitable Rooms	1-3 (ref)/4/5/6-7/8-10	Ordinal	
	Built Form	Detached/semi-detached (ref)/terraced	Nominal	
	Building Age	before 1900/1900-1929/1930-1949/1950-1966 (ref)/1967-1982/1983-2002/2003-2011/2012-2024	Ordinal	
	Property Facilities	Modern kitchen	Binary	
		Garage	Binary	
		Basement	Binary	
		Garden	Binary	
	School Quality		Ratio	Average Ofsted rating for nearest primary and nearest secondary school within same local authority (1 = lowest; 4 = highest)
	Listing End Time		Nominal	Year-quarter dummies (2017-Q3 ref)
	Energy Crisis		Binary	Prior to 2022 – “0”; 2022 onwards – “1”
Neighbourhood-level unit	LSOA		Nominal	
Neighbourhood-level variables	Population Density		Ratio	Natural log of 100 residents/km2
	Accessibility	Accessibility PC1	Ratio	Principal component 1 from PTAI measures
		Accessibility PC2	Ratio	Principal component 2 from PTAI measures
	Income Deprivation		Ratio	Income Deprivation score (% of residents on low-income benefits)

On listing/property level, we include eleven structural variables following usual practices for hedonic house price analysis (Chin & Chau, 2003; Ou et al., 2025):

EPC, tenure, property type, total floor area, habitable rooms, built form, building age, and property facilities (modern kitchen, garage, basement and garden). The variables of property facilities are constructed from listing description text using key word searches (Appendix D, Table D-3). Also, researchers e.g., (Orford, 2018; Owusu-Edusei et al., 2007) note property value is associated with proximity to school and school quality. School quality rating is graded on a four-point scale (1=low; 4=high) and we assign the average rating of closest primary and secondary school in the same local authority to each property. This is included in Level 1 of the model as it is measured at property level. We include variable of listing end time to absorb temporal changes.

At the neighbourhood level, we adopt three variables found in previous studies to affect house prices. First, house prices are suggested to rise with rising population density in the UK (Miles, 2012). The adopted population density variable is calculated as 100s of residents/km2 in each LSOA11 in this analysis. Second, accessibility measures the ease of reaching valued destinations, considering both the transport network and the spatial distribution of places (Levinson & Wu, 2020). Public transport accessibility is shown to influence house prices albeit with decreased impact with more rise in remote working (Du & Mulley, 2006; Georgiou et al., 2026). By examining the correlation between the adopted 55 numerical measures (including 48 cumulative service counts measures and seven minimum travel time measures) from the PTAI dataset, we find most values are highly correlated with each other (see correlation heatmap in Appendix D, Figure D-4). To represent overall accessibility for each LSOA11, we standardise these measures followed by applying two component Principal Component Analysis (PCA) which performs PCA and select the first two principal components (PC) for linear dimensionality reduction. The two PCs explain 73.5% of total variance, with PC1 accounts for 68.5% and PC2 for 5.0% (the correlation between each component and the underlying indices are showed in Appendix D, Table D-4). Finally, neighbourhood deprivation related to income levels are found to be associated with lower house prices (Cheshire et al., 2003; Gibbons, 2001). This analysis adopts the Income Deprivation score which measures the percentage of residents on low-income benefits in each LSOA11 to represent neighbourhood deprivation.

We group some values in categorical fields of "habitable rooms" and "EPC band" to ensure sufficiently large sample sizes for each group as well as reduce dimensions of variables. Habitable rooms are grouped as 1–3 (reference), 4, 5, 6-7, and 8–10. EPC bands are grouped as A/B, C, D (reference), E, and F/G. Additionally, the continuous variables of listing price, total floor area, and population density are natural log transformed to reduce skewness. All categorical fields are transformed to dummy variables. The descriptive statistics of full sample and the two sub-samples (before/after the energy crisis) are shown in Table 6.2.

Table 6.2 Descriptive statistics of variables.

Variable	Value of category	Full sample		Before energy crisis		After energy crisis	
		Mean/ %	Std	Mean/%	Std	Mean/ %	Std
Dependent variable							
Listing Price (log)		12.179	0.497	12.075	0.490	12.360	0.453
Property-level variables							
EPC band	A/B	0.58%		0.56%		0.61%	
	C	27.70 %		24.14%		33.91%	
	D	54.61 %		56.01%		52.18%	
	E	14.68 %		16.42%		11.65%	
	F/G	2.42%		2.87%		1.64%	
EPC score		62.344	9.903	61.559	10.156	63.711	9.291
Tenure	Freehold	54.96 %		54.10%		56.44%	
	Leasehold	45.04 %		45.90%		43.56%	
Property type	House	91.94 %		91.74%		92.29%	
	Bungalow	8.06%		8.26%		7.71%	
Total floor area (log)		4.457	0.278	4.452	0.276	4.465	0.280
Habitable rooms	1 - 3	9.35%		9.61%		8.89%	
	4	33.89 %		34.51%		32.81%	

	5	35.35%		34.92%		36.11%	
	6 - 7	18.79%		18.42%		19.45%	
	8 - 10	2.62%		2.55%		2.74%	
Built form	Detached	16.59%		16.37%		16.96%	
	Semi-detached	40.84%		40.35%		41.70%	
	Terraced	42.57%		43.28%		41.33%	
Building age	Before 1900	8.74%		9.18%		7.97%	
	1900 – 1929	22.59%		23.10%		21.70%	
	1930 – 1949	21.22%		21.02%		21.57%	
	1950 – 1966	15.87%		15.73%		16.11%	
	1967 – 1982	14.32%		14.05%		14.77%	
	1983 – 2002	12.28%		12.09%		12.60%	
	2003 – 2011	4.85%		4.80%		4.93%	
	2012 – 2024	0.13%		0.01%		0.34%	
Modern kitchen	True	23.57%		23.74%		23.27%	
Garage	True	33.57%		33.80%		33.18%	
Basement	True	1.20%		1.16%		1.25%	
Garden	True	87.29%		87.05%		87.72%	
School quality		2.873	0.414	2.874	0.412	2.870	0.417
Listing end time							
Energy crisis	True	36.49%					
Neighbourhood-level variables							
Population density (natural log)		3.463	0.831	3.470	0.832	3.451	0.830
Accessibility PC1		-1.273	4.834	-1.233	4.868	-1.343	4.772

Accessibility PC2	-0.009	1.585	0.003	1.593	-0.029	1.572
Income Deprivation	0.146	0.095	0.147	0.096	0.144	0.095
Observations	170,137		108,051		62,086	

Figure 6.3 shows spatial distribution of median house prices, energy-efficient homes (EPC Band D or above), population density, accessibility (PC1/PC2), and Income Deprivation at LSOA11 level in GM. We interpret PC1 as capturing general accessibility quality by public transport which primarily reflecting accessibility to the city centre. In contrast, PC2 appears to represent accessibility to local or district-level amenities. This suggests that the PCA has effectively produced variables aligned with the dimensions of accessibility relevant to our analysis.

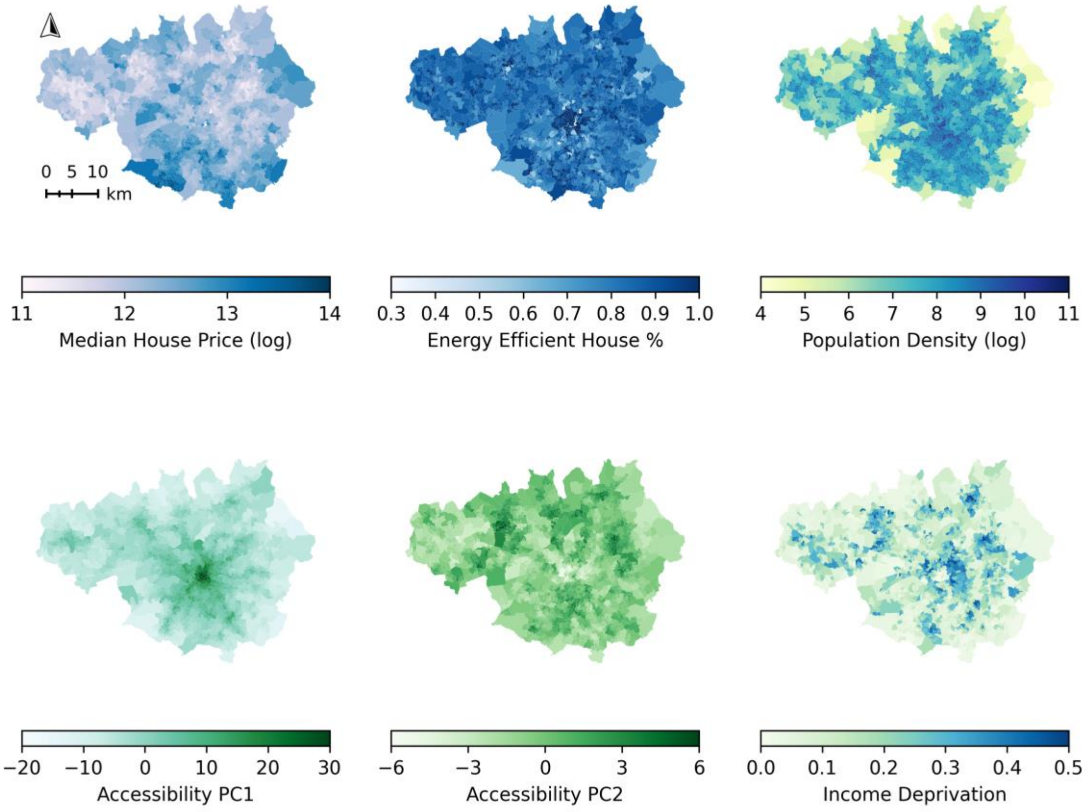


Figure 6.3 Distribution of key attributes at LSOA11 level.

6.5 Results

6.5.1 Price premium of energy efficiency

The results from the main MLMs are shown in Table 6.3. Model 1 shows the results using EPC bands to capture housing energy efficiency. In terms of model fit, the pseudo R^2 of this model is nearly 90% suggesting high explanatory power. Also, 63.1% of the total variance is attributed to the neighbourhood grouping structure. Additional model diagnostics are shown in Appendix D, Figure D-5. All independent variables have the expected signs, with most statistically significant.

EPC Band Dummies (Model 1) have the expected signs with 1% significant level. Taking EPC Band D as the reference, the Band A/B, C, E, F/G have price premiums of 2.2%, 1.3%, -1.5%, -4.2% respectively. This indicates that the "brown discount" on inefficient homes (esp. for Band F/G) is larger than the "green premium" for green homes (esp. for Band A/B).

Table 6.3 Main regression results.

Variable	Value of category	Model 1: EPC bands		Model 2: EPC score	
		Coef.	[95% CIs]	Coef.	[95% CIs]
Intercept		9.923		9.842	
Property-level variables					
EPC band	A/B	0.022***	[0.011, 0.033]	-	-
	C	0.013***	[0.011, 0.015]	-	-
	E	-0.015***	[-0.018, -0.013]	-	-
	F/G	-0.041***	[-0.047, -0.035]	-	-
EPC score		-	-	0.001***	[0.001,0.001]
Tenure	Leasehold	-0.007***	[-0.009, -0.005]	-0.007***	[-0.009, -0.005]
Property type	Bungalow	0.094***	[0.090, 0.097]	0.094***	[0.090, 0.097]
Total floor area (log)		0.496***	[0.491, 0.501]	0.496***	[0.491, 0.501]
Habitable rooms	4	0.014***	[0.010, 0.017]	0.013***	[0.010, 0.017]

	5	0.054***	[0.051, 0.058]	0.054***	[0.051, 0.058]
	6 - 7	0.126***	[0.121, 0.130]	0.126***	[0.121, 0.130]
	8 - 10	0.196***	[0.189, 0.203]	0.196***	[0.188, 0.203]
Built form	Detached	0.174***	[0.171, 0.177]	0.174***	[0.171, 0.177]
	Terraced	-0.172***	[-0.175, -0.170]	-0.172***	[-0.175, -0.170]
Building age	Before 1900	0.001	[-0.003, 0.005]	0.002	[-0.002, 0.006]
	1900 – 1929	-0.032***	[-0.035, -0.028]	-0.031***	[-0.034, -0.027]
	1930 – 1949	0.014***	[0.011, 0.017]	0.015***	[0.012, 0.018]
	1967 – 1982	0.026***	[0.023, 0.029]	0.025***	[0.022, 0.029]
	1983 – 2002	0.099***	[0.095, 0.103]	0.098***	[0.094, 0.102]
	2003 – 2011	0.132***	[0.127,0.137]	0.128***	[0.123,0.133]
	2012 – 2024	0.139***	[0.115, 0.162]	0.132***	[0.109, 0.156]
Property facilities	Modern kitchen	0.043***	[0.041, 0.045]	0.043***	[0.041, 0.045]
	Garage	0.057***	[0.055, 0.060]	0.058***	[0.055, 0.060]
	Basement	0.051***	[0.043, 0.059]	0.052***	[0.044, 0.060]
	Garden	0.073***	[0.070, 0.076]	0.073***	[0.070, 0.075]
School quality		0.008***	[0.003, 0.012]	0.008***	[0.003, 0.012]
Time		*Yes*		*Yes*	
<u>Neighbourhood-level variables</u>					
Population density (natural log)		-0.006	[-0.023, 0.010]	-0.006	[-0.023, 0.010]
Accessibility PC1		0.017***	[0.015, 0.019]	0.017***	[0.015, 0.019]
Accessibility PC2		-0.004	[-0.011, 0.003]	-0.004	[-0.011, 0.003]
Income Deprivation		-1.589***	[-1.694, -1.484]	-1.590***	[-1.694, -1.484]
σ_ϵ^2		0.031		0.031	

σ_u^2	0.053	0.053
σ_f^2	0.215	0.215
VPC	63.10%	63.10%
Pseudo R^2	89.60%	89.60%
Observations	170,137	170,137

Note: The variance partitioning coefficient (VPC) measures the proportion of total variance in an outcome variable that is attributable to the grouping structure. It is the level 2 random effect variance divided by level 1 and level 2 random effect variance: $VPC = \sigma_u^2/(\sigma_u^2 + \sigma_\epsilon^2)$. The Pseudo R^2 is calculated based on framework (Rights & Sterba, 2019): $R^2 = \sigma_f^2 + \sigma_u^2/(\sigma_f^2 + \sigma_u^2 + \sigma_\epsilon^2)$ where σ_f^2 is the variance explained by level 1 and level 2 predictors. *** *p < .001.* ** *p < .01.* * *p < .05.*

Results from Model 2 which uses continuous EPC score are very similar to that from Model 1, including model explanatory power and coefficients on all variables. Using the continuous score forces the change in log price to be the same at every point in the EPC scale which may well be unrealistic. This may explain the modest changes in the estimated age effects in Model 2 because of the strong correlation between building age and energy efficiency. Looking at the coefficient of EPC score in Model 2, each point of improvement in the score contributes to an average of 0.13% price increase. We also show that Models 1 and 2 give effectively the same result for the price premium of energy efficiency (details in Appendix D, Table D-5).

6.5.2 The impact of the energy crisis

Table 6.4 summarises Models 3 and 4 using bands and continuous score interacted with the energy crisis dummy, while Figure 6.4 shows results for the former in a more visual form. The overall performance of Models 3 and 4 is similar to the previous models.

Model 3 shows that the effect of each EPC band is more pronounced after the crisis. Specifically, the change of coefficient is: A/B (+0.5%), C (+0.1%), E (-0.8%), F/G (-1.9%). The relative change compared to the coefficients before the crisis for each band is: A/B (+25%), C (+8%), E (-22%), F/G (-53%). The changes for Band E-G are statistically significant while those for Band A-C are not significant. Compared to the average effect of 0.13% of EPC score on house prices found in Model 2, Model 4 reveals that WTP for energy efficiency changed significantly after the crisis. Specifically, the coefficient per unit of score increases by about 0.03% from 0.12% of price premium before the crisis.

Table 6.4 Price premium of energy efficiency with change after energy crisis.

Variable	Model 3: Interaction with EPC bands		Model 4: Interaction with EPC score	
	Coef.	[95% CIs]	Coef.	[95% CIs]
Variables of interest				
EPC A/B	0.020*	[0.006, 0.034]		
After energy crisis * EPC A/B	0.005	[-0.017, 0.028]		
EPC C	0.012***	[0.009, 0.015]		
After energy crisis * EPC C	0.001	[-0.003, 0.005]		
EPC E	-0.013***	[-0.016, -0.010]		
After energy crisis * EPC E	-0.008**	[-0.013, -0.003]		
EPC F/G	-0.036***	[-0.043, -0.030]		
After energy crisis * EPC F/G	-0.019**	[-0.032, -0.006]		
EPC score			0.0012***	[0.0011, 0.0013]
After energy crisis * EPC score			0.0003***	[0.0001, 0.0005]
VPC	63.02%		63.02%	
Pseudo R2	89.60%		89.60%	
Observations	170,137		170,137	

Note: Only variables of interest are presented. *** *p < .001. ** p < .01. * p < .05.*

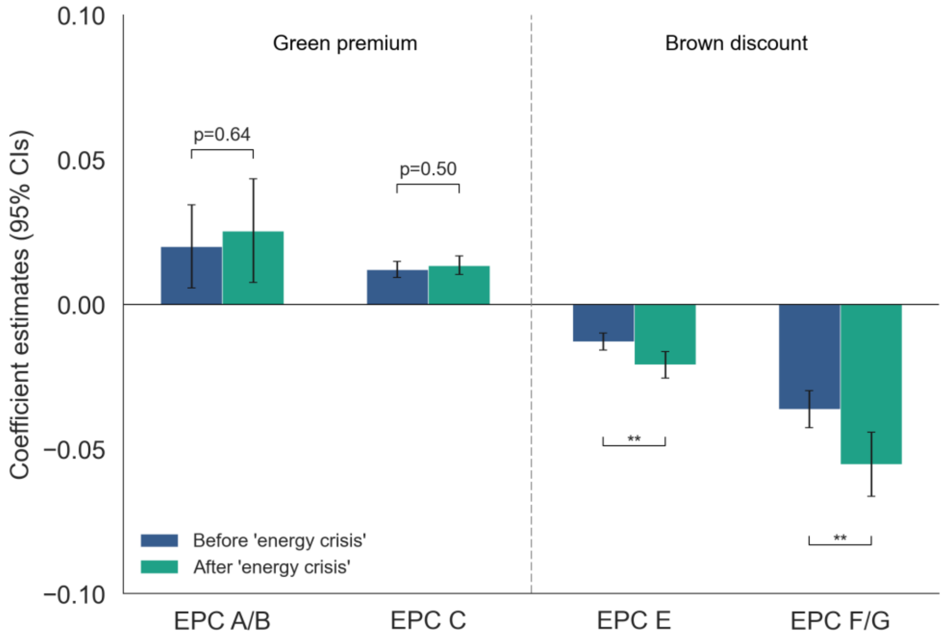


Figure 6.4 Price premium for EPC bands before and after the energy crisis.

Note: The coefficient estimates of effects in the presence of interactions i.e., “coefficients after energy crisis” is the addition of coefficient estimate of EPC Band and that of the corresponding interaction term. The confidence interval of “coefficients after energy crisis” is calculated based on (Figueiras et al., 1998). The p-values indicate the statistical significance of interaction components *EPC band*Energy crisis* i.e., difference between coefficients before and after the crisis. *** $p < .001$. ** $p < .01$. * $p < .05$.

We repeat Model 3 by interacting EPC bands with year-specific dummy variables using alternative cut-off years from 2018 to 2024. This permits us to see whether there was pre-existing temporal trend in WTP for energy efficiency prior to the crisis. It also permits us to see whether the effect of the crisis was instantaneous or emerged gradually. Any increase in WTP for energy efficiency reflects not just prices as the crisis strikes but beliefs about whether any energy price increase is likely to be long-lasting.

Figure 6.5 shows the coefficient estimates of EPC bands after different years (similar to the “coefficient of EPC Band after 2022” in Figure 4), based on the models using different years as cutoff in the interaction term. The price premium began to have a clear rising trend after 2022 especially for the “green premium”. In terms of the “brown discount”, the rising trend seems to start a bit earlier from 2019-2020. For Band F/G, a clear and consistent increase can be found from 2022 onwards where 2022 experienced the largest rise, while there is also a step increase in 2020. These confirm the WTP started to increase extensively from around 2022 i.e., the energy crisis, which continue to rise in the following years. More discussion around the temporal trend is presented in the following section.

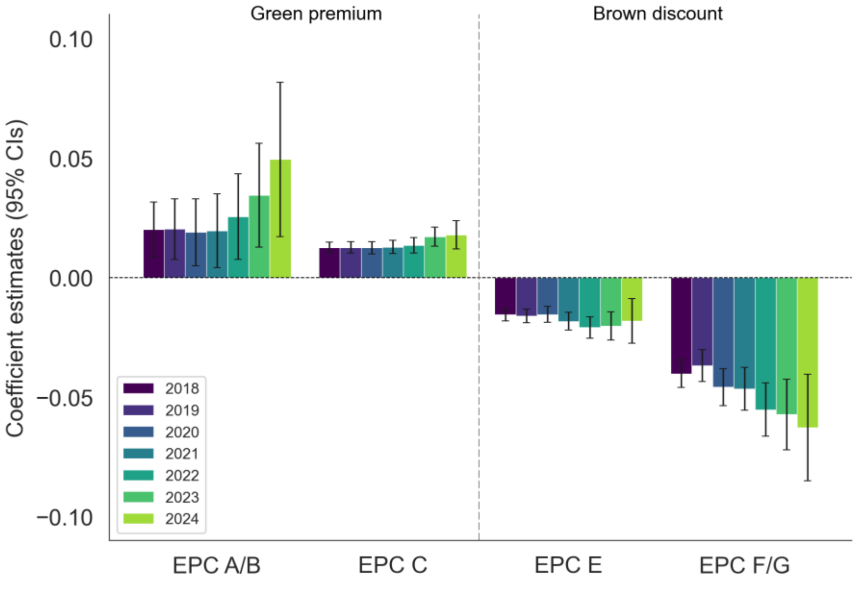


Figure 6.5 Estimates of price premium after different years.

Note: The coefficient estimates and confidence intervals are calculated using the same approach as specified in the note of Figure 4.

6.5.3 Robustness check

In our modelling, we use all Zoopla listings which we can link to an EPC record. In our work to validate the Zoopla data, we used a subset of listings (55.5% of all listings) which we could link to official registered transaction data (PPD) to check that the listing price was indeed a strong indicator of the agreed sales price. The unmatched Zoopla listings might indicate unsold properties where the listing price is not a good indicator of market value, but they may also indicate simply a failure in the address-based matching process. To check the robustness of results, the main regression models (Models 1 and 2) are repeated using only listings that can be matched to official transactions. Results show that estimations of WTP for energy efficiency remain consistent with those using all listings in the same period (Table 6.5).

Table 6.5 Robustness check: main regression on matched and complete listings.

Model	Variable	Matched listings (2017.09-2023.10)	All listings (2017.09-2023.10)
EPC band	A/B	0.018* [0.001, 0.035]	0.019** [0.007,0.031]
	C	0.012*** [0.009, 0.015]	0.012*** [0.010, 0.014]
	E	-0.014*** [-0.018, -0.011]	-0.016*** [-0.018, -0.013]
	F/G	-0.045*** [-0.053, -0.037]	-0.040*** [-0.046, -0.035]
EPC score	Score	0.001*** [0.001, 0.001]	0.001*** [0.001, 0.001]

Notes: *N = 64,292* for matched listings and *N = 149,526* for all listings.

6.6 Discussion

This study exploits a period with a dramatic increase in domestic energy costs to strengthen the evidence that energy efficiency has a causal impact on house prices. Previous studies relying on cross-sectional designs find a positive association but have the common problem limiting a causal interpretation that this may be (in part or in whole) the result of omitted variables associated with both energy efficiency and price (Ou et al., 2025). Some have examined the impact of short-term and relatively modest variations in energy prices, yielding mixed conclusions regarding their role in shaping WTP (Aydin et al., 2020; Mense, 2018; J. Olaussen et al., 2019). In contrast, the 2022 energy crisis represents a largely exogenous energy price shock of unprecedented scale, providing a unique opportunity to estimate the causal impact of energy efficiency on house prices since it is highly unlikely that the valuation of unobserved confounders would change at the same time. It also sheds some light on the underlying mechanism or driver.

Across the whole period, our models confirm the significant positive association between energy efficiency and house prices which is already well-documented in the wider literature (Ou et al., 2025). This implies around a 1% price premium for each Band above D, with a slightly larger discount for those below that level, especially those in Bands F/G. Crucially, our results indicate that this WTP increased following the onset of the energy crisis. While the price premium for properties rated above Band D remains broadly stable (non-significant increases), the discount applied to less efficient homes increases significantly in the post-crisis period. Using EPC scores rather than bands, we also see a significant increase in the premium for energy efficiency overall. This result is consistent with a recent UK study based on a more limited follow-up period (Jan 2021 to Aug 2022) using transaction price and a different research design (Braakmann et al., 2026), also finding modest price increases for high-rated properties alongside substantially larger price discounts for low-rated homes. We find this response emerges gradually rather than immediately, suggesting an adaptive response by market participants with beliefs about future energy prices evolving over time.

Over the same period as the energy crisis, house prices will have been impacted by a variety of economic factors, but we do not believe these would have had the same differential impact in relation to energy efficiency. In particular, the dramatic rise in interest rates in late 2022 led to higher mortgage costs, and likely resulted in reduced housing demand and downward pressure on prices overall. However, the rising mortgage rates would be expected to affect all properties similarly. More relevant perhaps was the introduction of a Minimum Energy Efficiency Standards (MEES) for the private rental market, prohibiting landlords from letting properties with EPC bands below E which came into force in April 2020. This policy is likely to have had some impact on energy efficiency price premiums at the bottom end and may help explain the increases in the “brown discount” observed for EPC F/G properties in 2020. However, it is unlikely to account for the much steeper rise in the “brown discount” seen from 2022 onwards.

Crucially, our results help to relieve the long-standing concern of omitted variable bias in estimates of the WTP for housing energy efficiency, which has weakened causal claims and limited the credibility of policy prescriptions. By utilising the natural experiment of the energy crisis, we conclude that coefficients on the EPC capture WTP for energy efficiency itself, at least to some extent. This confirmation provides a more credible message to the market that buyers do value more energy-efficient homes. The confirmation of the causal relationship allows more informed decision-making for policy (including government subsidy sizes, energy efficiency standards, green mortgage design, etc), businesses (in more effective investment decisions), and households (in choosing housing products).

