The Changing Value of Energy Efficiency in UK Homes: A Spatial Matching Approach with Hedonic Models

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Summary

This study assesses to what extent the energy price shock from the 2022 Ukraine war has affected UK home buyers' willingness to pay for energy efficient homes. Spatial matching techniques are implemented within a hedonic house price model framework to estimate the magnitude of such changes. Findings suggest an increase in the EPC premium in transactions over this period. This points to UK home buyers' increasing awareness of the value of energy efficiency, which has significant policy relevance. The spatial matching approach easily extends to similar settings with exogenous shocks and geo-referenced observational data.

KEYWORDS: Spatial matching, Housing price, Hedonic model, Energy efficiency

1. Background and motivation

Household energy use accounts for a major part of total energy consumption in an economy. Measuring and understanding the behaviour of households regarding energy efficiency is important for stakeholders in both public and private institutions. In the UK, a popular measure of building energy efficiency if the Energy Performance Certificate (EPC). All else equal, home buyers are likely to be willing to pay more for a property with higher EPC ratings. There are multiple drivers in the formation of such an EPC premium (e.g. Pommeranz and Steininger, 2021). Therefore, although there is strong evidence for the existence of an EPC premium in the UK (e.g. Fuerst et al., 2015), inferring its magnitude and dynamics is a challenging matter of empirical investigation.

This study aims to assess to what extent the energy price shock from the 2022 Ukraine war has affected the EPC premium in the UK. In light of the series of dramatic global events that has transpired over the past few years, we are urgently in need of new evidence on home buyers' willingness to pay for energy efficiency. The surging energy price following the 2022 Ukraine war should have nudged investors and home buyers towards a more acute awareness of the value of energy efficient homes, while the market conditions under the pandemic could have complicated aggregate trends. New empirical evidence will help us to better assess the magnitude of such changes, and to form reasonable expectations on what wider impacts and long-term effects this may lead to.

2. Analysis

2.1 Empirical setup

First, let's define 'when' the energy price shock was, and when the pre/post shock measurements are taken for this study. Households could have been exposed to the shock in several ways. It could be through media reports on the war and its impacts, from February 2022 onwards. It could also be directly through the energy price surge in the winter of 2022. This places the shock at a time window within 2022. To take measurements of the pre/ post shock residential property transaction prices, a buffer time period after the shock is also considered. This is to account for the lag in transaction prices' response to the energy price shock due to the lengthy process of property sales. Based on this timeline, this study

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takes the difference between the EPC premium's 2021 level and its 2023 level as a reflection of its response to the 2022 energy price shock in the UK.

2.2 Data

The study uses open data. The main dataset is linked Land Registry Price Paid Data (HMLR, 2024) and residential building EPC certificate records (MHCLG, 2024). The analysis uses all transactions in England and Wales in 2021-2023.

2.3 Empirical models

The study adopts a hedonic price model framework. The hedonic price model (Rosen, 1974) sees the value of houses at a certain time point as the sum of the values for each of their utility-bearing attributes. For this study, building energy efficiency ratings will enter the hedonic model as a physical characteristic of the property. Equation (1) demonstrates the basic form of a hedonic regression. EPC_i stands for the EPC rating level of property [i]. X_i stands for other hedonic attributes of property [i].

$$LogPrice_i = \mathrm{a} + \theta * EPC_i + \beta * X_i + year\_dummies + \varepsilon_i \qquad (1)$$

A differenced specification of the hedonic regression is devised in this study, implemented with spatial matching: Starting from equation (1), let's specify separate regressions (2) (3) for property [i] that has observed sale prices in both years *t1=2021* and *t2=2023*. This can be because the property was sold in *t1* and resold in *t2*. It can also be a matched pair of sales. That is, for property sale $[i, t_1]$ we have matched it to a property sale $[i', t_2]$ such that the sale price of $[i', t_2]$ is our best guess of the sale price of [i] if it were sold again in *t2*. In other words, the price of $[i', t_2]$ is a counterfactual prediction of $[i, t_2]$ which is not actually observed. The quality of the counterfactual prediction is based on the observed similarity between properties [i] and [i'], in terms of building characteristics and geographic location. Taking the difference on both sides of the equations (2) and (3) produces a reduced version, expressed as (4). Since the main interest here is the change in EPC premium (i.e. the treatment effect of the energy price shock), this reduced version directly yields the inference goal $\Delta\theta_{t2-1}$.

$$LogPrice_{i,t_1} = \mathrm{a}_{t1} + \theta_{t1} * EPC_i + \beta_{t1} * X_i + \varepsilon_{i,t_1} \qquad (2)$$
$$LogPrice_{i,t_2} = \mathrm{a}_{t2} + \theta_{t2} * EPC_i + \beta_{t2} * X_i + \varepsilon_{i,t_2} \qquad (3)$$

$$\Delta LogPrice_{i,t_{2-1}} = \mathrm{a}' + \Delta\theta_{t2-1} * EPC_i + \cdots + \varepsilon' \qquad (4)$$

This approach has certain benefits in efficiency and robustness compared with a standard hedonic regression or repeat sale (Case and Shiller, 1987) regression: The $\beta_i * X_i$ terms that are constant over periods *t1* and *t2* will be dropped out. This helps to mitigate omitted variable bias in a standard hedonic regression (Sirmans et al., 2005). Also, fitting the model with matched observation pairs ensures that all transactions are utilised. This helps to mitigate sample selection bias from using only repeat sales (Clapp et al., 1991). The use of matched transaction pairs is sometimes known as a pseudo repeat sale model (e.g. Guo et al., 2014). The method used in this study differs from existing pseudo repeat sale models as it is a unique combination of spatial matching and a differenced hedonic regression.

The spatial matching procedure used in this study is score based. Each transaction in 2021 is paired with its optimal match in 2023 based on a composite score of spatial proximity and feature similarity. The spatial matching procedures theoretically resembles the search process in the purchase of a residential