Furthermore, this result also indicates that people are at least partly driven to pay for more efficient homes by energy cost savings. Previous research analysing relationship between energy prices and WTP for efficient homes have found little influence of energy prices (Mense, 2018; J. Olaussen et al., 2019), suggesting the price premium does not come from energy cost considerations. This study, on the contrary, finds that energy costs do influence people's WTP for more energy-efficient homes. When energy prices are higher, the returns on investment in energy efficiency rise both through reduced operational costs and through increased house values. Other than expectations of high energy prices, one study found that people are highly uncertain about future trend of gas and electricity prices (Alberini et al., 2023), which could be another reason for customers to choose more energy efficient homes in order to reduce risks. This finding might encourage a greater policy focus on the monetary benefits of energy efficiency measures instead of environmental ones. However, recognising the importance of energy cost savings highlights the inequality between high- and low-income households. While the former can afford energy efficient improvements, the latter cannot and thereby suffer from higher burdens from energy costs. It is therefore important for Governments to support low-income households to minimise the gap.

Our finding of about a 1% price premium per band translates into £1900 or £2200 in house price capitalisation based on the median and mean house price respectively for listings in this study. The average cost to improve dwellings with EPC band of D to an EPC band of C or above is estimated at £6018 per dwelling (GOV.UK, 2024a) albeit with a wide range. For those planning to sell a dwelling in the near future, there still appears to be little market incentive to make significant energy efficiency improvements. For those planning to remain for some time, however, the increase in capital value does increase the overall returns on such investments. One analysis (Smeeton, G., 2022) suggests that the average annual energy cost saving of improving from EPC D to C was around £680 per year at the peak of the energy crisis. The capital value gains from energy efficiency improvement are therefore equivalent to around three years of running cost savings so forms a significant additional incentive.

There are some limitations to this study. One key limitation is the focus on the second-hand housing market in one UK metropolitan area, although we have no reason to doubt that results here would apply across the rest of the UK at least. Given the energy crisis is global in scale, generating different impacts across regions (Ozili & Ozen, 2023) and housing markets, future studies could analyse cross-regional or international markets to assess how the energy crisis influences the relationship between energy efficiency and house prices more widely. Another limitation lies in potential heterogeneity in WTP for housing energy efficiency across different socio-demographic groups, property types, etc. In reality, preferences to invest in energy efficiency improvements may vary significantly (Evangelista et al., 2022; Koengkan & Fuinhas, 2022). Ignoring this heterogeneity may lead to overgeneralised conclusions and limit the applicability of the findings to granular policy or market interventions. Therefore, a priority for future research is to explore and examine the heterogeneous WTP for housing energy efficiency.

6.7 Conclusions

Taking the dramatic price increase from the global energy crisis as an opportunity, this study investigates whether residents' willingness-to-pay for more energy-efficient homes increased following the crisis. The findings show that energy-efficient properties command a positive price premium of above 1% per band, and that this has increased in the post-crisis period. By documenting an increase of WTP after the crisis, we argue that the causal interpretation of the relationship between housing energy efficiency and house prices is strengthened. Furthermore, the results indicate that energy cost considerations play a substantive role in this WTP, rather than the effect reflecting only environmental concern or signalling.

Overall, this study provides new insights on the price premium associated with energy-efficient homes in the context of the energy crisis, offering a valuable contribution to the existing literature.

The findings have important policy and practical implications. First, the strengthened evidence of WTP for more energy-efficient homes could increase investors' willingness to finance retrofit works, enabling more homeowners to upgrade. It should also encourage policy makers to consider introducing minimum energy efficiency standards for the housing sales markets. Second, the identification of the association between WTP and energy costs suggests that policymakers could place more emphasis on energy bill reduction when promoting energy efficiency measures in policy design. Moreover, it is important for policymakers to recognise the disparity of the energy transition process among high- and low-income households, to provide targeted subsidies to ensure more equal outcomes. Finally, the increase in WTP following the recent energy crisis highlights its potential role as a catalyst for behavioural change, offering policymakers an opportunity to leverage this opportunity to reach broader sustainability objectives.

Chapter 7 Heterogeneous effects of home energy efficiency on the housing market in the UK: evidence from the causal machine learning approach of meta-learners

This Chapter is formatted as a manuscript to be submitted to a journal but with some cross-referencing here to other parts of the thesis. Building on the previous Chapter which provides estimates of the average energy efficiency price premium as well as its change after the energy crisis in Greater Manchester, this Chapter further investigates the heterogeneity of price premiums across housing submarkets in the same study area, addressing Research Question 3 of the thesis. The Chapter itself has three research questions which we number RQ7.1 to RQ7.3 to distinguish them from the overall Research Questions for the thesis.

7.1 Introduction

Improving the energy efficiency of domestic buildings has become a key priority for governments in developed countries to achieve Net Zero goals in the sector, e.g. the UK government (GOV.UK, 2023c), the Scottish government (GOV.SCOT, 2021), and the EU (EU/2024/1275, EPBD). The sector accounts for around one fifth (20%) of global greenhouse gas emissions and energy demand (IEA, 2023b), while it is significantly falling behind on the decarbonisation pathway (CCC, 2025b). A critical barrier to achieving the large-scale decarbonisation of housing stock lies in the substantial investment required (Amoah & Smith, 2022).

Environmental labelling is designed to provide energy efficiency information which can facilitate the investment process in two main ways: market incentives and government support. The labelling of Energy Performance Certificates (EPCs) is used to assess the energy efficiency of homes in EU and UK. It mainly provides the energy efficiency rating for homes on a scale (0-100), summarised in EPC bands (A-G). On the market side, the EPC is legally required to be displayed in any housing market advertisement in the EU (Directive 2010/31/EU, p.11) and the UK. This is expected to provide stronger financial incentives for homeowners and investors if there is a positive price premium for more energy efficient homes. On the policy side, governments can use the EPC ratings to target funding for retrofit, particularly for lower-income households at greatest risk of fuel poverty. However, resources from both private investors and governments are limited, making their efficient allocation crucial. Therefore, there is growing interest in gaining a more granular understanding of the market effects of energy labelling, and specifically, of the heterogeneous price effects of home energy efficiency.

Studies of the price impacts of housing energy efficiency have largely focused on *average* effects, generally identifying a 1-3% price premium per EPC band (Ou et al., 2025) and noting that this premium has increased following the energy crisis (Wei & Peiser, 2025). However, far less attention has been paid to the heterogeneity of these price premiums across submarkets, with a very limited number of studies exploring variations across house price segments (McCord, Haran, et al., 2020), time and regions, property types (Evangelista et al., 2022), or buyers' socioeconomic status (Geske, 2022).

Existing research studying house price premiums explicitly follows the theory-driven approach of specifying a hedonic model and estimating it with linear regression (Chin & Chau, 2003). Accordingly, studies typically focus on extensions of linear regression by including multiplicative interactions (Marmolejo-Duarte & Chen, 2019a), making separate models for sub-markets (Chegut et al., 2020; Evangelista et al., 2022), quantile regression (McCord, Haran, et al., 2020), or partially linear varying coefficient model (Shen et al., 2021). While linear regression is superior in the interpretability of parameters compared to nonlinear or nonparametric approaches, it has long been criticised for its methodological limitations, notably the assumptions of linear parameters or interaction effects (Hainmueller et al., 2019). Another common drawback of these approaches for heterogeneity analysis lies in requiring prior knowledge on attributes that affect prices or define submarkets (hence *theory-driven*) (Salditt et al., 2024). Though techniques such as hypothesis testing could inform the theory-driven submarkets selection process, testing for combination possibility remains overcomplicated and that it may fail to offer informative insights in the case of large sample sizes (Gan, 2025).

The recent rise in causal applications of machine learning (ML) offers tools for estimating treatment effects that capture complex, non-linear relationships between variables (Feuerriegel et al., 2024). A key advantage of these approaches is in allowing estimation of individualised treatment effects, thereby enabling *data-driven* analyses of heterogeneous effects (Salditt et al., 2024). Particularly, meta-learners decompose treatment effect estimation into subproblems that can be solved by any ML model (Künzel et al., 2019). They are gaining the attention of social scientists in heterogeneous effects analysis (A. Hu, 2023), including recent applications in related housing market areas such as estimating the house price premium of solar (photo-voltaic) panels (Asproudis et al., 2024). Compared with traditional hedonic models, meta-learners have several advantages, including that they can: (1) capture complex, non-linear relationships, (2) incorporate different types of data to reduce omitted variable bias, and (3) generate individualised treatment effects for heterogeneity analysis.

Despite their flexibility, there are potential limitations of using meta-learners. First, they do not remove potential problems of omitted variable bias and still rely on other causal assumptions including positivity and Stable Unit Treatment Value Assumption (SUTVA) (Salditt et al., 2024). Second, results may vary with the choice of meta-learners and of base learners but there is no clear basis for picking one over another (Okasa, 2022). There are some simulation studies comparing performance of different meta-learners, which generally recommend the group of pseudo-outcome learners (X-/DR-/R-learner) over others (S-/T-learner) when there is large sample size (Knaus et al., 2021; Okasa, 2022), unbalanced treatment assignment, and/or obvious problems of confounding variables (Salditt et al., 2024). However, among pseudo-outcome methods, it is difficult to make a determined decision. If there is lack of agreement in results and no basis for selection between meta-learners, we will fail to provide robust guidance for policy making. It is thus important to assess the consistency of results from different learners before offering evidence.

Therefore, this study aims to answer three research questions: (RQ7.1) Is there significant heterogeneity in price premiums for housing energy efficiency? (RQ7.2) If there is heterogeneity, is there consistency between the meta-learner models in their estimations of price premiums such that they can offer some guidance for policy? (RQ7.3) If there is consistency, in which types of properties and/or locations do the price premiums appear to be greater/smaller? Specifically, we apply the meta-learner approach to identify heterogeneous price effects of energy-efficient homes (EPC band of C and above) in the second-hand sales market of Greater Manchester (GM), UK, over the period 2017–24. We collate a dataset with detailed information on more than 150,000 secondhand house sales. By applying a set of meta-learner approaches (X-/DR-/R-learner) with stacked ML models (k-nearest-neighbour, random forest, XGB, lightGBM) as base learners, the individualised treatment effects of energy efficiency on house prices are estimated. Based on the individualised effects, the study examines the average price premium, tests for global heterogeneity, explores inter-model consistency, and examines heterogeneity across submarkets. By offering knowledge of heterogeneous price premiums for housing energy efficiency, this study provides insights into how governmental funding and private investment should be allocated, thereby facilitating a more efficient and equitable housing energy transition process to reach the climate goals.

7.2 Methodology

This section outlines the methodology adopted in the analysis, including defining the causal problem and discussing assumptions, setting up the meta-learners, detailing the heterogeneity analysis, and specifying the OLS/multilevel hedonic models used for comparison.

7.2.1 Causal problem definition and assumptions

The objective is to estimate the price premiums (i.e., treatment effect) of housing energy efficiency on house prices. The technical definitions of terms related to the causal problem are as follows:

- Observational unit: individual house i;
- Treatment variable: housing energy efficiency (T_i);
- Treatment group: energy efficient ($T_i = 1$);
- Control group: energy inefficient ($T_i = 0$);
- Outcome variable: natural log of house price (Y_i);

- Features X_i: property and neighbourhood characteristics, time and location.

The potential outcomes framework defines the treatment effect/causal effect as the difference between individual outcomes with and without treatment (Imbens & Rubin, 2015). In this analysis, each house has two potential outcomes: $Y_i(1)$, the house price if the house is energy-efficient; and $Y_i(0)$, the price if the same house is energy-inefficient. Then $Y_i(1) - Y_i(0)$ is the treatment effect of energy efficiency on house i. As only one potential outcome can be observed i.e., the fundamental problem of causal inference, it relies on counterfactuals to estimate the treatment effect.

To be able to rely on counterfactuals for treatment effect identification, three assumptions are needed, regardless of whether we are using traditional statistical or causal machine learning approaches (Feuerriegel et al., 2024): (1) conditional independence: no unobserved confounders affect both the treatment and outcome; (2) positivity: for any combination of covariate values, the treatment and control groups have non-zero probability; (3) stable unit treatment value assumption (SUTVA): the outcome of any unit is unaffected by treatment status of other units. Discussion on how these assumptions are met in this study is provided in Section 7.3.1.

7.2.2 Meta-learner

7.2.2.1 Meta-learner framework: pseudo-outcome learners

Meta-learners are frameworks that can incorporate any ML method to estimate conditional average treatment effects (CATEs). This method is inherently suitable for heterogeneity analysis, as the estimated treatment effects are available at individual level. The estimates can be used for a range of *post hoc* analyses, such as evaluating the covariates driving treatment effect heterogeneity and exploring the distribution of treatment effects across subgroups (Salditt et al., 2024).

There are several meta-learners models, among which the most common approaches can be divided into two categories: single-stage “conditional mean regression methods” (S-learner and T-learner) and two-stage “pseudo-outcome methods” (X-learner, DR-learner, and R-learner). There is no hard evidence on which ones are preferable for treatment effect estimation as no ground truth is available for validation. Simulation studies based on synthetic estimations do exist to provide some guidance (Jacob, 2021; Künzel et al., 2019; Okasa, 2022). They generally find that pseudo-outcome learners outperform single-stage learners, particularly when the sample size is large, treatment assignment is imbalanced or the confounding problem is considerable.

Among the three pseudo-outcome learners, each of them demonstrate different advantages in these simulations (Okasa, 2022). First, the X-learner performs well when treatment assignment is highly imbalanced and is most robust towards any violation of positivity assumption. Second, the DR-learner performs strongly with nonlinear and complex CATEs, and with large sample size but it can be unstable with extreme propensity scores (i.e., near-violation of the positivity assumption). Lastly, the R-learner provides theoretically grounded loss-based estimation but can also be unstable when there are extreme propensity scores.

As our dataset has a large number of properties and shows an imbalance in the distribution of ‘treated’ (energy efficient) properties (see Section 7.3.2), pseudo-outcome learners offer distinct advantages over single-stage learners. While the expected nonlinear and complex CATEs suggest we should favour the DR-learner according to the simulation studies, the strong imbalance in treatment assignment favours the X-learner. As no single pseudo-outcome learner can be shown to be clearly preferable, however, we implement all three pseudo-outcome learners (X-, DR-, R-learner) in this analysis and report individual estimates as well as the median estimates across learners in the results.

Executions of pseudo-outcome learners involve two stages, including firstly estimating outcome conditional mean functions (outcome estimation) and secondly estimating CATE functions (CATE estimation) (Table 7.1). Both stages can apply any ML method as the ‘base learner’ for estimation. The specific steps for each pseudo-outcome learner are as follows (more details of the algorithms can be found in Okasa (2022) and Salditt et al. (2024)). A visual representation of stages of learners is shown in Figure 7.1.

(1) X-learner

Stage 1: Estimate $\mu_1(x)$ and $\mu_0(x)$ on treatment and control groups separately, then impute the pseudo-outcome as the difference between actual outcome and the estimated missing outcome for each case:

$$\hat{\psi}(X_i) = \begin{cases} Y_i - \hat{\mu}_0(X_i), & T_i = 1 \\ \hat{\mu}_1(X_i) - Y_i, & T_i = 0 \end{cases}$$

Stage 2: Fit $\hat{\tau}_0(x)$ and $\hat{\tau}_1(x)$ on the control and treatment groups separately, by modelling $\hat{\psi}(X_i)$ as a function of features. Then, CATE $\hat{\tau}(x)$ is calculated as the propensity score-weighted average of $\hat{\tau}_0(x)$ and $\hat{\tau}_1(x)$:

$$\hat{\tau}(x) = \hat{e}(x)\hat{\tau}_0(x) + [1 - \hat{e}(x)]\hat{\tau}_1(x)$$

(2) DR-learner

Stage 1: The doubly-robust pseudo-outcome is computed based on $\mu_1(x)$ and $\mu_0(x)$, and the propensity scores:

$$\hat{\psi}(X_i) = \hat{\mu}_1(X_i) - \hat{\mu}_0(X_i) + \frac{T_i[Y_i - \hat{\mu}_1(X_i)]}{\hat{e}(X_i)} - \frac{(1 - T_i)[Y_i - \hat{\mu}_0(X_i)]}{1 - \hat{e}(X_i)}$$

Stage 2: Regresses $\hat{\psi}(X_i)$ on observed features to obtain final CATE estimates $\hat{\tau}(x)$.

(3) R-learner

Stage 1: Estimates single conditional mean function on both groups $m(x)$ and the propensity score model $e(x)$. The pseudo-outcome is:

$$\hat{\psi}(X_i) = \frac{Y_i - \hat{m}(X_i)}{T_i - \hat{e}(X_i)}$$

Stage 2: Use a specific loss function i.e., R-loss, minimising which gives the final estimates of CATE $\hat{\tau}(x)$:

$$\hat{L}(\tau) = \frac{1}{n}\sum_{i=1}^{n}[T_i - \hat{e}(X_i)]^2\big[\hat{\psi}(X_i) - \tau(X_i)\big]^2$$

Table 7.1 Common stages in all pseudo-outcome learners.

Stages	Steps
Stage 1: Outcome estimation	Step 1: The conditional mean function $\mu(x)$ of outcomes based on features is fitted for each treatment group, OR one conditional mean function $m(x)$ on both groups is estimated.
	Step 2: The estimated functions are used to construct pseudo-outcomes $\hat{\psi}(X_i)$ (i.e., the initial approximation of the treatment effect), sometimes incorporating the propensity score $\hat{e}(X_i)$ (i.e., the probability of treatment exposure conditional on covariates) to improve efficiency.
Stage 2: CATE estimation	Step 1: CATE $\hat{\tau}(x)$ is estimated by modelling $\hat{\psi}(X_i)$ as a function of predictors, often incorporating the propensity score $\hat{e}(X_i)$ to improve efficiency.

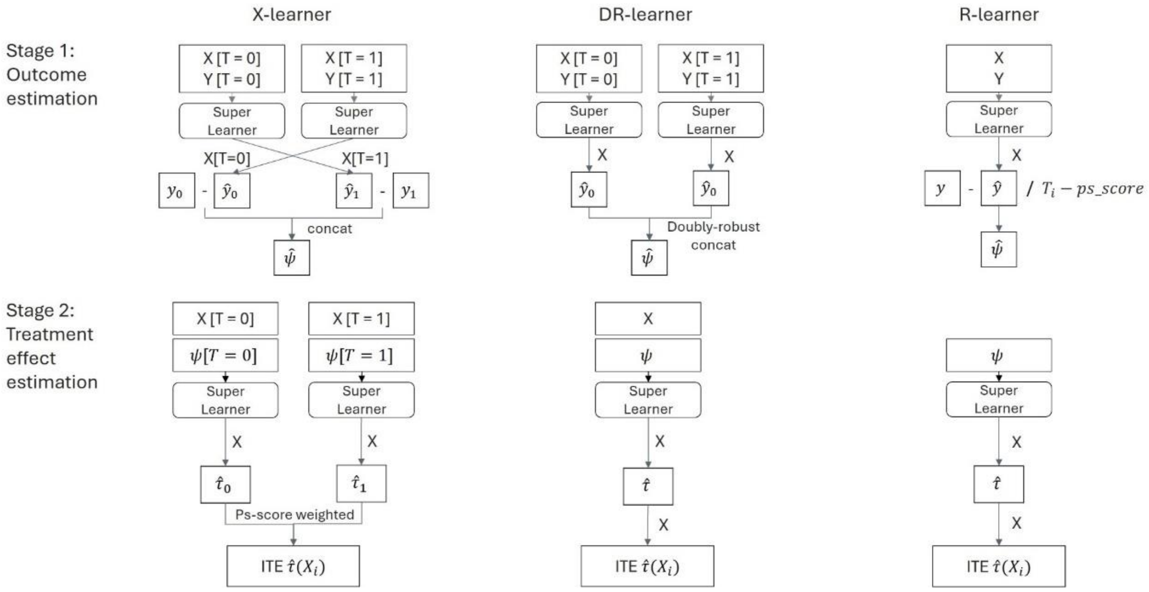


Figure 7.1 Stages in each pseudo-outcome learner: X-/DR-/R-learner.

7.2.2.2 Estimation procedure: cross-fitting and repetitions

The estimation procedure for meta-learners could be as simple as fitting all the data in both stages with only one end-to-end execution. However, there would be a high risk of overfitting, thus undermining reliability of the final estimates. Overfitting could happen in two aspects, both the result of using the same data in training and prediction. In the first stage, the data used to estimate outcome models is also used to compute pseudo-outcomes. Similarly, at the second stage, the same sample is used for fitting the CATE model and generating final CATE estimates.

The recommended solution to avoid overfitting is using the technique of cross-fitting (Okasa, 2022; Salditt et al., 2024), which is beneficial especially for large samples. The idea is that each model is trained on one subset and with predictions based on the other, ensuring separation between prediction and training data. This is usually implemented using *k-fold* splitting (Salditt et al., 2024). Moreover, to reduce the uncertainty caused by the specific way data was split into subsets, repetitions is recommended (Chernozhukov et al., 2023). In this paper, we adopt *5-fold* cross-fitting with *10* repetitions, taking the median estimate for each case across repetitions (Figure 7.2).

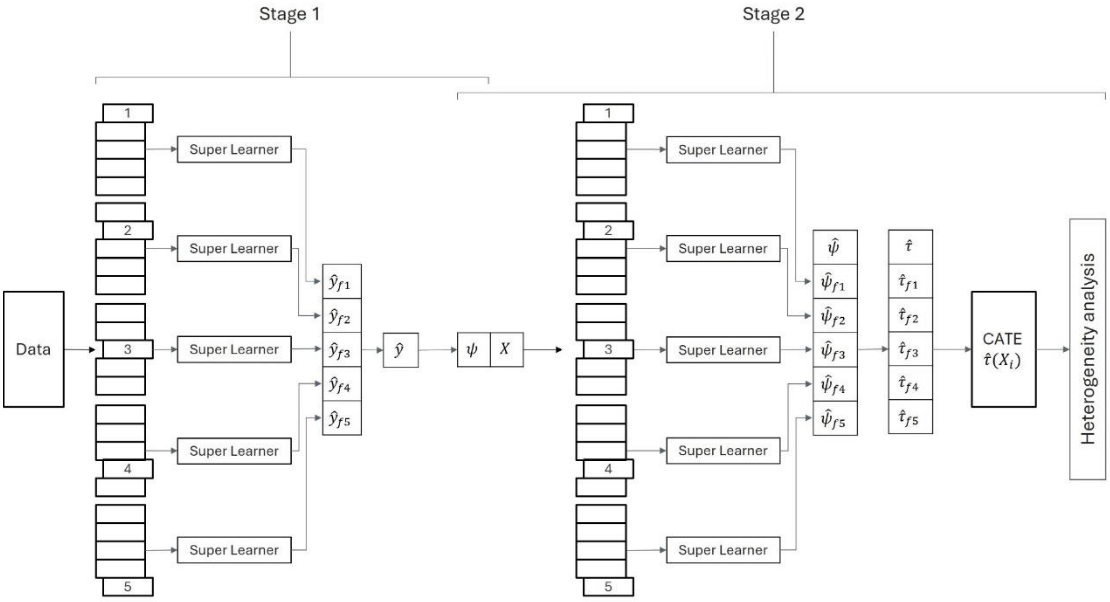


Figure 7.2 Cross-fitting and repetitions.

7.2.2.3 Base-learner: Super Learner

Meta-learners require user-defined models for estimating $\mu(x)\,/\,m(x)$ and $\tau(x)$ (the propensity score model $e(x)$ is estimated with logistic regression) i.e., the base-learner. In practice, it is recommended to apply the model with best accuracy in predicting outcomes, optimising its performance via hyperparameter tuning (Feuerriegel et al., 2024; Salditt et al., 2024). The main challenge in base-learner selection is that CATE estimation can be sensitive to model choice. We therefore use the Super Learner as base-learner. It is a stacked ML model combining multiple candidate models, which is guaranteed to perform at least as well as the best candidate model (van der Laan et al., 2007).

The training of a Super Learner involves two stages (Figure 7.3); more details of training Super Learners can be found in Naimi and Balzer (2018): (1) estimation of individual candidate model parameters and (2) estimation of weights for combining candidate models. In the first stage, each candidate model is fitted with the entire training dataset. In the second stage, training data is first split into *k* folds. Each candidate model is applied to generate out-of-fold predictions, followed by regressing true outcome on estimated outcomes from each candidate model (OLS regression is used here). The model weights are the coefficients from the OLS regression.

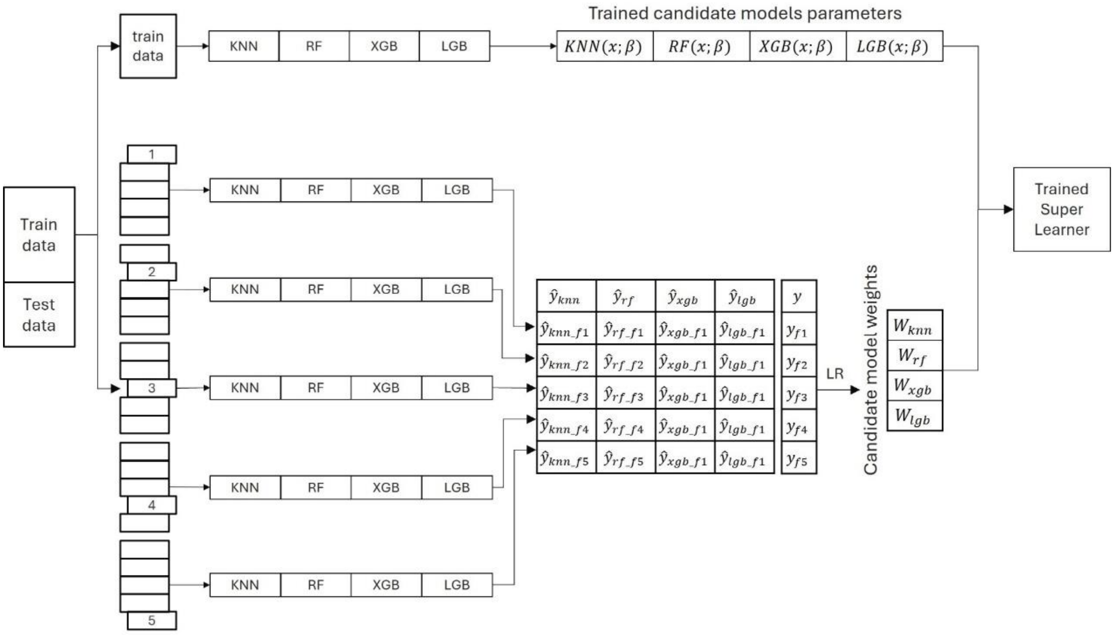


Figure 7.3 Super Learner training process.

Note: Author's drawing adapted from (Laan et al., 2007).

The inclusion of final candidate models is based on a preliminarily trained Super Learner, which includes a wide variety of models grouping into these categories: linear regression, support vector machine, nearest neighbours and tree-based models. These cover most of the supervised machine learning algorithms used for regression problem (El Mrabet et al., 2021). Neural networks are not considered due to time and computational constraints. The full list of models and the model weights of the preliminary Super Learner are attached in Appendix E, Table E-1. We finally choose models with relatively high model weights (greater than 0.1) as our candidate models. Here we include (1) LightGBM, (2) XGBoost, (3) random forest (RF) and (4) k-nearest neighbours (KNN).

Ideally, hyperparameter tuning of candidate models should be executed in every single training within the cross-fitting procedure. However, as the hyperparameter tuning is computationally expensive, in this paper, we only tune each candidate model once using a 70/30 train-test split and grid search with 5-fold cross-validation. The tuned hyperparameters are shown in Appendix E, Table E-1.

7.2.3 Heterogeneity analysis

Based on the individual CATE estimates, we refer to Salditt et al. (2024) to use three approaches for inferential heterogeneity analysis:

(1) Global test for the presence of heterogeneity

This test involves fitting the regression model:

$$Y_i - \widehat{m}(X_i) = \beta_1[T_i - \hat{e}(X_i)] + \beta_2\{[\hat{\tau}(X_i) - \hat{\tau}][T_i - \hat{e}(X_i)]\} + \epsilon,$$

$$\hat{\tau} = \frac{1}{n}\sum_{i=1}^{n} \hat{\tau}(X_i)$$

(7.1)

where $\widehat{m}(X_i)$ is the estimate from the conditional mean function, and $\hat{\tau}$ is the average treatment effect estimated from CATE estimates i.e. the average of the individualised estimates. Here the coefficient on the interaction term β_2 is used to measure the degree of heterogeneity: if β_2 is significantly greater than zero, then there is significant treatment effect heterogeneity from the CATE estimates.

(2) Subgroup treatment effects

Subgroup treatment effects are investigated by sorting observations based on the estimated CATEs and splitting into subgroups based on quantiles (more details in Salditt et al., (2024)). These subgroup treatment effects are called sorted group average treatment effects (GATES).

(3) Drivers of heterogeneity

Third, to investigate which features drive the heterogeneity, the average feature levels between the most and least affected subgroups are compared which is called classification analysis (CLAN) (Chernozhukov et al., 2023). To test if there is significant difference between feature levels of separate groups, we apply the Welch-test with Holm correction as recommended by (Salditt et al., 2024).

Additionally, we explore differences in CATE estimates across predefined submarkets i.e., exploratory heterogeneity analysis. For continuous variables, Locally Weighted Scatterplot Smoothing (LOWESS) plots are used to visualise the changes. As for categorical variables, boxplots and Kruskal-Wallis tests with Bonferroni correction are applied to examine the difference between groups.

7.2.4 OLS and multilevel hedonic model

To benchmark meta-learner results, we compare the estimated average treatment effect from meta-learners to the coefficient from standard hedonic regressions including OLS and multilevel models. The OLS regression model is specified as follows:

$$\ln(price_i) = \beta_0 + \beta_S X_i + \beta_E EnergyEfficiency_i + \beta_L Location_i + \beta_T Time_i + \epsilon_i,$$

$$\epsilon_i \sim N(0, \sigma_\epsilon^2)$$

where the coefficient β_E measures the average price premium associated with energy-efficient properties.

Also, the multilevel (two-level) regression model applied properties as level 1 and neighbourhood (LSOA11, details in the following section) as level 2. The full specification is therefore as follows (technical explanations can be found in Section 6.4.1.2):

Level 1 model:

$$ln\left(price_{ij}\right) = \beta_j + \beta_S X_{ij} + \beta_E EnergyEfficiency_i + \beta_L Location_i + \beta_T Time_i + \epsilon_{ij}$$

$$\epsilon_{ij} \sim N(0, \sigma_\epsilon^2)$$

Level 2 model:

$$\beta_j = \gamma_0 + \gamma_N Z_{jN} + u_j$$

$$u_j \sim N(0, \sigma_u^2)$$

7.3 Data

7.3.1 Data source and preprocessing

We match data from multiple sources covering property and neighbourhood characteristics. First, property listings are obtained from one of the most popular house sales listings services in the UK – Zoopla (Zoopla HomeTrack, 2023). In this analysis, we restrict the sample to second-hand houses advertised for sale from 2017-09-01 to 2024-05-31 in GM (justification presented in Section 5.1.3). Listings data offer property information including the Unique Property Reference Number (UPRN), listing price, listing closing date, local authority, some structured characteristics (including size and type) and property description text. We identify additional property features from the description text including the presence of a modern kitchen, garage and garden. Though listing prices may not accurately represent completed transaction prices, the validation in Section 5.3 supports the use of listing prices as a very reliable guide to recorded transaction prices.

Second, Energy Performance Certificate (EPC) data (OpenDataCommunities, 2024) includes information for all properties advertised for sale as a legal requirement in the UK. Corresponding to the period covered by the Zoopla data, we use the EPCs issued up to 2024-05-31. EPCs provide further rich property information including UPRN, energy efficiency rating, total floor area, number of habitable rooms, property type, built form and building age. We use the energy efficiency band from A (most energy efficient) to G (least energy efficient) for analysis, which is a cost-based measure reflecting both fabric energy efficiency (heat demand) and type of heating (and hence unit costs). It is the main ‘headline’ measure in the EPC so the factor most likely to influence buyer judgements. We create the binary treatment variable of ‘energy efficiency’ by dividing EPC Band C and above (treatment group) versus D and below (control group).

Third, neighbourhood characteristics are obtained from several research and administrative sources (justification of inclusion of these characteristics in Section 6.4.2). These datasets provide data at LSOA11 level (Lower layer Super Output Areas, 2011 boundaries), which contain about 400–1,200 households (1673 LSOA11s in GM). The Public Transport Accessibility Indices (Verduzco Torres & McArthur, 2024) offers indicators of public transport accessibility to a rich set of amenities at LSOA11 level, using a range of travel time thresholds. Following (Georgiou et al., 2026), we apply principal component analysis (PCA) to the set of indices in order to represent neighbourhood accessibility as two principal components (PC1 and PC2) in this analysis. The PCs together explain 78.5% of the variance in the indices, with PC1 accounting for 73.5% and PC2 for 5.0%. We interpret PC1 as primarily reflecting accessibility to the city centre, while PC2 appears to capture accessibility to smaller district centres (as discussed in Section 6.4.2). More details of the weightings of each component across the underlying indices are presented in Appendix D, Table D-4.

Also, we use the Income Deprivation score provided by English Indices of Deprivation (OpenDataCommunities, 2019), which measures the percentage of the population at LSOA11 level in receipt of a low income welfare benefit. Furthermore, LSOA population density is provided by Office for National Statistics (ONS, 2024b). We use the measures estimated at mid-2020 which lies at the mid-point of our study period. Finally, State-funded Schools Inspections data (Ofsted, 2024) provides school quality rating based on Ofsted's rating system and school type. We construct the variable of school quality using average rating of closest primary and secondary school to each property.

To match these datasets, Zoopla listings and EPC are linked using the UPRN. Neighbourhood datasets are joined using the LSOA11 code. One exception is on school quality data, which is linked based on Euclidean distance between properties and schools from the same local authority. To clean the dataset, we first drop observations with extreme listing prices (>£1.5 million or <£30k), which either exceed the top threshold of land tax or likely to represent non-market transactions. We further filter listings to exclude auctions/shared-homeownership/rent-to-buy schemes, by identifying key words from the Zoopla description text. Finally, outliers are dropped based on both domain knowledge and data distribution, and observations with missing data are filtered. More details of data linkage and preprocessing can be found in Chapters 5 and 6.

Here we discuss how the data meet the causal assumptions stated in Section 7.2.1. In terms of confounders, we have included a wide set of available variables to minimise the risk of omitted variables bias. However, there is still risk of unobserved confounders, as we do not include variables such as interior quality and other unobserved characteristics related to both energy efficiency and house prices. To check that our data satisfy the positivity assumption, we assess the distribution of covariates and propensity scores across treated and control groups. The results indicate that newer buildings risk violating the positivity assumption as there are very few which are energy inefficient. This is in line with expectations as building codes have greatly increased minimum standards over time (Vagtholm et al., 2023). We therefore exclude those built after 2003 and combine buildings constructed 1983-2002 into a single category. We also filter a small number of other observations with extreme propensity scores (<0.1/>0.9). Regarding the assumption of SUTVA, we primarily rely on domain knowledge. Although spatial spillover effects in house prices could potentially lead to a violation of this assumption (Tsai, 2015), the previous Chapter finds that spatial dependencies modelled with spatial multilevel model do not materially affect the estimated treatment effect of housing energy efficiency on house prices.

7.3.2 Descriptive statistics

The filtered dataset has 148,157 observations. Descriptive statistics are shown in Table 7.2. To define the energy efficiency variable, we split EPC ratings into EPC of C or above (energy efficient) versus those EPC of D or below (energy inefficient). There are 39,123 observations (26.4%) in the treatment group and 109,034 (73.6%) in the control group. The statistics of variables in the two groups are also shown, with results of Welch's two-sample t-test applied to each variable. On average, energy-efficient homes command higher prices and are generally smaller in floor area but have a greater number of rooms, and more frequently include features such as modern kitchens and gardens. They are more likely to be houses rather than bungalows and are more often detached than semi-detached or terraced. These properties also tend to be newer and are typically situated in areas with lower population density, lower accessibility, and higher income deprivation.

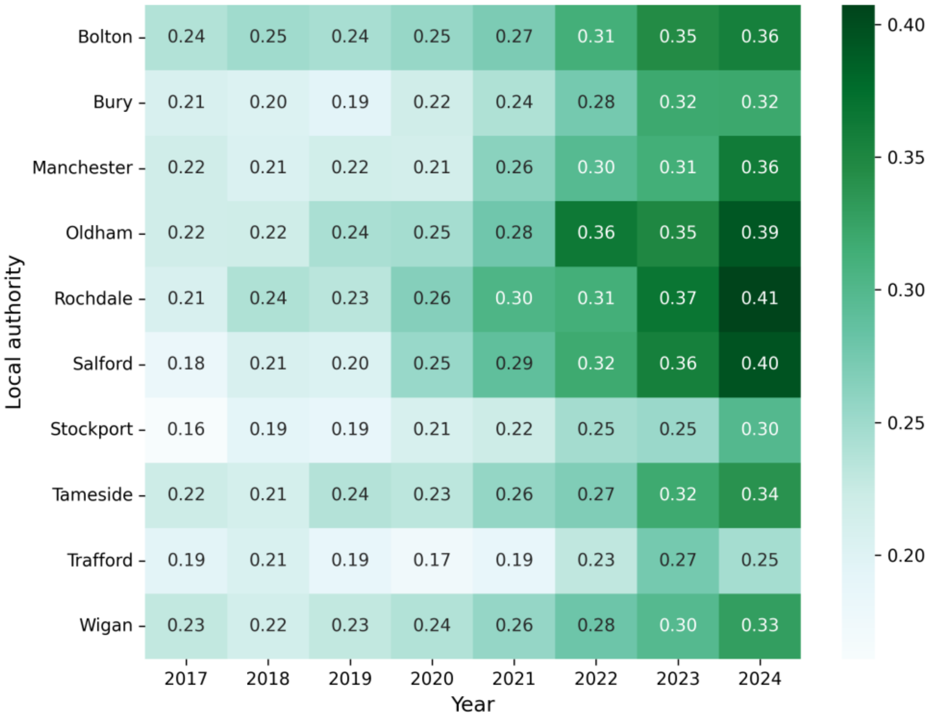
Table 7.2 Descriptive statistics.

Variable	Value of category	Full sample	Energy efficient	Energy inefficient	T-test statistics
Dependent variable					
Listing Price (log)		12.162	12.204	12.147	19.94****
Independent variables					
Energy efficiency	True	0.264	1.0	0.0	-
Tenure	Freehold	0.551	0.556	0.549	2.39*
	Leasehold	0.449	0.444	0.451	-2.38*
Property type	House	0.930	0.948	0.922	18.69****
	Bungalow	0.071	0.052	0.078	-18.69****
Total floor area (log)		4.448	4.442	4.450	-5.00****
Habitable rooms	1 - 3	0.088	0.089	0.088	-0.82
	4	0.347	0.336	0.352	-5.61****
	5	0.358	0.356	0.358	-0.91
	6 - 7	0.181	0.186	0.178	4.64****
	8 - 10	0.026	0.033	0.024	8.83****
Built form	Detached	0.145	0.170	0.137	15.15****
	Semi-detached	0.427	0.414	0.431	-5.69****
	Terraced	0.428	0.416	0.432	-5.59****
Building age	Before 1900	0.058	0.029	0.069	-35.00****
	1900 – 1929	0.236	0.159	0.263	-45.71****
	1930 – 1949	0.235	0.193	0.250	-23.64****
	1950 – 1966	0.169	0.165	0.170	-2.69**
	1967 – 1982	0.161	0.185	0.153	14.47****
	1983 – 2002	0.141	0.269	0.095	72.14****
Modern kitchen	True	0.240	0.261	0.233	10.90****
Garage	True	0.328	0.330	0.327	1.12
Garden	True	0.874	0.903	0.864	21.20****
Local authority	Bolton	0.153	0.165	0.149	7.52****
	Bury	0.105	0.099	0.107	-4.22****
	Manchester	0.090	0.089	0.090	-0.94

	Oldham	0.063	0.071	0.060	7.48****
	Rochdale	0.067	0.075	0.063	7.78****
	Salford	0.111	0.117	0.109	4.45****
	Stockport	0.091	0.076	0.096	-12.04****
	Tameside	0.102	0.101	0.102	-0.42
	Trafford	0.058	0.047	0.061	-10.53****
	Wigan	0.162	0.158	0.163	-2.18*
School quality		2.872	2.869	2.873	-1.42
Listing end time	2017	0.055	0.044	0.059	-11.66****
	2018	0.132	0.108	0.140	-16.76****
	2019	0.138	0.115	0.146	-16.08****
	2020	0.125	0.111	0.130	-10.47****
	2021	0.159	0.154	0.161	-2.95**
	2022	0.146	0.160	0.141	8.79****
	2023	0.138	0.167	0.127	18.72****
	2024	0.107	0.140	0.095	22.82****
Population density (natural log)		3.471	3.449	3.479	-6.30****
Accessibility PC1		-1.287	-1.516	-1.204	-11.23****
Accessibility PC2		-0.001	-0.053	0.018	-7.56****
Income Deprivation		0.149	0.154	0.148	10.30****
Observations		148,157	39,123	109,034	148,157

Note: * P ≤ 0.05, ** P ≤ 0.01, *** P ≤ 0.001, **** P ≤ 0.0001.

Figure 7.4 shows the proportion of energy-efficient houses across local authorities over the years covered in this study. Over time, the proportion of energy-efficient homes has risen, with a more pronounced increase starting around 2021-2022. Regarding regional variations, Rochdale, Salford and Oldham show the highest shares of efficient homes by the end of the period. By contrast, Stockport and Trafford generally show the lowest proportions throughout, while Bolton, Bury, Manchester, Oldham, Tameside and Wigan fall in between.



Local authority	2017	2018	2019	2020	2021	2022	2023	2024
Bolton	0.24	0.25	0.24	0.25	0.27	0.31	0.35	0.36
Bury	0.21	0.20	0.19	0.22	0.24	0.28	0.32	0.32
Manchester	0.22	0.21	0.22	0.21	0.26	0.30	0.31	0.36
Oldham	0.22	0.22	0.24	0.25	0.28	0.36	0.35	0.39
Rochdale	0.21	0.24	0.23	0.26	0.30	0.31	0.37	0.41
Salford	0.18	0.21	0.20	0.25	0.29	0.32	0.36	0.40
Stockport	0.16	0.19	0.19	0.21	0.22	0.25	0.25	0.30
Tameside	0.22	0.21	0.24	0.23	0.26	0.27	0.32	0.34
Trafford	0.19	0.21	0.19	0.17	0.19	0.23	0.27	0.25
Wigan	0.23	0.22	0.23	0.24	0.26	0.28	0.30	0.33

Figure 7.4 Proportion of energy efficient houses across regions over years.

Figure 7.5 shows key housing and neighbourhood characteristics at LSOA level. The spatial distribution of energy-efficient housing reveals a concentration in the city centre, with areas in the southern and eastern parts present lower proportions than northern parts. Conversely, higher-price properties are mainly located along the southern border, followed by those near the eastern boundary. This inverse geographical relationship indicates that neighbourhoods with lower property values tend to have higher rates of energy-efficient homes. The inverse relationship is also evident between house prices and income deprivation, showing spatial socioeconomic stratification in GM. Moreover, a clear monocentric urban structure is revealed through population density and public transport accessibility.

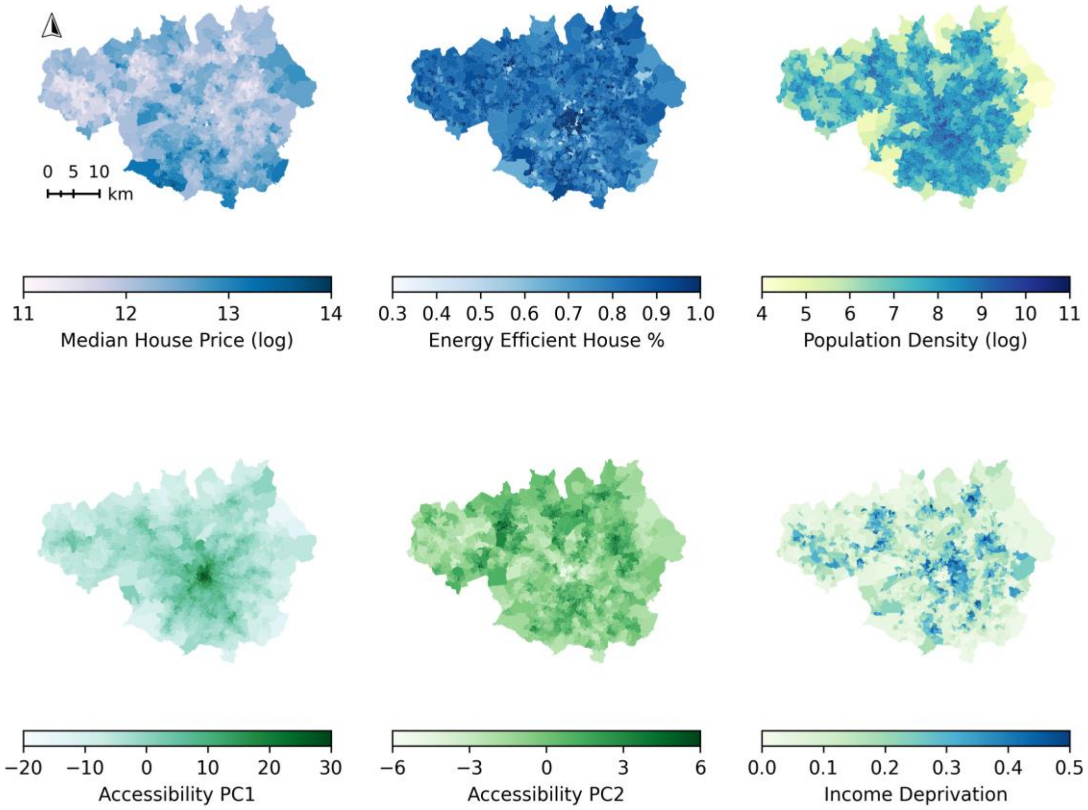


Figure 7.5 Spatial distribution of housing and neighbourhood characteristics (LSOA11 level).

7.4 Results

7.4.1 Average price premium of housing energy efficiency

Before examining heterogeneity in estimated premiums, we compare models in terms of their estimates of average effects. Table 7.3 summarises results from the three meta-learners, along with those from the hedonic regressions. Generally, there is similarity between meta-learners ranging 2.1-2.8%. Comparing treatment effect estimations from meta-learners with coefficients from traditional hedonic regressions, it is apparent that all meta-learners find a higher average price premium than typical hedonic regressions (1.3-1.6%). Confidence intervals of estimates from meta-learners are non-overlapped despite the similar point estimates, which mainly reflects the very large sample size instead of important differences between meta-learners.

Table 7.3 Average price premiums from meta-learner and typical hedonic regression models.

Model		Mean	Std.Err.	Min	Median	Max	95%CI
Meta-learner	X-learner	0.024	8.833e-05	-0.458	0.022	0.623	(0.024, 0.024)
	DR-learner	0.021	0.0002	-3.705	0.021	1.795	(0.021, 0.021)
	R-learner	0.028	0.0003	-3.225	0.027	2.463	(0.027, 0.028)
Typical hedonic regression	OLS Regression	0.013	0.002	-	-	-	(0.008, 0.017)
	Multilevel regression	0.016	0.001	-	-	-	(0.014, 0.018)

7.4.2 Inferential heterogeneity analysis

To address the RQ7.1, we apply the three inferential tests for heterogeneity outlined in Section 7.2.3.

7.4.2.1 Global Test for Heterogeneity

The coefficient β_2 in Equation 7.1 captures the presence of heterogeneity. As shown in Table 7.4, all three learners reject the null hypothesis of homogeneous treatment effects (i.e., that $\beta_2 = 0$), thus showing significant heterogeneity of price premiums ($p < 0.0001$). The X-learner finds the greatest evidence of heterogeneity, followed by DR- and R-learners. These provide strong evidence that heterogeneity is present in the data.

Table 7.4 Global heterogeneity test results (estimate of β_2) across meta-learners.

Meta Learner	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
X-learner	1.271	0.029	43.926	<0.0001	1.213	1.329
DR-learner	0.458	0.014	33.489	<0.0001	0.433	0.485
R-learner	0.295	0.011	27.253	<0.0001	0.273	0.316

7.4.2.2 Subgroup analysis (GATES)

The sorted group average treatment effects (GATES) for CATE-based quintiles show a strong gradient for all three meta-learners, again confirming heterogeneity in estimated premiums (Figure 7.6); further details in Appendix E, Table E-2.

Across all three meta-learners, Quintile 1 covers properties where the price premiums are estimated to be negative on average, while in the second Quintile they average close to zero. These null or negative effects are not apparent from the overall averages estimated in Chapter 6. The remaining three Quintiles show positive effects on average, with the highest 20% of units (Quintile 5) averaging over 8% for the X- and DR-learners. There are slight differences in the magnitude of estimated premiums: the R-learner predicts slightly smaller positive effects in Quintile 5 and slightly smaller negative effects in Quintile 1 compared to the X- and DR-learners.

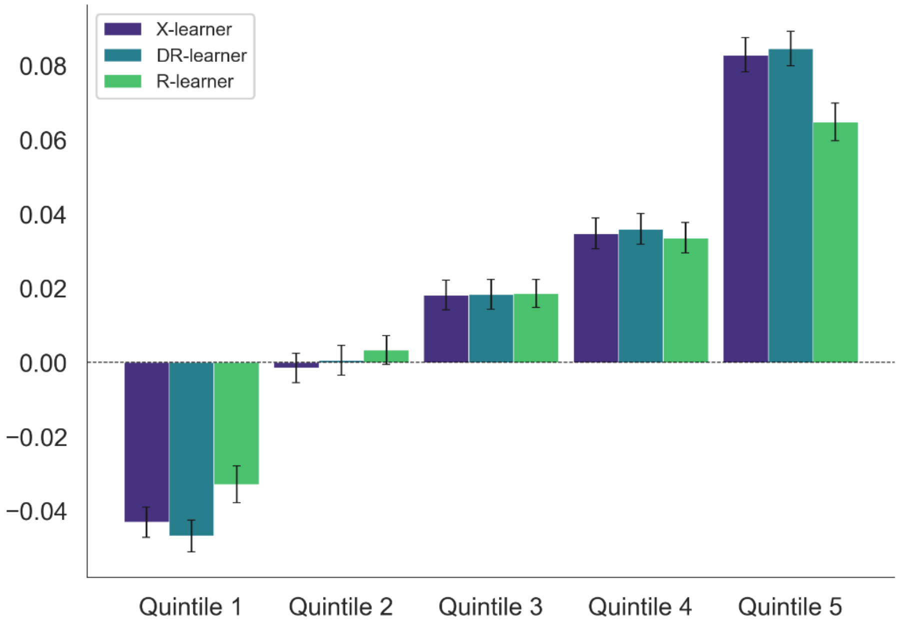


Figure 7.6 Estimated GATES across meta-learners.

7.4.2.3 Drivers of Heterogeneity (CLAN)

The CLAN analysis again provides evidence of heterogeneity, relating this to property characteristics. Table 7.5 shows the difference in average covariate levels between Quintiles 1 and 5 i.e., CLAN values. It shows the covariates with average absolute CLAN values greater than 0.05 in descending order (full results see Appendix E, Table E-3). The CLAN values for dummy variables are percentage differences, while those for numeric variables are differences in mean values.

Overall, the Spearman correlation coefficient shows high rank agreement of CLAN values between meta-learners (X-&DR-learner: r=*0.94*, p=*0.00*; X-&R-learner: *r=0.72*, *p=0.00*; DR-&R-learner: *r=0.88*, *p=0.00*), suggesting they identify similar covariates that are more likely to drive price premium heterogeneity. The covariates with largest average CLAN values are accessibility PC1 and PC2, followed by modern kitchen, leasehold, age 1983-2002, garage, terrace, and age 1900-1929. It is noted that PC1/PC2 have different measurement scales, making it difficult to compare them directly with the remaining binary factors in terms of the relative importance in driving heterogeneity.

The meta-learners mostly agree with each other on sign of difference. The covariates with different signs of difference include rooms (partly), property size, local authorities (partly), and years (partly). It is noted that these covariates are more likely to be correlated with omitted variables; local authority and year are often correlated with many other unobserved factors, while property size and rooms are highly correlated with each other. Regarding differences in magnitude of CLAN values, the difference between maximum and minimum values are also shown in Table 7.5 ('Range' column). This highlights several areas with relatively large differences such as accessibility PC1/2, property size, and 6-7 rooms.

Table 7.5 CLAN values from different learners on selected covariates.

Meta Learner	X-learner	DR-learner	R-learner	Mean	Range
accessibility_PC1	0.419	0.277	0.218	0.304	0.201
accessibility_PC2	0.275	0.104	0.059	0.146	0.216
modern_kitchen_True	-0.147	-0.125	-0.093	-0.121	0.054
tenure_mapped_leasehold	0.129	0.076	0.060	0.088	0.068
age_mapped_1983_2002	-0.134	-0.070	-0.040	-0.081	0.094
is_garages_True	-0.083	-0.076	-0.080	-0.080	0.007
BUILT_FORM_Terraced	0.069	0.067	0.082	0.073	0.015
age_mapped_1900_1929	0.106	0.066	0.040	0.071	0.066
LAD21NM_Wigan	0.080	0.043	0.036	0.053	0.044
is_gardens_True	-0.054	-0.047	-0.056	-0.052	0.009
BUILT_FORM_Detached	-0.050	-0.049	-0.054	-0.051	0.005

Note: for full results, see Appendix E, Table E-3.

7.4.3 Consistency between meta-learners

Having shown that there is substantial evidence of heterogeneity, we examine consistency between meta-learners in more detail (RQ7.2), including consistency of estimations from different meta-learners and alternative base learners. Overall, the consistency analysis suggests that heterogeneity results from meta-learners are sufficiently similar that they can provide a useful basis on which to offer policy guidance but some uncertainties remain.

7.4.3.1 Results consistency between meta-learners

To explore the consistency of treatment effect estimations across the three meta-learners, the distributions of estimated treatment effects and the cross-learner correlation are examined. Figure 7.7 shows the pairwise scatterplots of treatment effect estimates along with Pearson correlations.

According to the diagonal histograms, treatment effect estimates from three learners are similar in average values but differ in variability, with R-learner presenting greatest variability followed by DR- and X-learner. Spearman correlations show that correlations across all pairs are moderately to strongly positive. The DR- and X-learners are most closely aligned with .65. The DR-learner and R-learners produce slightly lower correlation at .52, while X- and R-learner and relatively low agreement with each other. These suggest that all three meta-learners capture broadly similar estimates of treatment effects.

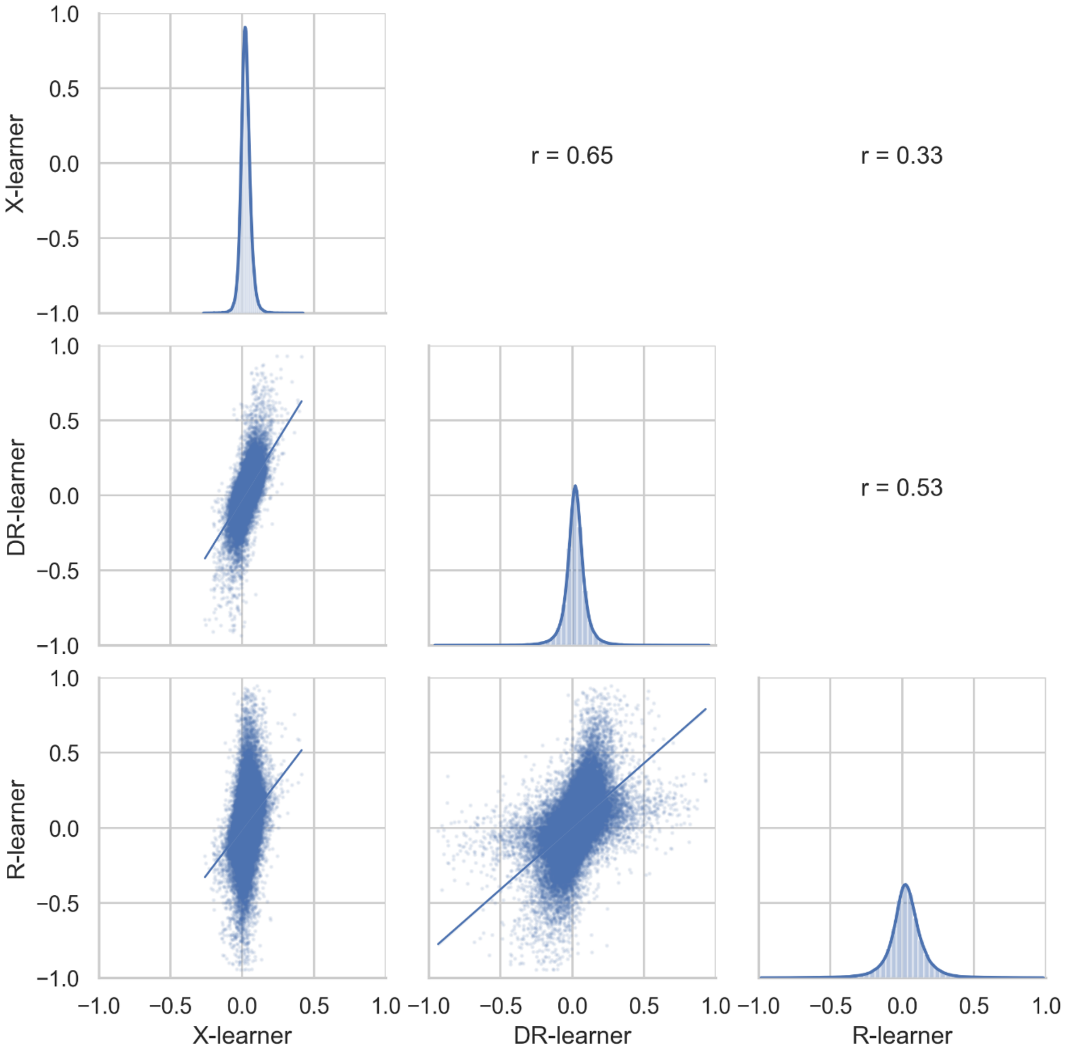


Figure 7.7 Correlation of ITEs from X-/DR-/R-learner with Pearson correlation coefficients.

7.4.3.2 Results consistency between alternative base-learners

An alternative treatment base-learner – Linear Regression – is used to give some insights into whether price premium estimations are model-dependent. For each meta-learner, Table 7.6 compares the estimates of overall average treatment effects with Super Learners and Linear Regression, and the correlations between the two. For X- and DR-learners, the average price premium remains consistent but, for the R-learner, Linear Regression produces a markedly lower average estimate then the Super Learner. The Table also shows that estimates from Linear Regression are less variable than those from Super Learners, which makes sense as one Linear Regression model would produce same price premium (i.e. coefficient) for all inputs.

The correlation between estimates from different base-learners are relatively low and variant (from .08 on R-learner to .41 on X-learner). Nonetheless, further tests on the rank agreement on drivers of heterogeneity using median results across all meta-learners from the two base-learners shows strong agreement (Spearman correlation $r = 0.87$, $p = 0.00$). Therefore, while the price premium estimations using different base-learners are only weakly correlated, they mostly agree on the covariates that more likely to generate price premium heterogeneity.

Table 7.6 Comparison and correlation of treatment effect estimates using treatment base-learner of Super Learner and Linear Regression.

	Base-learner: Super Learner		Base-learner: Linear Regression		Pearson correlation
	Mean	Std	Mean	Std	
X-learner	0.023769	0.034471	0.022172	0.023976	0.410****
DR-learner	0.021112	0.085944	0.021040	0.019222	0.157****
R-learner	0.027800	0.135342	0.019190	0.016845	0.077****

Note: * P ≤ 0.05, ** P ≤ 0.01, *** P ≤ 0.001, **** P ≤ 0.0001.

7.4.4 Exploratory heterogeneity analysis

We have established a fairly high degree of consistency between the models but have also noted that there is no basis for choosing one over the others. To conduct further analysis of the drivers of heterogeneity, we therefore use the median price premium estimation from the three learners for each observation. Figure 7.8 shows the distribution of median price premiums across selected submarkets, where p-values of the Kruskal-Wallis test with Bonferroni correction on each pair of groups are also shown.

The results show that, except for property type which is relatively weakly related with price premiums, all other property categorical values are found to significantly differentiate price premium distribution. First, people purchasing terraced houses tend to pay the highest price premiums for better energy efficiency, followed by buyers of semi-detached properties. In contrast, buyers of detached homes pay noticeably lower premiums at about 1% less than the premium paid for terraced houses. Although detached homes would theoretically benefit more from improved energy efficiency because heat can escape through the entire building envelope, their limited market availability and the fact that buyers who can afford them may be less concerned about energy savings likely reduce this responsiveness. It is also noted that this difference could potentially be confounded by property size and price, as the distribution of different built forms on size and price are mostly non-overlapped with each other (Appendix E, Figure E-1).

Leasehold homes tend to command a slightly larger price premium for higher energy efficiency compared with freehold homes, with an average gap of about 0.7%. This may be because freehold owners can more freely upgrade their properties, whereas leasehold owners often face restrictions on making improvements, increasing their preference for homes that are already energy-efficient. It may also reflect the fact that leasehold buyers are generally more cost-conscious and therefore place greater value on energy-efficient properties. As for property types, the difference in price premiums between houses and bungalows is relatively small and not strongly evident.

When comparing homes with and without a modern kitchen (as extracted from property listing text), we observe a notable 1.3% gap in energy-efficiency price premiums. Properties equipped with a modern kitchen tend to have smaller premiums, suggesting that a modern kitchen may trade-off energy efficiency in buyers' evaluations. This offers insights into the long-debated question of whether price premiums for energy efficiency represent a willingness-to-pay for energy efficiency itself or for broader aesthetic and functional upgrades which may be associated with energy efficiency. The findings imply that buyers value both features, but when one is already present, such as a modern kitchen, the additional value attributed to energy efficiency tends to be reduced. Alternatively, the energy efficiency price premium may be overstated when the modern kitchen is modelled as not included, as we do not necessarily identify all properties with a modern kitchen.

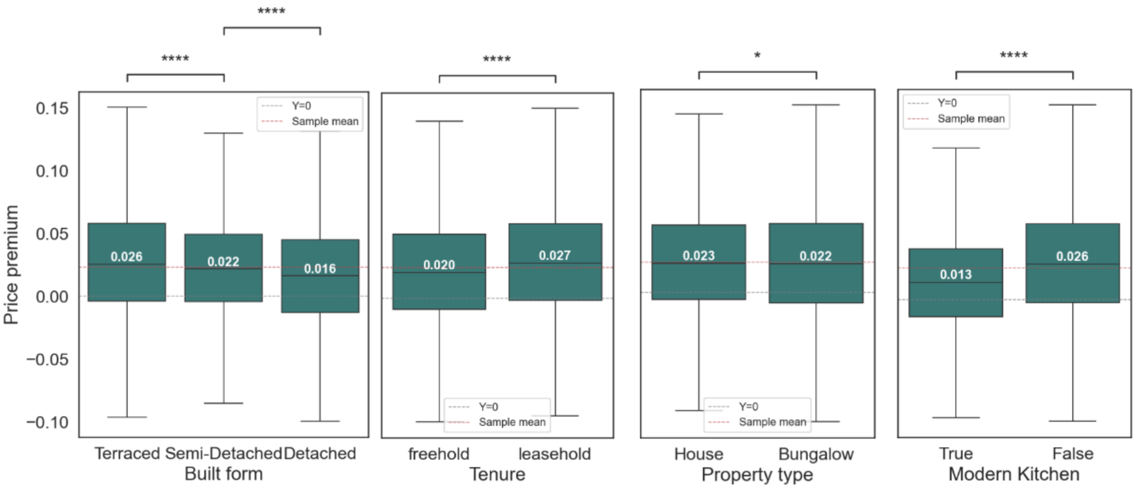


Figure 7.8 The heterogeneity of price premium of energy efficiency (1).

As shown in Figure 7.9(a) (upper panel), price premiums show a clear downward trend for newer properties, indicating that energy-efficiency improvements are likely more valuable for older homes. On average, the difference in premiums between properties built before 1900 and those constructed between 1983 and 2002 is around 2% - the largest gap observed across the categorical submarkets we examine. Additionally, older properties exhibit greater variability in their price premiums. Older properties often have outdated construction and inefficient systems, so energy upgrades could add substantial value. In comparison, newer properties are generally more energy-efficient to start with, leaving less room for improvement and resulting in smaller, more consistent premiums. Overall, the higher and more variable energy-efficiency premiums for older properties reflect their greater potential for improvement.

Figure 7.9(a) (upper right) also shows little evidence of any change over time when using the median estimated treatment effect. This is clearly at odds with the results discussed in Chapter 6 which show a marked increase in willingness-to-pay for energy efficiency after the energy price crisis which started in 2022. Figure 7.9(b) shows that the estimated trends in price premiums over time vary notably across the individual meta-learners. The X-learner indicates a general upward trend in premiums, whereas the DR-learner shows no obvious pattern and the R-learner suggests a slight decline. These differences imply that the modelled relationship between time and energy-efficiency price premiums is highly sensitive to the choice of meta-learner, likely because each method handles confounding differently. Although year-quarter fixed effects are included to absorb seasonal trends in house prices, the temporal variables are found to be correlated with house prices, energy efficiency ratings, and building age which can introduce significant confounding. The three meta-learners address confounding in different ways: the X-learner is often recommended for capturing heterogeneous effects (Acharki et al., 2023) as it explicitly constructs individual-level treatment effect estimates through outcome modelling, while the DR-learner may yield muted patterns because it averages information from the outcome and propensity models, and the R-learner can “residualise out” certain sources of variation. This aligns with our findings on the temporal evolution of price premiums.

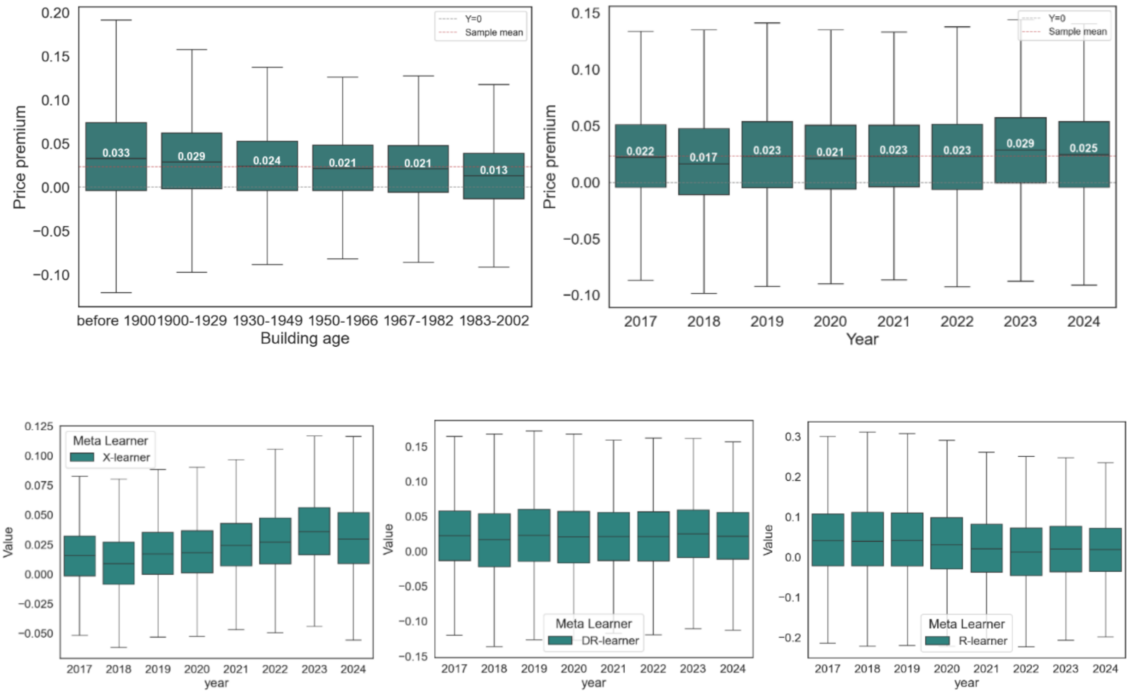


Figure 7.9 The heterogeneity of price premium of energy efficiency (2): (a) upper panel and (b) lower panel.

Price premiums vary across local authorities, as shown in Figure 7.10. An additional map shows median estimates at LSOA11 level as Figure 7.11. Results show that regions of Rochdale, Wigan, Manchester and Oldham present a relatively higher price premium with median value above 2.5%. In comparison, regions located at the south of GM have the lowest average price premiums from 1.4% to 1.6%, with lowest of Stockport, Trafford and Salford. The remaining areas of Tameside, Bolton and Bury have effects between 2.0% and 2.3%. These suggest an overall pattern that areas with generally higher house prices/lower deprivation present a lower price effect on housing energy efficiency.

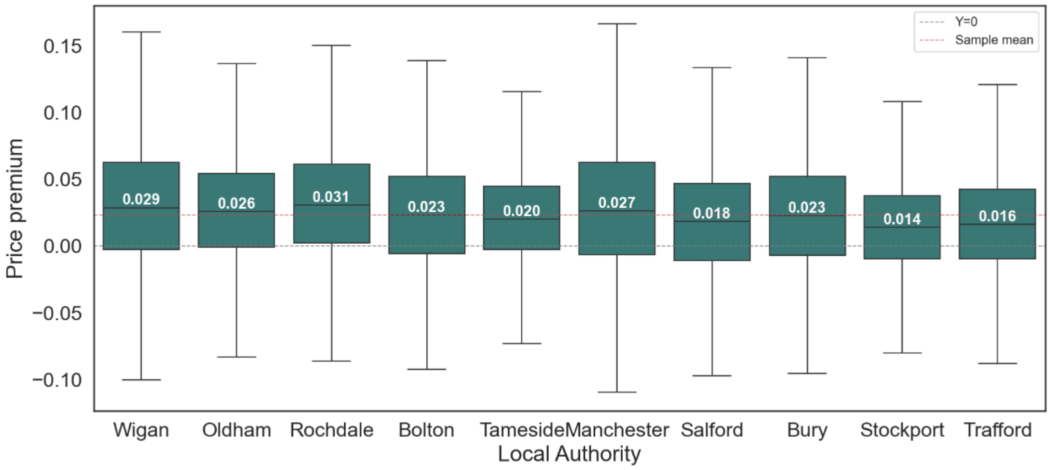


Figure 7.10 The heterogeneity of price premium of energy efficiency (3).

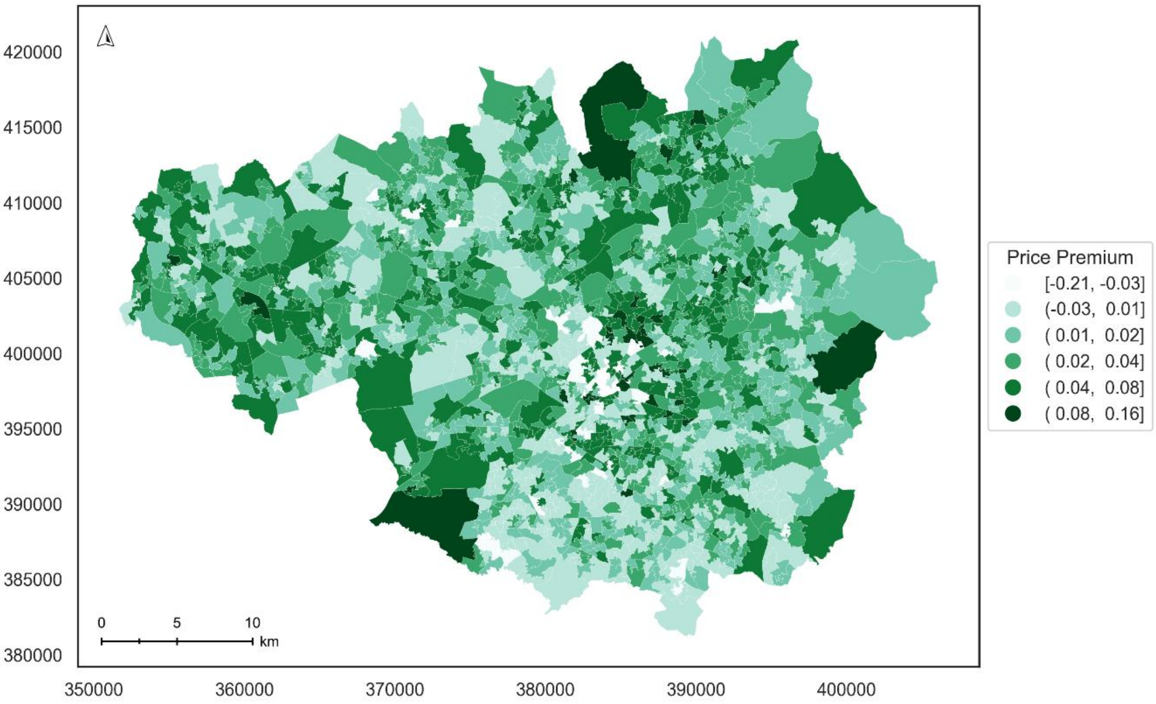


Figure 7.11 Median price premium estimations across meta-learners at LSOA11 level.

Figure 7.12 shows the estimated relationship between price premiums and neighbourhood characteristics, property sizes and house prices. Each panel displays the LOWESS (Locally Weighted Scatterplot Smoothing) plot of energy efficiency price premiums along the distribution of a covariate, with the solid line showing the smoothed curve fitted through local weighted regression and the shaded areas showing corresponding confidence intervals. Dashed lines indicate average values for each variable.

Income deprivation shows a rising pattern with higher premiums observed in more deprived areas, with a sharp increase from lower end to average income deprived levels and a more moderate increase upward. This generally suggests that residents with lower income value energy efficiency more than those with higher incomes, which also means they carry with higher burden to improve home energy efficiency. Price premiums exhibit an increasing trend with accessibility up to around average level, which stays basically unchanged with higher variance. For population density, the premium is stably smaller around average level, which goes up for areas with both higher and lower population density. For school quality, the estimated premium remains largely flat across the score range, suggesting limited heterogeneity.

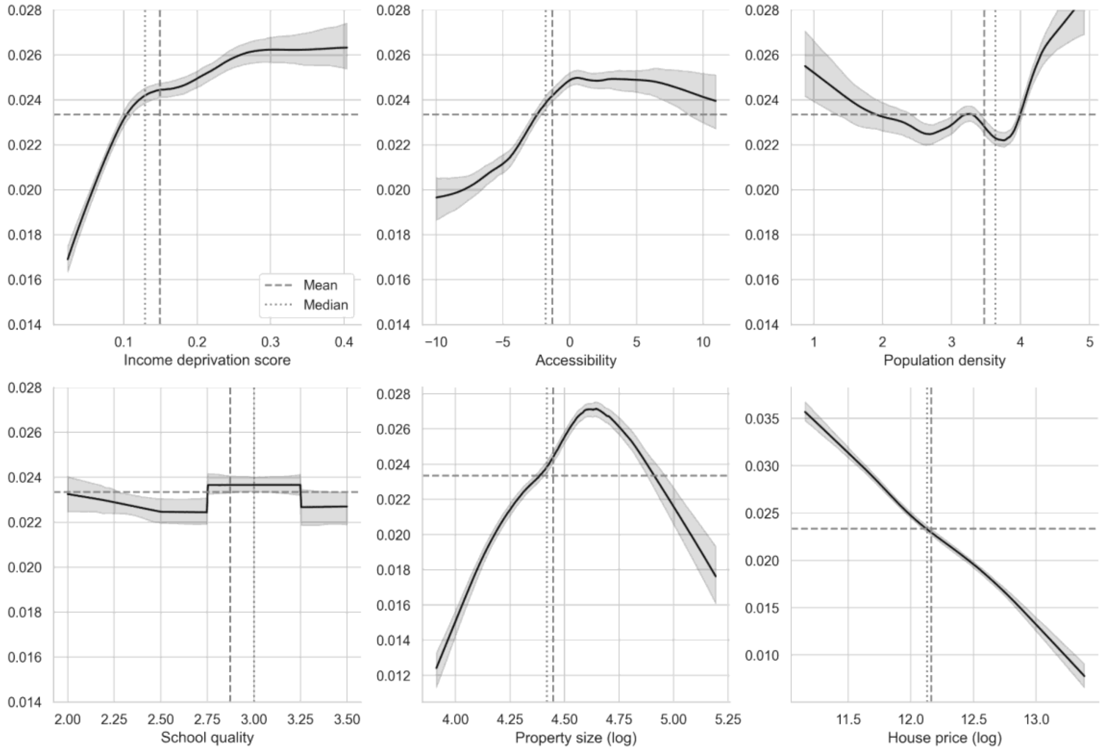


Figure 7.12 The heterogeneity of price premium of energy efficiency (4)

Note: dashed lines indicate average values for each variable

The relationship between property size and price premium displays a clear inverted U shape, with the largest premiums found for mid-sized properties, and lower premiums for both smaller and larger homes. For small-medium sized properties, the price premium increases with property size probably as larger property are considered more energy intensive. However, among medium to large properties, the energy-efficiency premium declines as size increases. This aligns with evidence from the last pane that higher-priced homes generally exhibit smaller energy-efficiency premiums. The range here is greater than for any of the covariates previously discussed. It is reasonable given that the premium is measured as a percentage of the overall property price.

In Figure 7.13, we further explore the relationship between absolute monetary gain from energy efficiency improvement and property size/house price by converting the percentage change into an absolute value. Compared to the inverted U relationship (property size) or negative gradient (price increase) in figure 7.12, the absolute monetary gain shows a clear increasing trend in both cases. It indicates that the absolute monetary gain in property values remains higher for larger or higher-priced properties, even if the relative (percentage) price premium is lower, especially for lower-priced properties.

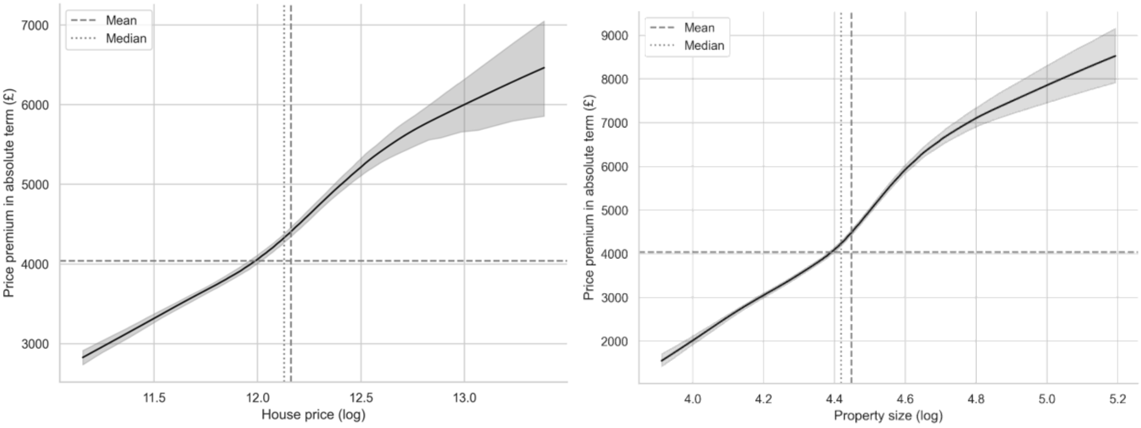


Figure 7.13 Relationship between absolute monetary gain of housing energy efficiency and property size/house price.

7.5 Discussion

This study comprehensively examines heterogeneity in the price premium associated with housing energy efficiency in Greater Manchester over the period 2017–2024. The price effects of housing energy efficiency are analysed for the first time using the causal machine-learning approach of meta-learners which allows for heterogeneity analysis across submarkets. Importantly, this analysis not only offers valuable information on the heterogeneous effects of energy efficiency on house prices but also provides an illustration of usefulness of meta-learner frameworks in estimating heterogeneity results, both of which are essential to provide tailored guidance for policy measures aimed at improving housing stock energy efficiency.

Energy efficiency is on average associated with a positive price premium estimated from meta-learners, which is higher than both prior UK hedonic studies (Fuerst et al., 2015) and the hedonic model applied to the same data in this study.

The latter indicates that the difference is due to methodology instead of data or market conditions. Methodologically, meta-learners could capture variation in price premiums while hedonic model typically impose a constant coefficient which tends to ignore the stronger premiums in high-demand or energy-sensitive submarkets. Additionally, meta-learners with the use of ensemble machine learning as a base learner could capture complex, non-linear price effects of energy efficiency, which is restricted in hedonic approaches. This means meta-learners have improved control for confounding while hedonic approach is more likely to have confounding issues that part of the energy efficiency effect may be incorrectly attributed to underestimate the price premium.

Relative to earlier studies that examined heterogeneity based on traditional hedonic approaches (Chegut et al., 2020; Evangelista et al., 2022), this study demonstrates the value of a meta-learner approach in producing individualised estimates of treatment effects. The results show significant heterogeneity in price premiums of energy efficient homes, which is robustly identified for the first time. Based on the individualised treatment effects, we extensively analyse the heterogeneity across submarkets. The price premiums vary substantially across submarkets of properties, locations, and market segments. Based on more flexible machine learning models, some of the findings on heterogeneity align with those found in previous studies using the hedonic approaches. Heterogeneity in house price segments has been studied most previously (Evangelista et al., 2022; McCord, Haran, et al., 2020), the results of which are consistent with this analysis that (relative or percentage) price premiums clearly decrease from lower house prices to higher ones. This analysis finds a pattern that higher returns on energy efficiency investment are more likely to be present in submarkets favoured by buyers with lower affordability, such as lower-priced homes, terraced properties, leasehold dwellings, older housing stock, lower-income areas, high-density neighbourhoods, and highly accessible locations. A similar finding is reported in previous analyses (Evangelista et al., 2022), which show that the market segments most affected by economic crises are rewarded more for energy efficiency. These findings suggest that energy efficiency plays a stronger value-enhancing role in affordability-constrained market segments, where buyers place relatively greater importance on energy cost savings and long-term affordability. They also indicate that the financial benefits from reduced energy costs play a more important role in driving price premiums than the environmental benefits associated with carbon savings.

As an empirical study employing the relatively recent meta-learner framework to examine heterogeneous price premiums, we explicitly assess the consistency of results across different meta-learners which remains a key limitation of these approaches in practical application (Okasa, 2022). The results indicate that, despite differences in estimation strategies, the meta-learners broadly agree on the overall patterns and distribution of treatment effect heterogeneity. However, greater disagreement is observed for covariates that are more likely to be affected by residual confounding, such as listing year and local authority fixed effects in this study. This suggests that, while meta-learners are effective in identifying robust heterogeneity associated with property and neighbourhood characteristics, their estimates may be more sensitive when locational or temporal factors are involved. Nonetheless, the rankings of price premium estimates are moderately to strongly positively correlated across meta-learners, implying that while magnitudes may differ, the direction and relative structure of heterogeneity are generally consistent. Accordingly, heterogeneity results generated from meta-learners should be interpreted with some caution when informing policy, particularly where estimated effects are driven by variables that are plausibly endogenous or only imperfectly controlled for.

Importantly, the broad consistency in the heterogeneity of energy-efficiency price premiums does allow some policy guidance to be drawn. Where market returns to energy-efficiency investments are higher, private owner investment is more likely and can be encouraged through supportive measures such as improved access to green finance, given the reduced risk associated with higher capitalisation. In contrast, government support may be more effectively targeted toward submarkets where market returns are weaker. However, these policy recommendations must be considered alongside household resource constraints. While this analysis finds that submarkets favoured by lower affordability households tend to exhibit higher price premiums, this does not necessarily imply a greater capacity for these households to finance the high upfront costs for retrofit. Therefore, a differentiated policy approach is suggested: facilitate private and lender investment in markets with stronger price signals (e.g. lower-priced/terraced properties/leasehold/older dwellings), while prioritising public subsidies to dwellings and households for which the financial benefits of energy efficiency improvement are lower or less accessible due to limited resources (e.g. low-income/fuel-poor households).

There are some limitations of this study. First, this study primarily focuses on heterogeneity in energy efficiency price premiums across property and neighbourhood characteristics while lacking analysis on buyer characteristics. Future research could incorporate richer data sources to explore heterogeneity across buyers' socio-demographic characteristics, such as age, income, and household composition, to better understand how preferences for energy efficiency vary across populations and offer human-centred support for energy retrofit. In addition, this analysis explicitly applies univariate heterogeneity analysis defined by single housing submarket but falls short of interactive analysis between submarkets. Further work could examine heterogeneity in price premiums across joint subgroups defined by multiple characteristics to offer more granular insights for policy design.

7.6 Conclusions

Improvement of housing stock energy efficiency has been priority for many governments seeking to reach Net Zero goals in the residential sector. Utilising the meta-learner approach to explore heterogeneous price effects of housing energy efficiency in the UK, this study offers valuable insight into the operation of the housing market which can guide resource allocation and policy design regarding home energy retrofit investments. We find significant heterogeneity in price premiums of home energy efficiency, where submarkets of lower-priced/terraced/leasehold/older building stock, and areas with lower-income/higher density/accessibility present higher (percentage) returns on energy efficiency investments. We also find temporal and spatial heterogeneity present in price premiums. The results suggest that policy could encourage private and lender investments in those markets with higher returns, and that government support could focus on markets with smaller returns as well as households with limited resources. These insights on policy guidance for housing energy efficiency investment would facilitate a faster and more efficient process of residential energy sustainable transition.

Chapter 8 Conclusions and discussion

8.1 Research summary

This thesis sets out to examine the price premiums of home energy efficiency as signalled by Energy Performance Certificates (EPCs). This is important to assess the effectiveness of market incentives for energy efficiency improvements and inform housing decarbonisation policy making. Although housing energy efficiency premiums are widely studied, important gaps remain in the literature. First, the empirical evidence on EPC-related price premiums is mixed, limiting its reliability in policy and individual decision-making. Second, omitted variable bias continues to challenge causal interpretation in hedonic models. Also, the mechanisms behind households' willingness-to-pay (WTP) for energy efficiency are still poorly understood, limiting theoretical understanding of the relationship. Finally, inadequate evidence on price premium heterogeneity across submarkets, constraining the design of granular and equitable policies which is necessary to facilitate an efficient decarbonisation process.

To address these limitations, this thesis establishes a clear and structured progression from knowledge synthesis to application of innovative methodology. It begins with a systematic scoping review to synthesise existing estimates on price premium and explores best practices in the field. Building on this foundation, it applies the predominant parametric hedonic model in line with current methodological standards and best practices as well as making innovative use of the 2022 energy crisis as a natural experiment to identify whether premiums reflect a causal effect of energy efficiency. Finally, it advances the field by integrating emerging data-driven modelling approaches i.e., causal machine learning into the hedonic framework, aiming to further investigate the heterogeneity of price premiums across housing submarkets.

8.2 Key findings and contributions

This thesis offers several key findings that advance understanding of price premiums for residential energy efficiency in housing markets. These findings contribute to the empirical, methodological, and theoretical development of the literature on housing energy efficiency price premiums.

8.2.1 Key findings

(1) Housing energy efficiency is capitalised in house prices, but modest in magnitude

The first key finding is that housing energy efficiency is positively associated with property prices, but the premium remains modest in magnitude. Previous studies have produced variable results but the systematic scoping review of European studies (Chapter 4) shows a clear positive effect on average. And the empirical analyses for Greater Manchester (Chapters 6 and 7) add further evidence on the positive price premium of home energy efficiency. The estimated premiums may not be enough to repay the high upfront costs of retrofit works, but they do provide an additional incentive alongside lower running costs and improved comfort and health.

(2) The price premium of energy efficiency increased after the energy crisis, mainly driven by the brown discount

The second key finding concerns the change in the energy efficiency price premium following the 2022 energy crisis (Chapter 6). The scoping review had not identified any increase in the premium in the time period covered (2011-2024), which is concerning from a policy perspective as we might hope that growing awareness of the climate crisis would increase WTP for energy efficiency. However, we add evidence on this with a novel study considering the energy crisis. Very few studies have previously examined this event (Aydin et al., 2020; Mense, 2018; J. Olaussen et al., 2019) and they had various limitations (Braakmann et al., 2026). Importantly, this study finds that buyers exhibit a stronger WTP for energy-efficient homes in the post-crisis context. We also find that this increase is primarily driven by a growing brown discount applied to energy-inefficient homes.

(3) Issues of omitted variable bias exist, but do not account for all the effect of energy efficiency on house prices

The third key finding concerns the robustness of the estimated price premium regarding omitted variable bias. The concern is that housing energy efficiency may be correlated with unmeasured aspects of quality so that the estimated premiums could be capturing something other than energy efficiency (Marmolejo-Duarte & Chen, 2022). The scoping review notes that concerns with omitted variable issues exist in most studies. The thesis takes two approaches to examining the influence of omitted variables. First, we control for an extensive set of house price-related variables and apply the multilevel hedonic modelling to account for neighbourhood heterogeneity (Chapters 6 and 7). The persistent, statistically significant positive effect after these controls reduces the concern that the observed effect is solely driven by unobserved confounders. Second, the finding of an increasing price premium after the energy crisis provides additional strong support for a causal interpretation (Chapter 6). If the estimated effect of energy efficiency on prices was wholly down to omitted variables, there is no reason to expect this to increase at the same time as energy prices. Overall, we argue that though issue of omitted variables exists, they do not eliminate the effect of energy efficiency on house prices.

(4) Energy cost savings at least form part of mechanism driving the price premium

A fourth key finding relates to the mechanisms underlying households' WTP, which is under debate on whether it is driven by energy cost savings or environmental awareness (IEA, 2022c). Evidence from the temporal analysis (Chapter 6) indicates that the energy efficiency premium increased following the energy crisis, primarily driven by a significant increase in the brown discount applied to inefficient properties. The strengthening of the premium during periods of elevated energy costs supports the interpretation that people at least respond to expected energy savings to some extent rather than being purely driven by environmental awareness.

(5) Price premiums are heterogeneous across submarkets

The final key finding is that the energy efficiency premium exhibits heterogeneity across housing submarkets (Chapter 7). At the broader European context, the scoping review identifies some variations between rental and sales markets, between houses and flats, and across geographic and temporal contexts. In general, however, previous studies have not explored heterogeneity in energy efficiency price premium in a systematic way. A few studies have only applied theory-driven approaches to test a limited number of explicit differences among submarkets (Dell'Anna, 2022; Evangelista et al., 2022). Within the Greater Manchester second-hand housing market, this study applies data-driven methods of causal machine learning to show heterogeneous effects across a wide range of characteristics including various property, neighbourhood, temporal, and spatial characteristics (Chapter 7). The heterogeneity effects found are consistently significant across the models, suggesting that reliance on average treatment effects may obscure variations in how different submarkets value energy performance.

8.2.2 Contributions

8.2.2.1 Empirical contributions

Empirically, this thesis provides new empirical evidence on the price premium of residential building energy efficiency in both the European and UK contexts. Within the European literature, empirical findings on EPC-related price premiums are somewhat mixed. Although a few review studies exist (Cespedes-Lopez et al., 2019; Fregonara & Rubino, 2021; Marmolejo-Duarte et al., 2019; Wilkinson & Sayce, 2020), they lack systematic methodologies and transparent synthesis procedures, limiting the reliability, comparability and robustness of their conclusions. In contrast, this thesis conducts a systematic and transparent review of English-language European studies of EPC price effects (Chapter 4). By applying systematic search and screening procedures and explicitly mapping study characteristics and reported estimates, the review provides a rigorous synthesis of the European evidence base. This establishes a consolidated empirical benchmark for EPC price premiums and offers comprehensive evidence mapping that supports more consistent comparison and future research development.

In the UK context, the thesis offers further new empirical evidence on price premiums of housing energy efficiency. First, existing UK studies are spread in limited regions/cities and took place before the 2022 energy crisis (Fuerst et al., 2015; Fuerst, McAllister, et al., 2016; McCord, Haran, et al., 2020; McCord, Lo, et al., 2020), leaving recent shifts in energy markets due to the energy crisis insufficiently examined. In particular, the energy crisis has significantly influenced household energy costs, yet empirical evidence capturing its impact on house price premiums remain scarce. By analysing data from 2017 to 2024 within a major UK metropolitan housing market covering both pre- and post-energy crisis periods (Chapter 6), this thesis provides a systematic examination of how EPC price premiums changed in response to changing energy costs and offers up-to-date evidence on the current state of energy efficiency capitalisation in the UK housing market.

Furthermore, while much of the existing empirical literature focuses on estimating average price premiums using traditional parametric hedonic models, this thesis advances the empirical approach by employing data-driven modelling techniques in Chapter 7. Using causal machine learning approaches within the hedonic framework, the analysis moves beyond average effect estimation to examine heterogeneity in price premiums. Therefore, it offers new empirical contributions into the systematic investigation of variation of price premiums across housing submarkets.

8.2.2.2 Methodological contribution

Methodologically, the thesis contributes to current practice of house price hedonic modelling in green premium research in two important ways: follows good practice in parametric modelling by using multilevel models and by advancing the field through the integration of emerging data-driven approaches. At the same time, these help mitigate potential omitted variable bias problems and relax the linear parametric assumptions in traditional hedonic models.

First, the thesis follows good practice of parametric hedonic modelling by incorporating multilevel modelling techniques and include a sufficiently large number of variables for modelling. Multilevel modelling accounts for hierarchical housing market structures and neighbourhood heterogeneity, ignoring which can lead to biased and inconsistent estimates. This study also explores the potential of accounting for spatial effects using spatial multilevel model but found them unnecessary in this context. The inclusion of a sufficiently rich set of control variables marks a further data practice to mitigate the omitted variables bias. Overall, these practices strengthen internal validity and improve the credibility of estimated price premiums using parametric modelling approaches.

Second, the thesis further introduces non-parametric, data-driven techniques into the hedonic pricing framework to estimate energy efficiency price premiums. By incorporating causal machine learning methods in hedonic modelling, it advances traditional parametric modelling in relaxing the restrictive parametric and linear assumptions, making it possible to capture more complex relationships between variables, as well as enabling individualised price premium estimations and heterogeneity analysis. With the existing literature dominated by traditional hedonic models which are superior in their interpretability, this thesis demonstrates the methodological potential of data-driven techniques within hedonic pricing research.

8.2.2.3 Theoretical contribution

The thesis contributes to theoretical understanding by shedding light on the mechanisms underpinning the observed price premium. Existing research on energy efficiency premiums largely focused on examining the existence and magnitude of such premiums, with little attention to the conceptual mechanisms that drive the premiums. Utilising the exogeneous price shock of the energy crisis, this thesis demonstrates that the price premium is economically mediated, underpinning the mechanism that expected energy costs constitute a significant driver rather than symbolic environmental preferences though these and other factors cannot be ruled out.

8.3 Policy implications

This thesis demonstrates that (1) energy efficiency is capitalised into house prices, (2) the credibility of its causal interpretation is strengthened, (3) the capitalisation intensified following the energy crisis primarily through an amplified brown discount, and (4) price premiums vary systematically across submarkets. Fundamentally, the strengthened causal evidence enhances the reliability of interpretations of energy efficiency price premiums, providing firmer empirical evidence for decision making. Based on this, the relatively modest magnitude of average premiums, their sensitivity to the energy price shocks, and their heterogeneity across housing segments suggest that market forces alone are insufficient to deliver the levels of improvement expected in housing decarbonisation strategies (CCC, 2025a; Directive 2024/1275/EU, 2024). The findings on heterogeneity of price premiums also offer direct insights for designing targeted decarbonisation policies e.g., EU member states are free to choose which buildings to target as long as the climate and energy targets are met (Directive 2024/1275/EU, 2024). Overall, the findings carry important implications for regulatory, informational, subsidies, and financial market policies. This section provides a detailed discussion of policy implications organised by these policy domains.

8.3.1 Regulatory policy

The confirmed positive price premium of home energy efficiency suggests that EPCs and related labelling systems function not only as informational tools but also as market-shaping instruments. The fact that energy efficiency as presented by EPCs is capitalised into property values provides empirical justification for maintaining and strengthening energy labelling frameworks and corresponding regulations.

Currently the introduction and regulation of energy labelling systems vary across countries and regions globally. In regions without established labelling systems, especially the Global South, the introduction of structured and standardised certification mechanisms may provide an essential first step toward market-incentives for action on decarbonisation. In areas where there is an existing labelling system, but housing market disclosure remains voluntary, the findings support consideration of mandatory energy performance disclosure in the housing market to enhance market transparency and incentive alignment.

However, the estimated premiums of home energy efficiency remain modest relative to the substantial upfront costs of much housing retrofit work. This suggests that disclosure alone is unlikely to generate the scale of improvement required to meet climate targets. If governments want faster action on energy efficiency improvement, they may need mandatory minimum standards as it appears the market incentive sufficiently strong. In the UK context, minimum standards currently apply primarily to the rental sector, while the owner-occupied sales market remains less regulated despite evidence of growing market valuation of efficiency. Extending minimum energy performance requirements to the sales market, particularly at the point of transaction as proposed in the Scottish

Government consultation on the *Heat in Buildings Bill* (Scottish Government, 2023), may therefore be justified.

8.3.2 Information policy

There exist various critiques of the quality, measurement, awareness, and data availability of EPCs, motivating relevant EPC information policies. Overall, information policies would need to make EPC data to be more accurate, reliable, and open.

Despite the fact that EPCs are often built on poor quality data (Hardy & Glew, 2019), the positive price premium in the UK exists. Nonetheless, higher data quality of EPCs may lead to greater confidence in the ratings and hence larger price premium for higher EPCs. There have been a lot of discussions about the EPCs reform in terms of its assessment methodology (National Retrofit Hub, 2024), which is fundamental to improve the data quality.

Additionally, various critiques are around what EPCs should measure, with options including fabric rating, cost rating, heating rating, and energy use rating (CCC, 2023). The content of the current EPC system in the UK focuses on the cost metric, which is critically important as we find energy cost savings may form an important part of the mechanism for individual investment. In addition to the current energy efficiency rating (EER) which provides abstract information on expected energy cost, more details on energy cost savings could be provided such as: (1) projected lifetime energy cost savings; (2) changes in energy bills from exposure to future energy price shocks; (3) comparisons between retrofit costs and expected financial returns. The reform of EPC content is also under active discussion in the UK (National Retrofit Hub, 2024).

Meanwhile, aligning EPC content with cost importance should not come at the cost of environmental objectives. The current EPCs provide two separate measures including the cost metric and carbon metric, with more emphasis on the former. As cheaper energy does not necessarily generate lower carbon emissions, a dual metric which integrates both cost savings and carbon reduction may be more effective in delivering climate targets while connecting with consumer priorities.

Alternatively, aligning domestic energy prices with their emission levels for example by carbon pricing would act as an effective approach to decarbonisation.

Furthermore, the findings about the energy cost saving mechanism offer insight into policy designs aiming to increase public awareness and knowledge of EPCs, which remains limited in the UK (GOV.UK, 2025a). When the government deploys EPC information campaigns and promotes retrofit initiatives, greater emphasis could be placed on the relevance to household bills, to elevate public awareness thus fostering faster improvement. Again, directly providing cost-saving relevant measurement in EPCs as introduced above serves as an important transparency tool.

A final implication for information related policy regards EPC data availability. Results from the scoping review find that existing empirical evidence on housing energy efficiency price premium is highly limited to regions/countries having publicly available EPC data (Chapter 4), highlighting the critical importance of EPC data availability. As a fundamental tool revealing energy performance information, open EPC data is vital for researchers, local authorities, environmental organisations, and businesses to analyse housing stock and to inform investment decisions. It is therefore crucial for governments to publish EPC data publicly, while also implement complementary regulations to protect personal data privacy.

8.3.3 Subsidy policy

The modest average price premium relative to retrofit costs indicates that private returns alone are unlikely to generate socially optimal levels of energy efficiency investment. This provides justification for continued governmental subsidy to bridge the gap between private market incentives and public climate objectives. The UK government is actively implementing direct and indirect subsidy schemes to improve housing energy efficiency including those for privately-owned homes (GOV.UK, 2025).

However, the intensified brown discount following the energy crisis (Chapter 6) and the observed heterogeneity in price premiums (Chapter 7) imply that uniform subsidy schemes may produce inefficient and inequitable outcomes. Government subsidies should therefore adopt more granular targeting strategies. First, crisis-responsive subsidies may be necessary during periods of energy price volatility to support households facing heightened cost pressure, justifying various household support from UK government to tackle the 2022 energy crisis e.g., Energy Bills Support Scheme (EBSS) as introduced in Section 6.2.1. Second, subsidies should prioritise homes with poorer energy performance and households with lower incomes, given the stronger brown discount identified in the analysis. Third, in submarkets where market incentives are insufficient, public financial support may be particularly necessary to stimulate retrofit activities.

8.3.4 Financial market policy

While public authorities primarily influence housing markets through regulation and subsidies, financial institutions shape market dynamics through capital allocation and housing lending practices.

Investment into large scale housing stock retrofits need not only governmental subsidies, but also private investment through capital allocation. To drive private investment towards greener projects and activities, the UK government introduced regulations related to the disclosure of organisations' exposure to climate change risks (Financial Conduct Authority (FCA), 2020). In terms of housing stock energy efficiency improvement, this financial market disclosure acts as an additional incentive which could encourage capital allocation towards private retrofit projects and activities.

Other than higher property value and energy cost savings, another financial incentive for individual investment relates to green finance products from finance providers. Supported by the Green Home Finance Accelerator from UK government which is however withdrawn at present (GOV.UK, 2024d), many lenders offer green housing finance products which provide preferential rates for lending on more energy-efficient properties and thus encouraging a green housing transition. As we find that financial incentives form part of the mechanism for individual investment and that individual's willingness to invest has increased, there is rationale for government to reopen such support for green finance products.

Even without green finance product support, the finance providers themselves have incentives for promoting green home products, due to the lower risks to exposure of future climate extremes and energy price volatility. Energy performance is thus expected to introduce an extra dimension to property risk assessment (Schuetze, 2020), which can further promote investment in energy efficient homes. Policymakers may therefore consider encouraging finance providers to incorporate energy performance metrics into risk assessment models, for example by providing future climate risk/energy bills metrics for reference.

Furthermore, the documented heterogeneity in price premiums provides a basis for more granular financial market policy design. In submarkets where energy efficiency commands stronger price premiums, policy design could leverage these stronger incentives and expand by encouraging preferential rates for energy-efficient homes. On the other hand, green housing finance products could provide better rates for those submarkets with weaker price premiums, along with targeted government subsidies. However, the availability of better mortgage rates and subsidies itself would be capitalised into house prices. Nevertheless, differentiated policy designs and financial strategies could enhance both efficiency and equity in the transition process to green homes.

8.4 Limitations and future research

8.4.1 Limitations

There are several limitations of this thesis that should be acknowledged, relating to data, methodology and research coverage. In terms of data limitations, this study relies extensively on Zoopla property listing price data as a proxy for actual transaction price. Listing prices may differ from final sale prices, potentially introducing measurement error and bias into the estimated house price effects (Bishop et al., 2020). To address this concern, listing prices were validated against available transaction price data where a match could be established (see Section 5.3), which increases confidence in their suitability for empirical analysis. Nevertheless, some degree of measurement bias cannot be entirely ruled out. Another data limitation lies in the temporal granularity of the neighbourhood dataset. While some datasets provide longitudinal information, this study only used cross-sectional data on neighbourhood conditions around the mid-point of the study period, which may lead to the temporal mismatch issues and biases in estimation.

Methodologically, omitted variable bias remains a potential concern in both empirical chapters. The analyses are grounded in the hedonic framework which requires controlling for all relevant determinants of house prices and energy efficiency, but certain variables such as aesthetic quality and interior condition are unavailable and thus not included. Their omission may affect the precision of the estimated price premiums. In terms of the multilevel modelling, it does not capture any spatial autocorrelation between neighbouring areas though this study does explore spatial multilevel model in Chapter 6 and found that it had little effect.

As for the causal machine learning approach, limitations arise primarily in interpretability (Salditt et al., 2024). The treatment effects estimated from ML models cannot always be directly interpreted as precise monetary price premiums as in traditional parametric hedonic models. Also, although more advanced approaches such as neural network based meta-learners may offer improved predictive performance, they are not implemented due to constrains related to time and computational resources required for large model training and hyperparameter tuning.

The scope of the research imposes further constrains. While the scoping review synthesises evidence across European housing markets, it is limited to studies in English and no studies are found in some EU countries potentially due to limited availability of open EPC data. The mapped evidence base may therefore not be fully representative of the entire European context. In addition, both empirical studies focus on a specific market segment in a single metropolitan area in the UK. While this allows for detailed and context-specific insights, it limits the generalisability of the findings to other housing markets with different contexts.

8.4.2 Future research

Through a structured progression from a scoping review to the implementation of the dominant parametric hedonic model, and further to the incorporation of emerging data-driven approaches, this thesis identifies multiple methodological and conceptual directions for advancing research on green housing premium estimation.

Considering the data limitations discussed earlier, future studies should strengthen the integration of transaction price datasets with energy performance information to generate more reliable evidence based on observed market prices. Enhancing the temporal alignment between neighbourhood-level datasets and property transaction dates would also improve the accuracy of estimates by ensuring that contextual characteristics accurately reflect conditions at the time of sale.

Regarding empirical scope, the present analysis concentrates exclusively on the second-hand housing sales market. However, other housing segments may exhibit distinct responses to energy efficiency attributes and potentially generate different premium effects, e.g., the scoping review suggests lower price premiums for flats and for rental markets (Chapter 4). Future studies could therefore extend the investigation to these additional segments. Expanding the geographical coverage of empirical analysis particularly to regions characterised by substantial housing stock and low levels of housing energy performance would also contribute to policymaking.

Several methodological dimensions remain open for further exploration. Omitted variable bias continues to represent a central challenge in the literature, which could typically be addressed through the inclusion of additional relevant covariates. Although this study makes extensive use of available structured datasets to mitigate potential biases, unstructured data sources such as images and texts have not yet been exploited. For example, street view images and remotely sensed images are found to be related to building energy efficiency (Sun et al., 2022, 2026). With recent developments in causal AI, future research could incorporate unstructured inputs such as street view images, remotely sensed images, housing interior images and text descriptions, which are likely to capture those important confounders such as aesthetic quality thus holding substantial potential for reducing estimation bias.

Methodological advancements are also needed to further mitigate omitted variable biases and enhance the credibility of causal inference in green premium estimation. Data-driven techniques such as causal AI present promising methodological advances. While this thesis demonstrates the application of meta-learner frameworks, future investigations could extend this work by embedding more sophisticated machine learning and deep learning models within these frameworks, such as neural networks (Shi et al., 2019). Additional causal AI strategies such as double machine learning (Chang, 2020; Hull & Grodecka-Messi, 2022) can also be systematically examined. Meanwhile, price premium estimates derived from causal AI models often raise concerns regarding estimation interpretability. Accordingly, future research should undertake systematic comparison and validation exercises between traditional hedonic specifications and causal AI-based estimators to clarify differences in their magnitude and variance to improve its robustness in decision-making.

Appendices

Appendix A Literature inventory

Table A Literature inventory.

id	reference	title	year	publisher	country	scale	start	end	time_span	rd_1	rd_2	sample	ht_1	ht_2	pt	tenure	ee_aspect	ee_scale	ee_time	meth	res
1	McCord et al., 2020(c)	A spatial analysis of EPCs in The Belfast Metropolitan Area housing market	2020	Journal of Property Research	United Kingdom	Urban	2013 q3	2014 q3	1.25	Observational	Cross-sectional	1478	all	all	transaction	sales	EER	Score	Current	Spatial regression	depends
2	Morano et al., 2020	An Analysis of the Energy Efficiency Impacts on the Residential Property Prices in the City of Bari (Italy)	2020	Values and Functions for Future Cities	Italy	Urban	2016	2017	1	Observational	Cross-sectional	200	all	all	transaction	sales	EER	Band	Current	Linear extension	positive
3	McCord et al., 2020(a)	An exploratory investigation into the relationship between energy performance certificates and sales price: a polytomous universal model approach	2020	Journal of Financial Management of Property and Construction	United Kingdom	Urban	2017	2018	1	Observational	Cross-sectional	3797	all	all	transaction	sales	EER	Band	Current	Linear extension	no impact
4	Bottero et al., 2017	Buildings energy performance and real estate market value: An application of the spatial auto regressive (SAR) model	2017	Appraisal: From Theory to Practice	Italy	Urban	not mentioned	not mentioned	0.5	Observational	Cross-sectional	500	all	all	listing	sales	EER	Band	Current	Spatial regression	positive

5	Stenvall et al., 2022	Does energy efficiency matter for prices of tenant-owned apartments?	2022	Environmental Science and Pollution Research	Sweden	Regional	2019	2020	1	Observational	Cross-sectional	21696	apartment	private	transaction	sales	EER	Band	Current	OLS	positive
6	Fuerst et al., 2015	Does energy efficiency matter to home-buyers? An investigation of EPC ratings and transaction prices in England	2015	Energy Economics	United Kingdom	National	1995	2012	17	Observational	Longitudinal	333095	all	all	transaction	sales	EER	Band And Score	Current	OLS	positive
7	Wahlstrom, 2016	Doing good but not that well? A dilemma for energy conserving homeowners	2016	Energy Economics	Sweden	National	2009	2010	2	Observational	Cross-sectional	69698	house	all	transaction	sales	EER	Energy consumption	Current	OLS	no impact
8	Chegut et al., 2016	Energy efficiency and economic value in affordable housing	2016	Energy Policy	Netherlands	National	2008	2013	5.5	Observational	Cross-sectional	11411	all	social	transaction	sales	EER	Band	Current	OLS	positive
9	von Platten et al., 2022	Energy efficiency at what cost? Unjust burden-sharing of rent increases in extensive energy retrofitting projects in Sweden	2022	Energy Research and Social Science	Sweden	National	2013	2019	2	Observational	Longitudinal	32150	apartment	all	listing	rents	EER	Band	Current	ANOVA and OLS	depends
10	Chegut et al., 2020	Energy Efficiency Information and Valuation Practices in Rental Housing	2019	The Journal of Real Estate Finance and Economics	United Kingdom and Netherlands	Regional	2010	2015	1	Observational - comparative	Longitudinal	12289	all	social	appraisal	sales	EER	Band And Score	Current	OLS	positive

11	Cerin at al., 2014	Energy Performance and Housing Prices	2014	Sustainable Development	Sweden	National	2009	2010	2	Observational	Cross-sectional	64753	all	all	transaction	sales	EER	Energy consumption	Current	OLS	depends
12	Olaussen et al., 2017	Energy performance certificates ?C Informing the informed or the indifferent?	2017	Energy Policy	Norway	Urban	2000	2014	13	Observational	Longitudinal	4674	all	all	transaction	sales	EER	Band	Current	OLS	no impact
13	McCord et al., 2020(b)	Energy performance certificates and house prices: a quantile regression approach	2020	Journal of European Real Estate Research	United Kingdom	Urban	2018 q2	2019 q1	1	Observational	Cross-sectional	1478	all	all	transaction	sales	EER	Band And Score	Current and Potential	Advanced regression	positive
14	Wilhelmsson, 2019	Energy performance certificates and its capitalization in housing values in Sweden	2019	Sustainability (Switzerland)	Sweden	National	2013	2018	6	Observational	Cross-sectional	80260	house	all	transaction	sales	EER	Band	Current	Advanced regression	positive
15	Fregonara et al., 2017	Energy performance certificates in the Turin real estate market	2017	Journal of European Real Estate Research	Italy	Urban	2011	2014	4	Observational	Cross-sectional	879	apartment	all	transaction and listing	sales	EER	Band	Current	OLS	no impact
16	Olaussen et al., 2019	Energy Performance Certificates - The Role of the Energy Price	2019	Energies	Norway	Urban	2000	2014	11	Observational	Longitudinal	4397	all	all	transaction	sales	EER	Band	Current	OLS	no impact

17	Fuerst et al., 2016(a)	Energy performance ratings and house prices in Wales: An empirical study	2016	Energy Policy	United Kingdom	Regional	200301	201402	11	Observational	Longitudinal	62464	house	all	transaction	sales and rents	EER	Band And Score	Current	OLS	positive
18	DellAnna et al., 2019	EPC Green Premium in Two Different European Climate Zones: A Comparative Study between Barcelona and Turin	2019	Sustainability (Switzerland)	Spain and Italy	Urban	2014	2018	4	Observational - comparative	Cross-sectional	15288	apartment	all	listing	sales	EER	Band	Current	Spatial regression	positive
19	Barreca et al., 2021	Epc labels and building features: Spatial implications over housing prices	2021	Sustainability (Switzerland)	Italy	Urban and intra-urban	2015	2018	3	Observational - comparative	Cross-sectional	2092	all	all	listing	sales	EER	Band	Current	Spatial regression	positive
20	Taruttis and Weber, 2022	Estimating the impact of energy efficiency on housing prices in Germany: Does regional disparity matter?	2022	Energy Economics	Germany	National	2014	2018	4	Observational	Cross-sectional	422242	house	all	listing	sales	EER	Energy consumption	Current	OLS	positive
21	Massimo et al., 2022	Green and Gold Buildings? Detecting Real Estate Market Premium for Green Buildings through Evolutionary Polynomial Regression	2022	Buildings	Italy	Intra-urban	not mentioned	not mentioned	not mentioned	Observational	Cross-sectional	515	apartment	all	transaction	sales	EER	Band	Current	Linear extension	positive
22	Taltavull et al., 2019	Green Premium Evidence from Climatic Areas: A Case in Southern Europe, Alicante (Spain)	2019	Sustainability?	Spain	Regional	not mentioned	not mentioned	not mentioned	Observational	Cross-sectional	8948	all	all	listing	sales	EER and EIR	Band And energy consumption	Current	OLS	positive

23	Fuerst et al., 2016(b)	Green signalling effects in the market for energy-efficient residential buildings	2016	Applied Energy	Finland	Urban	2009	2012	3	Observational	Cross-sectional	6194	apartment	private	transaction	sales	EER	Band	Current	OLS	positive
24	Koengkan and Fuinhas, 2022	Heterogeneous Effect of 'Eco-Friendly' Dwellings on Transaction Prices in Real Estate Market in Portugal	2022	Energies	Portugal	National	2014	2019	5	Observational	Cross-sectional	not applicable	all	all	transaction	sales	EER	Band	Current	Advanced regression	positive
25	Evangelista et al., 2022	How heterogeneous is the impact of energy efficiency on dwelling prices? Evidence from the application of the unconditional quantile hedonic model to the Portuguese residential market	2022	Energy Economics	Portugal	National	2009	2013	5	Observational	Cross-sectional	1556145	all	all	transaction	sales	EER	Band	Current	Advanced regression	positive
26	Copiello and Donati, 2021	Is investing in energy efficiency worth it? Evidence for substantial price premiums but limited profitability in the housing sector	2021	Energy and Buildings	Italy	Urban	2019q3	2019q4	0.25	Observational	Cross-sectional	378	all	all	listing	sales	EER	Band	Current	Spatial regression	positive
27	Fuerst et al., 2020	Is there an economic case for energy-efficient dwellings in the United Kingdom private rental market?	2020	Journal of Cleaner Production	United Kingdom	National	1995	2013	18	Observational	Cross-sectional	8208	all	all	transaction	sales and rents	EER	Band And Score	Current	OLS	positive
28	Sejas-Portillo et al., 2020	Limited Attention in the Housing Market: Threshold Effects of Energy-Performance Certificates on Property Prices and Energy-Efficiency Investments	2020	Conference	United Kingdom	National	201207	201909	7.2	Observational	Cross-sectional	over 5 million	all	all	transaction	sales	EER	Band And Score	Current	Advanced regression	positive

29	Jensen et al., 2016	Market response to the public display of energy performance rating at property sales	2016	Energy Policy	Denmark	National	200701	201209	5.7	Observational	Cross-sectional	72326	all	all	transaction	sales	EER	Band	Current	OLS	positive
30	Bisello et al., 2020	Measuring the price premium of energy efficiency: A two-step analysis in the Italian housing market	2020	Energy and Buildings	Italy	Urban	201803	201804	0.0833333	Observational	Cross-sectional	825	apartment	all	listing	sales	EER	Band	Current	Spatial regression	positive
31	Davis et al., 2015	Modelling the effect of energy performance certificate rating on property value in the Belfast housing market	2015	International Journal of Housing Markets and Analysis	United Kingdom	Urban	not mentioned	not mentioned	not mentioned	Observational	Cross-sectional	3797	all	all	transaction	sales	EER	Score	Current	OLS	positive
32	Brounen and Kok, 2011	On the economics of energy labels in the housing market	2011	Journal of Environmental Economics and Management	Netherlands	National	200801	200909	1.6666667	Observational	Cross-sectional	31993	all	all	transaction	sales	EER	Band	Current	OLS	positive
33	Harsman et al., 2016	On the quality and impact of residential energy performance certificates	2016	Energy and Buildings	Sweden	National	2009	2010	2	Observational	Cross-sectional	69698	house	all	transaction	sales	EER	Energy consumption	Current and Potential	OLS	no impact
34	Evangelista et al., 2020	On the use of hedonic regression models to measure the effect of energy efficiency on residential property transaction prices: Evidence for Portugal and selected data issues	2020	Energy Economics	Portugal	National	2009	2013	5	Observational	Cross-sectional	256145	all	all	transaction	sales	EER	Band	Current	Advanced regression	positive

35	Olaussen et al., 2021	Real Estate Price Formation: Energy Performance Certificates and the Role of Real Estate Agents	2021	Journal of Sustainable Real Estate	Norway	Urban	2000	2014	14	Observational	Longitudinal	3844	all	all	appraisal	sales	EER	Band	Current	OLS	no impact
36	DellAnna, 2022	Spatial Econometric Analysis of Multi-family Housing Prices in Turin: The Heterogeneity of Preferences for Energy Efficiency	2022	International Conference on Computational Science and Its Applications	Italy	Urban	2014	2021	8	Observational	Cross-sectional	5899	apartment	all	listing	sales	EER	Band	Current	Spatial regression	positive
37	Marmolejo-Duarte et al., 2019	Spatial implications of EPC rankings over residential prices	2019	Values and Functions for Future Cities (book)	Spain	Urban	not mentioned	201604	not mentioned	Observational	Cross-sectional	5497	apartment	all	listing	sales	EER	Band	Current	Spatial regression	positive
38	Cajias et al., 2019	Tearing down the information barrier: the price impacts of energy efficiency ratings for buildings in the German rental market	2019	Energy Research and Social Science	Germany	National	2013q1	2017q4	5	Observational	Cross-sectional	1029202	all	private	listing	rents	EER	Band	Current	OLS	positive
39	Aydin et al., 2020	The capitalization of energy efficiency: Evidence from the housing market	2020	Journal of Urban Economics	Netherlands	National	2008	2015	8	Observational	Cross-sectional	1810	house	all	transaction	sales	EER	Energy consumption	Current	OLS and RDD	positive
40	Marmolejo-Duarte and Chen, 2022	The effect of energy performance ratings over residential prices or how an insufficient control of architectural-quality may render spurious conclusions	2022	Cities	Spain	Urban	not mentioned	not mentioned	not mentioned	Observational - comparative	Cross-sectional	2327	apartment	all	listing	sales	EER	Band	Current	Spatial regression	no impact

41	Marmolejo-Duarte and Chen, 2019(a)	The evolution of energy efficiency impact on housing prices. An analysis for UrbanBarcelona	2019	Revista de la Construccion	Spain	Urban	201411	201604	0.5	Observational	Longitudinal	6492	apartment	all	listing	sales	EER	Band	Current	Spatial regression	positive
42	Fregonara et al., 2014	The impact of Energy Performance Certificate level on house listing prices. First evidence from Italian real estate	2014	Aestimum	Italy	Urban	2012	2012	1	Observational	Cross-sectional	577	apartment	all	listing	sales	EER	Band	Current	OLS	no impact
43	Hogberg, 2013	The impact of energy performance on single-family home selling prices in Sweden	2013	Journal of European Real Estate Research	Sweden	Urban	2009	2009	1	Observational	Cross-sectional	1073	house	all	transaction	sales	EER	Energy consumption	Current	OLS	positive
44	Cespedes-Lopez et al., 2020	The influence of energy certification on housing sales prices in the province of alicante (Spain)	2020	Applied Sciences (Switzerland)	Spain	Regional	201706	201805	1	Observational	Cross-sectional	9194	apartment	all	listing	sales	EER	Band	Current	OLS	no impact
45	Cespedes-Lopez et al., 2022	The influence of housing location on energy ratings price premium in Alicante, Spain	2022	Ecological Economics	Spain	Regional	201706	201805	1	Observational	Cross-sectional	70170	all	all	listing	sales	EER	Band	Current	Advanced regression	no impact
46	Kholodilin et al., 2017	The market value of energy efficiency in buildings and the mode of tenure	2017	Urban Studies	Germany	Urban	201106	201412	3.5	Observational	Cross-sectional	20664	apartment	all	listing	sales and rents	EER	Energy consumption	Current	OLS	positive

47	Stanley et al., 2016	The price effect of building energy ratings in the Dublin residential market	2016	Energy Efficiency	Ireland	Urban	200901	201406	5.5	Observational	Cross-sectional	2792	all	all	listing	sales	EER	Band	Current	OLS	positive
48	Marmolejo-Duarte and Chen, 2019(b)	The uneven price impact of energy efficiency ratings on housing segments and implications for public policy and private markets	2019	Sustainability (Switzerland)	Spain	Urban	201501	201503	0.25	Observational	Cross-sectional	3479	apartment	all	listing	sales	EER	Band	Current	OLS	no impact
49	Hyland et al., 2013	The value of domestic building energy efficiency - evidence from Ireland	2013	Energy Economics	Ireland	National	200801	201203	4.25	Observational	Cross-sectional	35885	all	all	listing	sales and rents	EER	Band	Current	OLS	positive
50	Mense, 2018	The Value of Energy Efficiency and the Role of Expected Heating Costs	2018	Environmental and Resource Economics	Germany	National	201504	201607	1.25	Observational	Cross-sectional	229072	house	all	listing	sales	EER	Energy consumption	Current	OLS	positive
51	Brounen et al., 2020	The value effects of green retrofits	2020	Journal of European Real Estate Research	Germany	Urban	2012	2015	4	Observational	Cross-sectional	8928	all	all	listing	sales	EER	Band	Current	Linear extension	positive
52	Morano et al., 2018	The value of the energy retrofit in the Italian housing market: Two case-studies compared	2018	WSEAS Trans. Bus. Econ	Italy	Urban	2016	2017	1	Observational - comparative	Cross-sectional	200	all	all	transaction	sales	EER	Band	Current	Linear extension	positive

53	Khazal and Sonstebo, 2020	Valuation of energy performance certificates in the rental market ?C Professionals vs. nonprofessionals	2020	Energy Policy	Norway	National	201101	201801	8	Observational	Cross-sectional	101277	all	all	listing	rents	EER	Band	Current	Advanced regression	positive
54	Pommeranz and Steininger, 2021	What Drives the Premium for Energy-Efficient Apartments ?C Green Awareness or Purchasing Power?	2021	The Journal of Real Estate Finance and Economics	Germany	National	2007q1	2019q1	13	Observational	Cross-sectional	377426	apartment	all	listing	rents	EER	Energy consumption	Current	OLS	positive
55	Cajias and Piazolo, 2012	Green performs better: energy efficiency and financial return on buildings	2013	Journal of Corporate Real Estate	Germany	National	2008	2010	3	Observational	Cross-sectional	2613	all	all	appraisal	rents	EER	Band	Current	Advanced regression	positive
56	Liu et al., 2018	Do renters skimp on energy efficiency during economic recessions? Evidence from Northeast Scotland	2018	Energy	United Kingdom	Urban	2013q3	2017q2	4	Observational	Cross-sectional	9451	all	all	transaction	rents	EER	Band	Current	OLS	positive
57	Gerassimenko et al., 2023	The impact of energy certificates on sales and rental prices: a comparative analysis	2023	International Journal of Housing Markets and Analysis	Belgium	Regional	2016	2021	6	Observational	Cross-sectional	177670	all	all	listing	sales and rents	EER	Band	Current	OLS	positive
58	Gerassimenko et al., 2024	Does the market value energy efficiency within EPC-labels? An analysis of the residential real estate market in Flanders	2024	International Journal of Housing Markets and Analysis	Belgium	Regional	2019	2023	5	Observational	Cross-sectional	706778	all	all	listing	sales and rents	EER	Band	Current	OLS	positive

59	Wilhelmsson, 2023	How Does the Presentation of Energy Performance Affect the Price of Houses? A Case Study of Detached Houses in Stockholm, Sweden	2023	Buildings	Sweden	Urban	2012	2018	7	Observational	Cross-sectional	2882	house	all	transaction	sales	EER	Band	Current	OLS	positive
60	Galvin, 2023(b)	How prebound effects compromise the market premium for energy efficiency in German house sales	2023	Building Research and Information	Germany	National	2019	2021	3	Observational	Cross-sectional	244256	house	all	listing	sales	EER	Energy consumption	Current	OLS	positive
61	Sieger and Weber, 2023	Inefficient markets for energy efficiency? – The efficiency premium puzzle in the German rental housing market	2023	Energy Policy	Germany	Regional	201405	202012	6.5	Observational	Cross-sectional	842229	apartment	all	listing	rents	EER	Energy consumption	Current	OLS	positive
62	Sieger, 2024	Investigating inefficiencies in the German rental housing market: The impact of disclosing total costs on energy efficiency appreciation	2024	Energy and Buildings	Germany	National	201405	202112	7.5	Observational	Cross-sectional	3903473	apartment	all	listing	rents	EER	Energy consumption	Current	OLS	depends
63	Galvin, 2023(a)	Rental and sales price premiums for energy efficiency in Germany's pre-War apartments: Where are the shortfalls and what is society's role in bringing fairness?	2023	Energy Research and Social Science	Germany	National	201901	202112	3	Observational	Cross-sectional	18153	apartment	all	listing	sales and rents	EER	Energy consumption	Current	OLS	depends
64	Micelli et al., 2023	The economic value of sustainability. Real estate market and energy performance of homes	2023	Valori e Valutazioni	Italy	Regional	not mentioned	202301	not mentioned	Observational	Cross-sectional	900	all	all	listing	sales	EER	Band	Current	OLS	positive

65	Copiello and Coletto, 2023	The Price Premium in Green Buildings: A Spatial Autoregressive Model and a Multi-Criteria Optimization Approach	2023	Buildings	Italy	Urban	202203	202207	0.416	Observational	Cross-sectional	321	all	all	listing	sales	EER	Band	Current	Spatial regression	positive
66	Micelli et al., 2024	Urban Disparities in Energy Performance Premium Prices: Towards an Unjust Transition?	2024	Land	Italy	Regional	not mentioned	202307	not mentioned	Observational - comparative	Cross-sectional	2034	all	all	listing	sales	EER	Band	Current	OLS	positive
67	Ruggeri et al., 2023	What Is the Impact of the Energy Class on Market Value Assessments of Residential Buildings? An Analysis throughout Northern Italy Based on Extensive Data Mining and Artificial Intelligence	2023	Buildings	Italy	Regional	not mentioned	not mentioned	not mentioned	Observational	Cross-sectional	13093	all	all	listing	sales	EER	Band	Current	Random forest	positive
68	Groh et al., 2022	Does Retrofitting Pay Off? An Analysis of German Multifamily Building Data	2022	Journal of Sustainable Real Estate	Germany	National	2016	2020	5	Observational	Cross-sectional	533780	apartment	all	listing	rents	EER	Band	Current	Linear extension	positive

Appendix B Table of model inventory

Table B Model Inventory.

mid	pid	model	loc	spa	tem	fform	var_hp	var_all	struct	neigh	qual	score	A	B	C	D	E	F	G	rd	rd_tag	pp	r2
1	1	GWR	Yes	Yes	Yes	semi-log	log price	size, property type (terrace/detach/apartment), age (pre1919/early modern/inter war), garage, gas heat	Yes	No	No	0.0023								0		0	0.715
2	1	SLM	Yes	Yes	Yes	semi-log	log price	size, property type (terrace/detach/apartment), age (pre1919/early modern/inter war), garage, gas heat	Yes	No	No	0.0012								0		0	0.67
3	2	EPR	Yes	No	No	semi-log	log price	size, age, number of bathrooms, floor number, lift, parking, maintenance condition (dummy), distance to highway, distance to subway, municipal trade area (some variables are excluded in final selected model)	Yes	Yes	Yes		0.2794	hold-out	hold-out	hold-out	hold-out	hold-out	-0.2644	1	EPR	1	0.714
4	3	OR	No	No	No	semi-log	log price	sale price, size, property type, age	Yes	No	No									1	GLM	0	0.391
5	4	SAR	Yes	Yes	No	linear	price	size, floor, residential unit address (latitude, longitude), spatially lagged variable	Yes	No	No									1	Ordinal EER and linear	1	0.829

6	5	OLS	Yes	No	Yes	semi-log	log price	size, age, number of rooms, rent, postcode, sale month	Yes	No	No	0.007	0.007	hold-out	hold-out	hold-out	hold-out	hold-out	0		1	0.943
7	6	OLS	Yes	No	Yes	semi-log	log price per m2	property type, age, number of bedrooms, deprivation index score, urban-rural index score, postcode area, sale quarter	Yes	Yes	No	0.05	0.05	0.018	hold-out	-0.007	-0.009	-0.068	0		0	0.693
8	6	OLS	No	No	Yes	linear	price change per m2	property type, age, number of bedrooms, deprivation index score, urban-rural index score, regional price index, sale quarter	Yes	Yes	No	-0.015	-0.015	0.013	hold-out	-0.018	-0.026	-0.001	1	Longitudinal: price change as dependent variable	0	0.788
9	7	OLS	Yes	No	Yes	log-log	log price	age, direct consumer satisfaction (including neighborhood attributes), indoor climate comfort (including local climate), seller's yearly consumption of energy	Yes	Yes	No								1	Energy consumption and log-log	1	0.729
10	8	OLS	Yes	No	Yes	semi-log	log price per m2	size (log), property type, age, number of rooms, number of stories, other building characteristics (basement, attic, garden, parking, monument, ground lease, partial lot), thermal and quality	Yes	No	Yes	0.063	0.02	hold-out	-0.007	-0.016	-0.017	-0.013	0		0	0.9

								characteristics, transaction characteristics, location, year-quarter															
11	9	ANOVA	No	No	No	linear	rent increase per square meter and year (%)	renovation investment (light: <20% of construction cost; extensive), aggregate variables to group (e.g. initial EPC rating, construction period - according to building codes), residents' income, classification of municipalities	Yes	Yes	No									1	EP imrpvement and rent increase	1	
12	9	OLS	Yes	No	No	linear	rent increase per square meter and year (%)	age, renovation type, housing company (private/public etc), municipality type, initial rent level, initial EPC, residential income	Yes	Yes	No									1	EP imrpvement and rent increase	1	0.145
13	10	OLS	Yes	No	No	log-log	log price per m2	size (log), property type, age, number of rooms, location	Yes	No	No									1	EER score and log-log	1	0.98
14	10	OLS	Yes	No	No	log-log	log price per m2	size (log), property type, age, number of rooms, location	Yes	No	No									1	EER score and log-log	1	0.98
15	10	OLS	Yes	No	No	semi-log	log price	size (log), property type, age, number of rooms, location	Yes	No	No		-0.017	0	hold-out	-0.027	-0.031	-0.02	-0.042	0		0	0.84

							per m2																
16	10	OLS	Yes	No	No	semi-log	log price per m2	size (log), property type, age, number of rooms, location	Yes	No	No		0.065	0.031	hold-out	-0.037	-0.005	-0.038	-0.07	0		0	0.9
17	11	OLS	Yes	No	Yes	log-log	log price per m2	property type, age, location, year	Yes	No	No									1	Energy consumption and log-log	1	0.43
18	12	OLS	Yes	No	No	semi-log	log price per m2	size (dummy), property type, age, location	Yes	No	No		0.043	0.189	0.122	0.075	0.005	hold-out	0.054	0		0	0.5
19	12	OLS	Yes	No	Yes	semi-log	log price per m2	size (dummy), property type, age, location, year	Yes	No	No									1	Pre-label model	0	0.63
20	12	OLS	Yes	No	Yes	semi-log	log price per m2	age, location, dwelling type, property size, fixed effect (conrtol for all time invariant variables)	Yes	No	No		not mentioned	-0.005	0.019	-0.012	-0.024	0.02	0.051	0	fixed effect model	0	0.02
21	13	OLS	Yes	No	No	semi-log	log price	size, property type, age, heating type, garage, location	Yes	No	No			0.072	0.0315	hold-out	1.04E-05	-0.0166	-0.132	0		0	0.6805
22	13	QR	Yes	No	No	semi-log	log price	size, property type, age, heating type, garage, location	Yes	No	No									1	QR	0	
23	13	OLS	Yes	No	No	semi-log	log price	size, property type, age, heating type, garage, location	Yes	No	No		not mentioned	0.1227	hold-out	0.007	-0.009	-0.098	not mentioned	1	QR and potential EER	0	0.677

24	13	QR	Yes	No	No	semi-log	log price	size, property type, age, heating type, garage, location	Yes	No	No									1	QR and potential EER	0	
25	14	OLS	Yes	No	Yes	semi-log	log price	size (log), age (log), number of rooms, plot size, inverse propensity score, location, month	Yes	No	No	0.041	0.041	0.041	hold-out	hold-out	hold-out	hold-out	0		1	0.8653	
26	14	QR	Yes	No	Yes	semi-log	log price	size (log), age (log), number of rooms, plot size, propensity score, location, month	Yes	No	No									1	QR	0	
27	15	OLS	Yes	No	Yes	semi-log	log price	size, age, apartment condition, building quality, building condition (new/refurbished), location, time	Yes	No	Yes	0.2	0.036	0.039	hold-out	-0.011	-0.042	-0.056	0		0	0.68	
28	15	OLS	Yes	No	Yes	semi-log	log price	size, age, apartment condition, building quality, building condition (new/refurbished), location, time	Yes	No	Yes	0.14	0.084	0.013	hold-out	-0.021	-0.023	-0.046	0		0	0.626	
29	16	OLS	Yes	No	No	log-log	log price per m2	size (small, medium, large), property type, age, location	Yes	No	No									1	other energy variable	1	0.47
30	16	OLS	Yes	No	No	log-log	log price per m2	size (small, medium, large), property type, age, location	Yes	No	No									1	other energy variable	1	0.4
31	17	OLS	Yes	No	Yes	semi-log	log price per m2	property type, age, number of rooms, tenure, urban-rural index score, location, time	Yes	Yes	No	0.113	0.113	0.0206	hold-out	-0.0209	-0.0473	-0.0717	0		0	0.505	

32	17	OLS	Yes	No	Yes	semi-log	log price per m2	property type, age, number of rooms, tenure, urban-rural index score, location	Yes	Yes	No		0.185	0.185	0.04	hold-out	-0.022	-0.017	-0.072	0		0	0.497
33	17	OLS	Yes	No	No	linear	price change per m2	property type, age, number of rooms, tenure, urban-rural index score, location, time	Yes	Yes	No		-0.00169	-0.00169	0.032	hold-out	-0.0449	-0.0591	-0.0153	1		0	0.256
34	18	SLM	No	Yes	Yes	semi-log	log price	size, new/retrofitted, dwelling level, air conditioning, building (swimming pool, lift), accessibility (highway, urban park, sea coast), year, lag coefficient	Yes	Yes	Yes									1	ordinal EPC	1	0.8202
35	18	SEM	No	Yes	Yes	semi-log	log price	size, new/retrofitted, dwelling level, air conditioning, building (swimming pool, lift), accessibility (highway, urban park, sea coast), year, lambda	Yes	Yes	Yes									1	ordinal EPC	1	0.7926
36	18	SLM	No	Yes	Yes	semi-log	log price	size, new/retrofitted, dwelling level, air conditioning, building (swimming pool, lift), accessibility (highway, urban park, sea coast), year, lag coefficient	Yes	Yes	Yes									1	ordinal EPC	1	0.7757
37	18	SEM	No	Yes	Yes	semi-log	log price	size, new/retrofitted, dwelling level, air conditioning, building (swimming pool, lift), accessibility	Yes	Yes	Yes									1	ordinal EPC	1	0.7787

								(highway, urban park, sea coast), year, lambda							
38	19	SEM	No	Yes	No	semi-log	log price per m2	construction time, property type, number of rooms, number of bathrooms, large terrace, number of views, custodian service, penthouse, car box, lift, maintenance level, building category, air conditioning, lambda	Yes	No	Yes	1	ordinal EPC	1	0.532
39	19	SEM	No	Yes	No	semi-log	log price per m2	construction time, property type, custodian service, car box, large terrace, lift, maintenance level, building category, air conditioning, lambda	Yes	No	Yes	1	ordinal EPC	1	
40	20	OLS	Yes	No	Yes	semi-log	log price per m2	construction year, living space, lot size, number of rooms and floors, heating type, renovation, neighborhood structure (socio-economic characteristics, predominant building type), location, time, time*region, region*energy consumption	Yes	Yes	Yes	0		1	0.7899
41	21	EPR	Yes	No	Yes	linear	price	size, age, number of bathrooms, floor level, maintenance, location, time	Yes	No	Yes	1	variation of changes of selling price	1	

																					corresponding to EPC variable		
42	22	OLS	Yes	No	No	semi-log	log price	size, property type, age, age2, number of rooms (bedrooms/bathrooms/rooms), improvement, orientation, view, first/second, public/rented, neighborhood characteristics, building characteristics, location	Yes	Yes	No		-0.016	-0.016	-0.016	0.01	0.005	0.018	hold-out	0		0	0.791
43	22	OLS	Yes	No	No	log-log	log price	size, property type, age, age2, number of rooms (bedrooms/bathrooms/rooms), improvement, orientation, view, first/second, public/rented, neighborhood characteristics, building characteristics, location	Yes	Yes	No									1	EIR co2 emission	1	0.762
44	22	OLS	Yes	No	No	semi-log	log price	size, property type, age, age2, number of rooms (bedrooms/bathrooms/rooms), improvement, orientation, view, first/second, public/rented, neighborhood	Yes	Yes	No		-0.063	-0.063	-0.063	0.019	0.011	0.018	hold-out	1	EIR rating	0	0.761

								characteristics, building characteristics, location														
45	22	OLS	Yes	No	No	semi-log	log price	size, property type, age, age2, number of rooms (bedrooms/bathrooms/rooms), improvement, orientation, view, first/second, public/rented, neighborhood characteristics, building characteristics, location	Yes	Yes	No		-0.23	-0.23	-0.08	0.03	0	-0.01	hold-out	1	IV-OLS	0	0.43
46	23	OLS	Yes	No	Yes	semi-log	log price	size, age, condition, floor, maximum floor, penthouse, sauna, CBD distance, neighborhood characteristics (socio-economic, housing stock), time, location, maintenance cost	Yes	Yes	No		0.013	0.013	0.013	hold-out	0	0.0002	0.0002	0		0	0.931
47	24	QR	No	No	No	linear	median price per m2	Municipality GDP, incentive policy, credit agreement, number of completed dwellings, number of completed reconstructions	No	Yes	No									1		1	
48	25	QR	No	No	No	semi-log	log price	size, land area,number of bedrooms	Yes	No	No									1	QR	1	

49	25	QR	No	No	No	semi-log	log price	size, land area,number of bedrooms	Yes	No	No								1	QR	1	
50	25	QR	No	No	No	semi-log	log price	size, land area,number of bedrooms	Yes	No	No								1	QR	1	
51	25	QR	No	No	No	semi-log	log price	size, land area,number of bedrooms	Yes	No	No								1	QR	1	
52	26	SAR	No	Yes	No	semi-log	log price	property type, age, number of rooms, number of bathrooms, garage, parking, unusual equipment, distance to shopping center, distance to beltway	Yes	Yes	No	0.4806	0.4767	0.2802	0.2631	0.2172	0.1378	hold-out	1		0	0.7574
53	27	OLS	Yes	No	Yes	semi-log	log price per m2	size (log), property type, age, number of bedrooms, tenure, rural/urban, IMD score (log), location, time	Yes	Yes	No	not mentioned	0.061	0.061	hold-out	0.004	-0.101	-0.101	0		0	0.44
54	27	OLS	Yes	No	Yes	semi-log	log monthly rent per m2	size (log), number of bedrooms, tenure, urban/rural, IMD score (log), location, time	Yes	Yes	No	not mentioned	0.038	0.049	hold-out	-0.001	-0.035	-0.035	0		0	0.63
55	28	RDD	Yes	No	Yes	semi-log	log price per m2	treatment variable (whether rating cross band threshold), property characteristics, location, time	Yes	No	No								1		0	
56	29	OLS	Yes	No	Yes	semi-log	log price per m2	age, type of heating, roof, walls, location, time	Yes	No	No	0.066	0.066	0.002	hold-out	-0.015	-0.035	-0.093	0		0	0.603

57	29	OLS	Yes	No	Yes	semi-log	log price per m2	age, type of heating, roof, walls, location, time	Yes	No	No		0.062	0.062	0.051	hold-out	-0.054	-0.129	-0.243	0	0	0.678
58	30	SLM	Yes	Yes	No	semi-log	log price per m2	size, number of rooms, number of bathrooms, lift, parking, garden, balcony, location	Yes	No	No		0.0619	0.0515	0.0255	not mentioned	not mentioned	not mentioned	hold-out	0	0	0.601
59	31	OLS	No	No	No	semi-log	log price	size, property type, age, number of bedrooms, garage, new build	Yes	No	No	0.004								0	0	0.637
60	32	OLS	Yes	No	Yes	semi-log	log price per m2	size (log), property type, age, number of rooms, neighborhood characteristics (housing dentisty, time on market, household income), thermal and quality characteristics (central heating, exterior maintenance, insulation quality), selection variable	Yes	Yes	Yes		0.102	0.055	0.021	hold-out	-0.005	-0.023	-0.048	0	0	0.527
61	33	OLS	Yes	No	Yes	log-log	log price	energy consumption (log), age, other housing attributes (kitchen standard), location, household attributes (education, green car), neighborhood (income, education)	Yes	Yes	Yes									1	0	0.761
62	33	OLS	Yes	No	Yes	log-log	log price	energy consumption (log), age, other housing attributes (kitchen standard), location, household	Yes	Yes	Yes									1	0	0.762

								attributes (education, green car), neighborhood (income, education)															
63	34	QR	Yes	No	Yes	semi-log	log price	size, age, number of bedrooms, quality, gas, floor, location, central heating, parking, renovation, view, swimming pool,	Yes	No	Yes		0.207	0.15	hold-out	-0.014	-0.006	-0.028	-0.064	0		0	0.678
64	34	QR	Yes	No	Yes	semi-log	log price	size, age, number of bedrooms, quality, gas, floor, location, central heating, parking, renovation, view, swimming pool,	Yes	No	Yes		0.204	0.135	hold-out	0.014	-0.036	-0.001	0.067	0		0	0.74
65	34	QR	Yes	No	Yes	semi-log	log price	size, age, number of bedrooms, quality, gas, floor, location, central heating, parking, renovation, view, swimming pool,	Yes	No	Yes		-0.008	0.01	hold-out	-0.033	-0.041	-0.059	-0.076	0		0	0.671
66	34	QR	Yes	No	Yes	semi-log	log price	size, age, number of bedrooms, quality, gas, floor, location, central heating, parking, renovation, view, swimming pool,	Yes	No	Yes		0.077	0.048	hold-out	-0.019	-0.05	-0.046	-0.124	0		0	0.754
67	35	OLS	Yes	No	Yes	semi-log	log price per m2	size (dummy), property type, age, location, time	Yes	No	No			0.483	0.139	0.098	0.026	hold-out	0.036	0		0	0.66
68	35	OLS	Yes	No	Yes	semi-log	log price per m2	size (dummy), property type, age, location, time	Yes	No	No		0.142	0.203	0.143	0.114	0.015	hold-out	0.046	0		0	0.47

69	36	GWR	No	Yes	Yes	semi-log	log price	size, dwelling level, age, maintenance, market segment, parking, lift	Yes	No	Yes									0		1	0.864
70	37	GWR	No	Yes	No	semi-log	not applicable	architectonic(size, number of bathrooms, lift, swimming pool, terrace, air cond, heating, high quality, high quality of kitchen, lift*story level, recently refurbished, chimney, EPC), environment (empolyment, distance to highway/CBD, near to sea), socioeconomic (university popo, med low income PC)	Yes	Yes	Yes									1		1	0.17
71	38	OLS	Yes	No	Yes	semi-log	log rent per month	size (log), age, number of rooms, distance to center, neighborhood (number of households, purchasing power of household), bathtub, built-in-kitchen, parking lot, terrace, balcony, elevator, new built, refurbished, location, time	Yes	Yes	No		0.014	0.009	0.002	hold-out	0	-0.001	-0.003	0		0	0.84
72	39	OLS	Yes	No	Yes	log-log	log price	EPI (log), size, property type, age, number of rooms, number of floors, quality, type of parking, location relative to center,	Yes	Yes	Yes									1	EPI	1	

								road, park, water, forest															
73	39	OLS	Yes	No	Yes	log-log	log price	EPI (log), size, property type, age, number of rooms, number of floors, quality, type of parking, location relative to center, road, park, water, forest	Yes	Yes	Yes									1	EPI	1	
74	39	RDD	No	No	Yes	log-log	log price	EPI (log), size, property type, age, number of rooms, number of floors, quality, type of parking, location relative to center, road, park, water, forest	Yes	Yes	Yes									1	RDD	1	
75	40	SEM	No	Yes	No	semi-log	log price	size, age, number of floors, quality structural attributes (bathrooms, storeroom, lift, air conditioner, central heating, etc), qualitative quality attributes (computed by PCA), locative attributes (computed by GIS - buffer analysis; commuting time, personal services density, distance to CBD, sea shore, etc)	Yes	Yes	Yes		0.039	0.042	0.006	0.031	0.001	hold-out	0.001	0		0	0.923
76	40	SEM	No	Yes	No	semi-log	log price	size, age, number of floors, quality structural attributes (bathrooms, storeroom, lift, air conditioner, central	Yes	Yes	Yes		0.063	0.063	0.009	0.003	0.01	hold-out	0.005	0		0	0.89

								heating, etc), qualitative quality attributes (computed by PCA), locative attributes (computed by GIS - buffer analysis; commuting time, personal services density, distance to CBD, sea shore, etc)															
77	41	SEM	Yes	Yes	Yes	semi-log	log price	size (unitary and square), age (inverse), number of bathrooms, other structural characteristics (air conditioner, central heating, retrofited apartment, swimming pool, lift), locative attributes (transport, centrality, amenities), socio-economic (income), year, EPC*year interaction	Yes	Yes	No		0.086	not mentioned	0.011	0	0.007	0.019	hold-out	0		0	0.764
78	42	OLS	Yes	No	No	semi-log	log price per m2	size, apartment condition, building quality, location	Yes	No	Yes		not mentioned	hold-out	-0.03	-0.1	-0.06	-0.14	-0.1	0		0	0.76
79	43	OLS	No	No	No	semi-log	log price	size(ln), lot size(ln), lot size square(ln), property type, quality index, age, age square, recommendation measures (construction, installation, operation)	Yes	No	No									0		1	0.8977

80	44	OLS	Yes	No	No	semi-log	log price	size, typology, age, number of floors, number of bedrooms, number of bathrooms, other dwelling characteristics (wardrobe, air-conditioner, terrace, building quality), building characteristics (elevator, parking, pool, storeroom, garden), location characteristics (district, proximity to facilities), neighborhood characteristics (socio-economic attributes), market characteristics (seller, occupancy, housing tenure)	Yes	Yes	Yes		-0.026	-0.091	0.014	hold-out	-0.081	-0.08	-0.087	0		0	0.71
81	45	MLR	Yes	No	No	semi-log	log price	size, property type, age, number of floor, number of bedrooms, number of bathrooms, new construction, renovation, other dwelling characteristics (closet, air conditioner), building characteristics (elevator, parking, pool, garden, floor area ratio), location characteristics (district, costal region, proximity), neighborhood characteristics	Yes	Yes	No		0	-0.079	0.006	hold-out	-0.097	-0.09	-0.125	0		0	

								(socio-economic attributes)													
82	46	OLS	Yes	No	Yes	semi-log	log price	size, age, vintage class, number of rooms, other dwelling characteristics (elevator, cellar, fitted kitchen, guest bathroom, parking lot, garden, balcony), dwelling quality, refurbishment status, accessibility (to two main city centers), amenity (school, supermarket, metro stations), neighborhood population density, mode of tenure (rented out/available to use), district, sales month	Yes	Yes	Yes							0		1	0.75
83	46	OLS	Yes	No	Yes	semi-log	log price	size, age, vintage class, number of rooms, other dwelling characteristics (elevator, cellar, fitted kitchen, guest bathroom, parking lot, garden, balcony), dwelling quality, refurbishment status, accessibility (to two main city centers), amenity (school, supermarket, metro stations), neighborhood	Yes	Yes	Yes							0		1	0.69

								population density, mode of tenure (rented out/available to use), district, sales month													
84	47	OLS	Yes	No	Yes	linear	price	size, property type, age, district, time	Yes	No	No								0	1	0.771
85	48	OLS	Yes	No	No	semi-log	log price	size (unitary and square), age, number of bathrooms, number of floor, heating, air conditioner, quality-retrofit indicator, lift, swimming pool, floor area ratio, centrality indicator, socuial hierarchy (education, doorman service, CP high socioeconomic level)	Yes	Yes	Yes	0.024	not mentioned	-0.012	0.019	0.021	0.006	hold-out	0	0	0.655
86	49	OLS	Yes	No	Yes	linear	price	property type, number of bedrooms, number of bathrooms, new development, district, time	Yes	No	No	0.093	0.052	0.017	hold-out	-0.004	-0.106	-0.106	0	1	
87	49	OLS	Yes	No	Yes	linear	price	property type, number of bedrooms, number of bathrooms, garden, parking, alarm, dishwasher, microwave, furnished, long term lease, le tby agent, is price change, new development, district, time	Yes	No	No	0.018	0.039	-0.006	hold-out	-0.019	-0.032	-0.032	0	1	
88	50	OLS	Yes	No	Yes	semi-log	log price	size, property type, age, age2, numbr of rooms, under	Yes	Yes	Yes								0	1	0.704

								construction, dwelling quality, heating type, parking, population density, district, time															
89	51	GAM	Yes	No	No	semi-log	log price per m2	size, age, number of floor, number of rooms, number of bedrooms, number of bathrooms, elevator, parking price, guest wc, dwelling quality, balcony, cellar, garden, fitted kitchen, retrofit from 2014, district	Yes	No	Yes		0.055	0.024	hold-out	-0.014	0.005	0.016	0.002	0		0	0.678
90	52	EPR	Yes	No	No	semi-log	log price	size, age, number of bathrooms, floor level, lift, parking, dwelling quality, location (distance from motorway, distance from subway, trade area) (some variables are excluded in final selected model)	Yes	Yes	Yes									1		0	0.713
91	52	EPR	Yes	No	No	semi-log	log price	size, age, number of bathrooms, floor level, lift, parking, dwelling quality, location (distance from motorway, distance from subway, trade area) (some variables are excluded in final selected model)	Yes	Yes	Yes									1		0	0.754
92	53	MLR	Yes	No	Yes	semi-log	log rent	size (unitary and square), property type, age, number of bedrooms, floor,	Yes	No	No		0.0284	0.0131	0.0092	hold-out	-0.025	-0.035	-0.0308	0		0	0.77

								furnished, balcony, broadband, central location															
93	54	OLS	Yes	No	Yes	log-log	log rent	size, age, number of rooms, number of floor, time on market, dwelling quality, energy related variables (epc requirement, epc with rating, log heating cost, log utility cost), sociodemographic (Household Size, Number of Households, Immigration Rate, Unemployment Rate), log proximity, time, space, SE cluster (time/spatial), environmental awareness (both base and interaction with epc), purchasing power (both base and interaction with epc)	Yes	Yes	Yes									0		1	0.72
94	55	OLS	Yes	No	Yes	semi-log	log rent	size (log), age, maintenance cost, GDP, CBD, latitude, longitude, district, time	Yes	No	No		not mentioned	0.125	0.127	0.151	0.147	0.032	hold-out	0		0	0.6638
95	55	QR	Yes	No	Yes	log-log	log rent	size (log), age, maintenance cost, GDP, CBD, latitude, longitude, district, time	Yes	No	No									0		1	0.6546
96	56	OLS	Yes	No	Yes	semi-log	log rent	number of bedroom, number of bathroom, heating, cloakroom, garage, garden,	Yes	No	No		0.075	0.075	0.0402	0.03	hold-out	-0.0267	-0.0684	0		0	0.8109

							per year	property type, parking, newbuilt, tom, furnish, year, spatial coordinates,														
97	57	OLS	Yes	No	No	linear	price per m2	age, property type, location	Yes	No	No									0	1	0.2127
98	57	OLS	Yes	No	No	linear	rent per m2 per month	age, property type, location	Yes	No	No									0	1	0.1889
99	58	OLS	Yes	No	Yes	semi-log	log price per m2	property type, age, number of rooms, location, year	Yes	No	No		0.22	0.12	0.06	hold-out	-0.06	-0.14	not mentioned	0	0	0.4588
100	58	OLS	Yes	No	Yes	semi-log	log rent	property type, age, number of rooms, location, year	Yes	No	No		0.07	0.04	0.01	hold-out	-0.01	-0.03	not mentioned	0	0	0.5266
101	59	OLS	No	No	No	semi-log	log price	size, age, number of rooms, distance to CBD/subway	Yes	Yes	No		0.0537	0.0473	0.00803	hold-out	-0.0166	-0.021	-0.0598	0	0	0.888
102	60	OLS	Yes	No	Yes	log-log	log price	size, age, number of rooms, location, land size, guest tiolet, car park, location, month	Yes	No	No									0	1	0.4018
103	61	OLS	Yes	No	Yes	linear	rent per m2 per month	size, age, number of rooms, number of floors, neighbourhood characteristics (population density, employment, purchase power), balcony, garden, kitchen, region, quarter-year,	Yes	Yes	Yes									0	1	0.784

								condition, heating system														
104	62	OLS	Yes	No	No	semi-log	warm rent per m2 per month	size, age, number of rooms, number of floors, neighbourhood characteristics (population density, employment, purchase power), balcony, garden, kitchen, region, quarter-year, condition, heating system	Yes	Yes	Yes									0		1	0.741
105	63	OLS	Yes	No	No	log-log	log rent per month	size, age, number of bathrooms, balconies, kitchen, basement, parking, location, energy bill	Yes	No	No									0		1	0.7499
106	63	OLS	Yes	No	No	log-log	log rent per month	size, age, number of bathrooms, balconies, kitchen, basement, parking, location, energy bill	Yes	No	No									0		1	0.6277
107	64	OLS	Yes	No	No	semi-log	log price per m2	size, property type, number of bathrooms, proximity to transport, maintenance status, region	Yes	Yes	Yes									0		1	0.5
108	65	SAR	No	Yes	No	semi-log	log price	size, property type, age, number of rooms, garage, lots, garden, lift, number of floor, heating system, maintenance, distance to city center, mall, beltway	Yes	Yes	Yes		0.5086	0.1611	0.1611	hold-out	hold-out	-0.103	-0.245	0		0	0.6034

109	66	OLS	Yes	No	No	semi-log	log price	size, property type, number of bathrooms, proximity to infrastructure, maintenance status, location	Yes	Yes	Yes									0		1	
110	67	RF	Yes	No	No	not applicable	price	size, property type, number of rooms, number of floors, maintenance, central heating, lift, garden, parking, location	Yes	No	Yes									1		1	
111	68	GAM	Yes	No	Yes	semi-log	log rent per month	size (log), age, number of rooms, number of floors, elevator, balcony, kitchen, garden, cellar, guest wc, interior equipment (simple, sophisticated, luxury), neighbourhood (purchasing power, households)	Yes	Yes	Yes		0.039	0.021	0.008	0.003	0.001	0.002	hold-out	0		0	0.934

Appendix C Additional materials of scoping review (Chapter 4)

Table C-1 Summary of search strategies and records retrieved.

Database	Interface	Search command	Search date	Records retrieved
SCOPUS	Elsevier	(((TITLE (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*) OR ABS (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*))) AND ((TITLE ("green value" OR "green premium") OR ABS ("green value" OR "green premium")))) OR ((((TITLE ((value OR cost OR price) W/3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)) OR ABS ((value OR cost OR price) W/3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)))) OR ((TITLE ("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value") OR ABS ("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value")))) AND ((TITLE ("energy efficiency" OR "energy rating" OR "energy performance certificates" OR "epc") OR ABS ("energy efficiency" OR "energy rating" OR "energy performance certificates" OR "epc"))))	2024/05/02	833
WoS	Clarivate	(TS=(house* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)) AND TS=("green value" OR "green premium") OR (((TS=((value OR cost OR price) NEAR/3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)))) OR TS=("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value")) AND TS=("energy efficiency" OR "energy rating" OR "energy performance certificates" OR "epc")	2024/05/02	797
IBSS	ProQuest	(noft(hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*) AND noft("green value" OR "green premium")) OR ((noft((value OR cost OR price) W/3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)) OR noft("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value")) AND noft("energy efficiency" OR "energy rating" OR "energy performance certificates" OR "epc"))	2024/05/02	253
EconLit & Business Source Ultimate	EBSCOhost	S1 TI (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*) OR AB (hous* OR "domestic	2024/05/02	394

	propert*" OR "residential propert*" OR dwelling* OR apartment*)	
	S2 TI ("green value" OR "green premium") OR AB ("green value" OR "green premium")	
	S3 S1 AND S2	
	S4 TI ((value OR cost OR price) W3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)) OR AB ((value OR cost OR price) W3 (hous* OR "domestic propert*" OR "residential propert*" OR dwelling* OR apartment*)) OR TI ("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value") OR AB ("housing market" OR "real estate" OR "hous* sales" OR "house prices" OR "housing prices" OR "housing value" OR "domestic property prices" OR "domestic property value" OR "residential property prices" OR "residential property value")	
	S5 TI ("energy efficiency" OR "energy rating" OR "energy performance certificates" OR "epc") OR AB ("energy efficiency" OR "energy rating" OR "energy performance certificates" OR "epc")	
	S6 S4 AND S5	
	S7 S3 OR S6	
Total		2277

Table C-2 Links to the openly available national EPC databases of included studies.

Country/region	Link
England and Wales (UK)	https://epc.opendatacommunities.org/ (accessed 29/09/2024)
Scotland (UK)	https://statistics.gov.scot/data/domestic-energy-performance-certificates (accessed 29/09/2024)
Sweden	https://www.boverket.se/sv/energideklaration/sok-energideklaration/ (accessed 29/09/2024)
Norway	https://www.nve.no/energy-consumption-and-efficiency/energy-labelling-of-housing-and-buildings/ (accessed 29/09/2024)

Netherlands	https://www.ep-online.nl/PublicData (accessed 29/09/2024)
Portugal	https://www.sce.pt/pesquisa-certificados/ (accessed 29/09/2024)
Ireland	https://ndber.seai.ie/BERResearchTool/ber/search.aspx (accessed 29/09/2024)
Denmark	https://old.sparenergi.dk/offentlig/vaerktoejer/find-bygningens-energimaerke (accessed 29/09/2024)

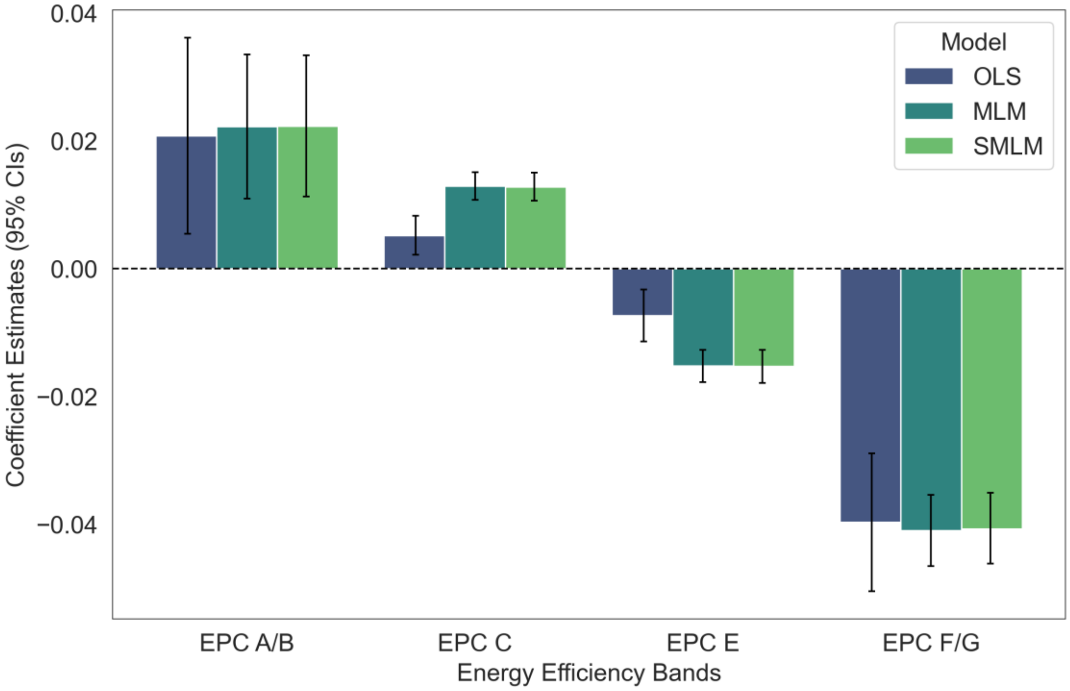
Note: the availability of EPC data in Italy and Spain depends on regions, and thus not included in the table.

Table C-3 Measurement of housing quality variable from identified sources.

Source type	Source platform	Country/region	Field	Variables
Online listing	immobilienscout24.de	Germany	‘Interior quality’	Categorical: ‘luxury’, ‘good’, ‘normal’, and ‘simple’
			‘Condition’	Categorical: ‘refurbished’, ‘need of renovation’, ‘first time use’, Etc.
	idealista.com	Spain	‘Dwelling state’	Categorical: ‘luxury’, ‘good’, etc.
Real-estate agent association	Dutch Association of Realtors	Netherlands	‘Interior and exterior maintenance’	Binary
Research centre	The Real Estate Observatory of the City of Turin	Turin (Italy)	‘Building quality’	Categorical: ‘council housing’, ‘economical’, ‘medium-level’, ‘distinguished’ and ‘classy’

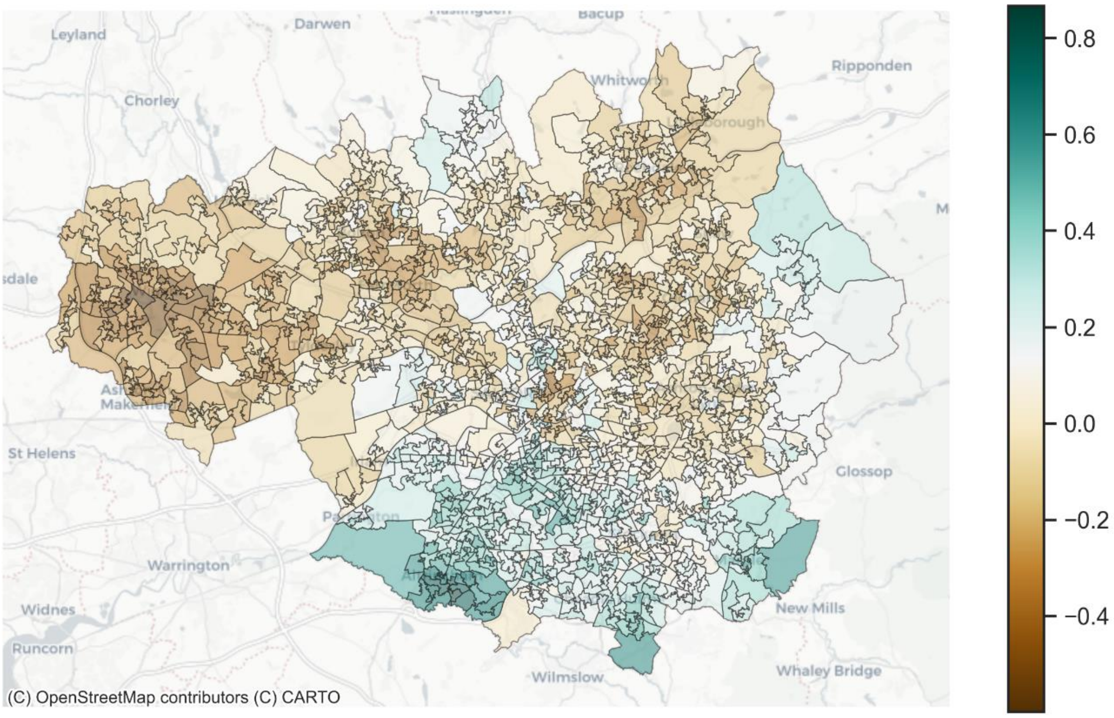
Appendix D Additional materials of MLM modelling on average effect and energy crisis impact (Chapter 6)

Figure D-1 Comparison of coefficient estimates of OLS, MLM, and Spatial MLM.



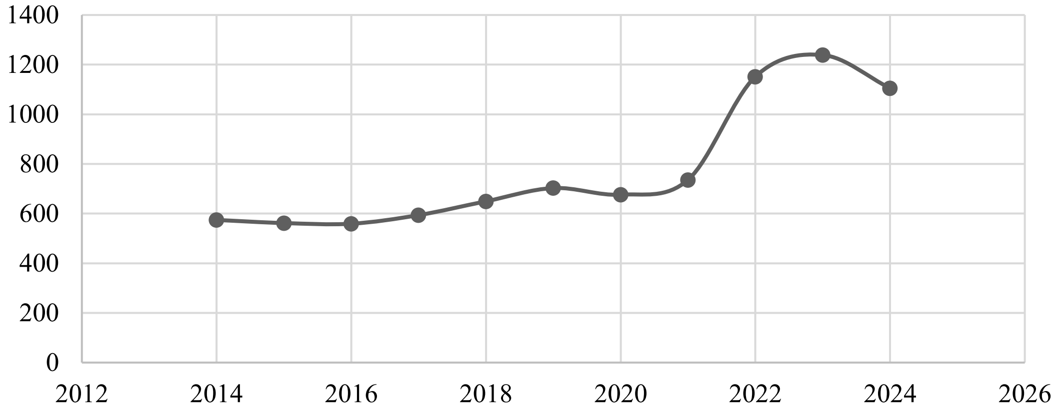
Note: Residual variance of OLS at *0.070* and MLM at *0.031*.

Figure D-2 Spatial diagnostics of neighbourhood (LSOA11s in Greater Manchester) residuals from MLM model.



Note: The spatial diagnostics of Moran’s I test shows house prices in neighbourhoods are significantly correlation with each other (Queen contiguity matrix: Moran’s I value=0.812, p=0.0; KNN matrix: Moran’s I value=0.834, p=0.0).

Figure D-3 Domestic annual energy bills (Pounds) across years in Northwest England.



Note: data source (GOV.UK, 2025c). Based on weighted average of cost for consuming fixed quantity of energy from data provided by energy suppliers.

Figure D-4 Correlation heatmap on adopted 55 numerical measures from PTAI.

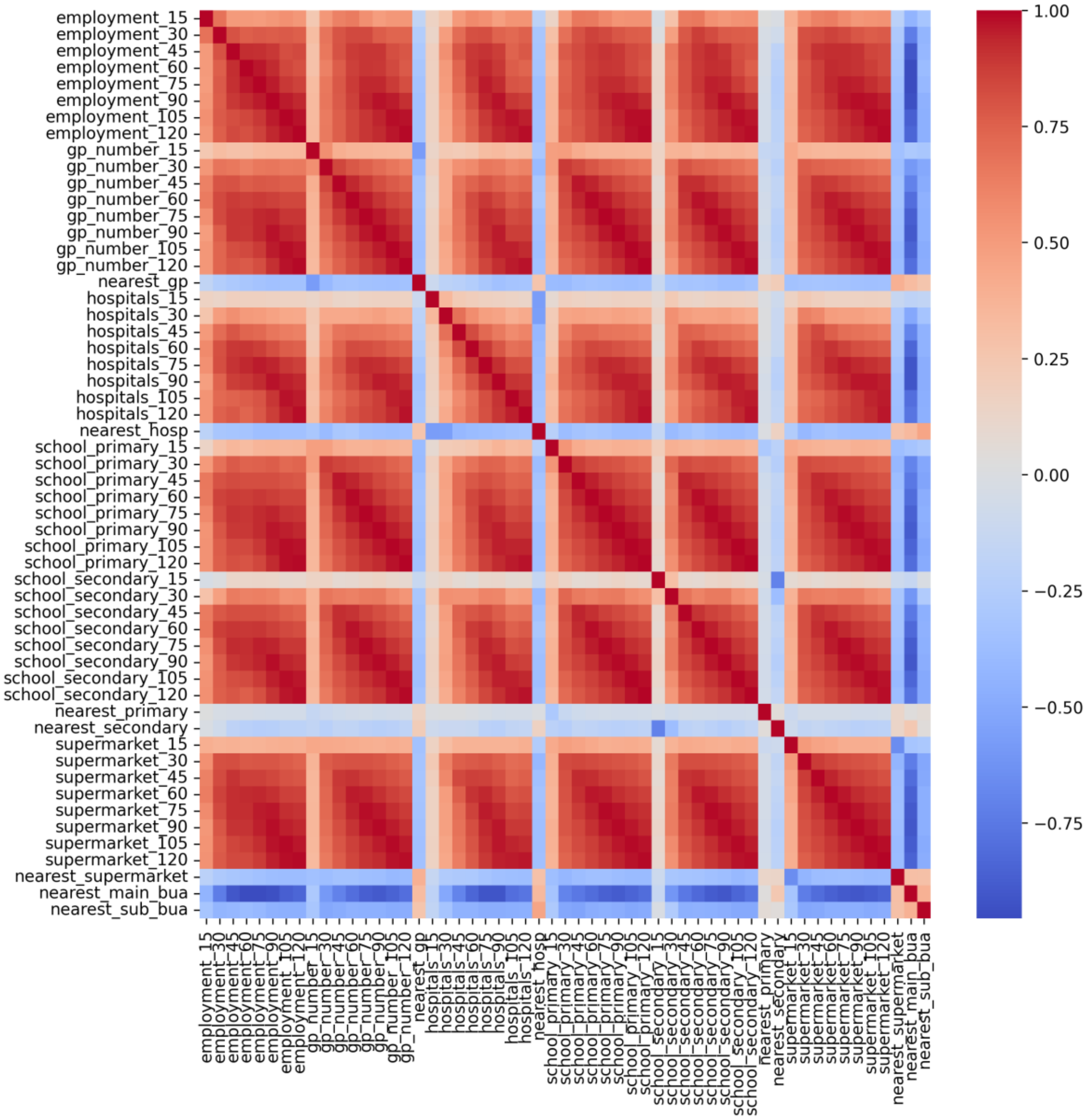


Figure D-5 Model diagnostics of heteroskedasticity and q-q plot for MLM.

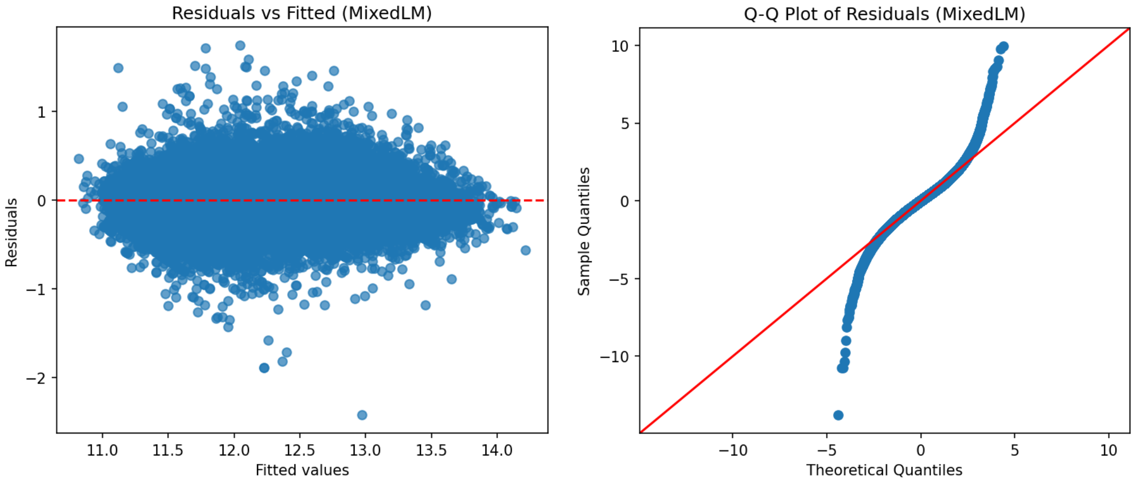


Table D-1 Key words for identification of invalid listings in listing text description.

Invalid type	Key words
Auction	'public auction', 'auction'
Shared homeownership	'share ownership', 'shared ownership'
Rent-to-buy	'rent to buy', 'rent-to-buy'

Table D-2 Trimming criteria for filtering outliers.

Field	Trimming criteria	Percentage
House price	>1.5 million or <30 thousand	0.18%
Total floor area	>200 m^2 or <20m^2	2.21%
Habitable rooms	<1 or >10	6.94%

Table D-3 Searching criteria to identify property facilities in listing text description.

Property facilities	Searching criteria
Modern kitchen	'kitchen' and 'modern' appear within three words
Garage	'garage' or 'garages' appear
Basement	'basement' or 'basements' appear
Garden	'garden' or 'gardens' appear

Table D-4 Correlations between each principal component and the underlying indices from PTAI.

	PC1	PC2
employment_15	0.605500	-0.015040
employment_30	0.847248	-0.044500
employment_45	0.919757	-0.033135
employment_60	0.914644	-0.062596

	PC1	PC2
employment_75	0.942502	-0.064132
employment_90	0.965385	-0.120787
employment_105	0.949263	-0.175689
employment_120	0.940117	-0.166444
gp_number_15	0.404933	0.557361
gp_number_30	0.773841	0.365799
gp_number_45	0.883596	0.127004
gp_number_60	0.942442	-0.003577
gp_number_75	0.969611	-0.054867
gp_number_90	0.968690	-0.085429
gp_number_105	0.952675	-0.135266
gp_number_120	0.924383	-0.173394
nearest_gp	-0.383645	-0.438876
hospitals_15	0.195356	0.324677
hospitals_30	0.532560	0.303199
hospitals_45	0.748627	0.102705
hospitals_60	0.864291	-0.046560
hospitals_75	0.944618	-0.100350
hospitals_90	0.948050	-0.139890
hospitals_105	0.892448	-0.208730
hospitals_120	0.898841	-0.186931
nearest_hosp	-0.404637	-0.419879
school_primary_15	0.421455	0.482432
school_primary_30	0.844668	0.301301
school_primary_45	0.913532	0.136301
school_primary_60	0.952365	0.010172
school_primary_75	0.973126	-0.060950

	PC1	PC2
school_primary_90	0.978314	-0.079978
school_primary_105	0.965554	-0.124234
school_primary_120	0.944334	-0.155029
school_secondary_15	0.130705	0.363240
school_secondary_30	0.668708	0.366120
school_secondary_45	0.882934	0.131913
school_secondary_60	0.940548	-0.008140
school_secondary_75	0.970245	-0.049840
school_secondary_90	0.974460	-0.080606
school_secondary_105	0.955970	-0.126224
school_secondary_120	0.925529	-0.172411
nearest_primary	-0.069450	-0.232489
nearest_secondary	-0.220149	-0.331491
supermarket_15	0.467427	0.444185
supermarket_30	0.864485	0.193737
supermarket_45	0.920476	0.087750
supermarket_60	0.961442	-0.022594
supermarket_75	0.977783	-0.081623
supermarket_90	0.977684	-0.095408
supermarket_105	0.967296	-0.134220
supermarket_120	0.950699	-0.169036
nearest_supermarket	-0.416371	-0.407348
nearest_main_bua	-0.895869	0.101608
nearest_sub_bua	-0.523372	-0.198512

Table D-5. ‘Normalised’ coefficients on EPC bands and coefficient on EPC score.

	EPC score range	Weighted mid-point score	Model 1 coef.	‘Normalised’ Model 1 coef.
EPC A/B	81-100+	24.7	0.0222	0.0009
EPC C	69-80	13	0.0129	0.0010
EPC D	55-68	0	-	-
EPC E	39-54	-15	-0.0152	0.0010
EPC F/G	1-38	-35.7	-0.0410	0.0011

Note: To compare Models 1 and 2 from Table 6.3, we ‘normalise’ the coefficients of EPC bands according to weighted average mid-point score of each EPC band relative to Band D i.e., translate categorical Band Coefficients to linear coefficients.

Appendix E Additional materials of Causal ML on heterogeneous analysis (Chapter 7)

Table E-1 Super Learner preliminary model summary.

Model	Hyperparameter setting	Coefficient
LinearRegression()	-	0.018
SVR()	C=1, epsilon=0.1	-0.001
KNeighborsRegressor()	metric='manhattan', n_neighbors=np.int64(15), weights='distance'	0.102
AdaBoostRegressor()	-	-0.077
BaggingRegressor()	-	0.029
RandomForestRegressor()	n_estimators=200, max_depth=30, min_samples_leaf = 1, min_samples_split = 2, n_jobs=-1, oob_score=True, bootstrap = True, random_state=42	0.163
XGBRegressor()	colsample_bytree=0.5, max_depth=10, n_jobs=-1, subsample=0.95, random_state=42	0.313
LGBMRegressor()	verbosity=0, extra_trees=True,colsample_bytree=1.0, learning_rate=0.1, n_estimators=200, num_leaves=150, subsample=0.6	0.465

Table E-2 Sorted group average treatment effects (GATES) results.

ntile	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
1	-0.042993	0.002171	-20.669156	1.723965e-94	-0.047085	-0.038900
2	0.000524	0.002002	0.257630	4.622398e-01	-0.003466	0.004514
3	0.018205	0.002021	8.970927	3.115249e-19	0.014216	0.022194
4	0.034574	0.002123	16.314452	7.807374e-59	0.030372	0.038776
5	0.082736	0.002379	34.811392	5.316518e-264	0.078098	0.087374

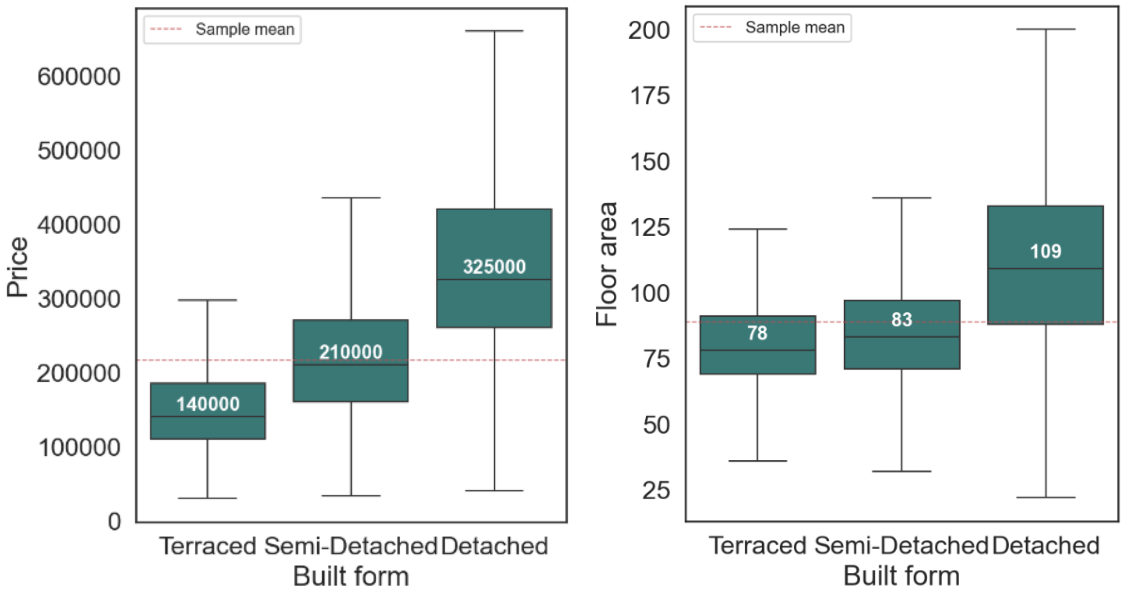
Table E-3 Drivers of heterogeneity (CLAN) results on full covariates.

Meta Learner	X-learner	DR-learner	R-learner
BUILT_FORM_Detached	-0.049558	-0.049372	-0.054013
BUILT_FORM_Terraced	0.068861	0.067056	0.082327
LAD21NM_Bolton	-0.012132	-0.007154	0.003830
LAD21NM_Bury	0.002278	0.000354	-0.012065
LAD21NM_Manchester	0.028989	0.025192	0.004708
LAD21NM_Oldham	0.011120	0.007846	0.015608

LAD21NM_Rochdale	0.040851	0.021446	0.027183
LAD21NM_Salford	-0.047837	-0.035603	-0.013415
LAD21NM_Stockport	-0.066820	-0.034000	-0.031992
LAD21NM_Trafford	-0.025294	-0.013701	-0.024771
LAD21NM_Wigan	0.080251	0.042758	0.035857
PROPERTY_TYPE_Bungalow	0.005315	-0.004995	-0.009348
accessibility_PCA1	0.418830	0.276939	0.217580
accessibility_PCA2	0.275443	0.104362	0.059317
age_mapped_1900_1929	0.106102	0.065993	0.040463
age_mapped_1930_1949	0.026897	0.015456	-0.004286
age_mapped_1967_1982	-0.035570	-0.024838	-0.008133
age_mapped_1983_2011	-0.134483	-0.069553	-0.040227
age_mapped_before_1900	0.055481	0.022661	0.012267
energy_efficient_C	-0.031655	-0.018139	-0.006260
income_score	0.007189	0.008791	0.017857
is_garages_True	-0.082883	-0.076269	-0.079728
is_gardens_True	-0.054367	-0.046926	-0.056139
log_popden_100	0.001269	0.003884	0.035643
log_size	0.126256	0.033414	-0.062040
modern_kitchen_True	-0.146565	-0.124966	-0.092822
rooms_mapped_4	-0.049389	-0.014545	0.041003
rooms_mapped_5	0.030356	0.027960	-0.001164
rooms_mapped_6_7	0.091405	0.023707	-0.034287
rooms_mapped_8_10	-0.018072	-0.024231	-0.027707
school_quality	0.000034	0.009449	-0.019287
tenure_mapped_leasehold	0.128678	0.075510	0.060256
year_quarter_2017_Q4	-0.036245	-0.000641	0.020248
year_quarter_2018_Q1	-0.038050	-0.004623	0.014680
year_quarter_2018_Q2	-0.033781	-0.005889	0.015237
year_quarter_2018_Q3	-0.028230	-0.001924	0.015591
year_quarter_2018_Q4	-0.062500	-0.016334	0.006395
year_quarter_2019_Q1	-0.012149	0.005011	0.020215
year_quarter_2019_Q2	-0.021716	0.001755	0.011356
year_quarter_2019_Q3	-0.010884	0.003476	0.013431
year_quarter_2019_Q4	-0.022459	-0.004269	0.008757
year_quarter_2020_Q1	-0.021261	-0.003020	0.009635
year_quarter_2020_Q2	-0.003797	-0.001401	0.003948

year_quarter_2020_Q3	-0.013296	-0.005180	0.000945
year_quarter_2020_Q4	-0.006176	0.003138	0.001974
year_quarter_2021_Q1	-0.006159	-0.003206	-0.003476
year_quarter_2021_Q2	0.011423	0.003476	-0.005703
year_quarter_2021_Q3	-0.005163	-0.004303	-0.011980
year_quarter_2021_Q4	0.026964	0.005636	-0.003527
year_quarter_2022_Q1	0.023826	0.004387	-0.007694
year_quarter_2022_Q2	0.021160	0.002902	-0.011930
year_quarter_2022_Q3	0.008352	-0.003138	-0.017920
year_quarter_2022_Q4	0.010495	-0.003240	-0.019202
year_quarter_2023_Q1	0.024787	0.002548	-0.011322
year_quarter_2023_Q2	0.045829	0.008741	-0.002447
year_quarter_2023_Q3	0.038691	0.004168	-0.010107
year_quarter_2023_Q4	0.042589	0.007627	-0.005906
year_quarter_2024_Q1	0.046791	0.006935	-0.009635
year_quarter_2024_Q2	0.018730	-0.003290	-0.020586

Figure E-1 Distribution of property price/size across built forms.



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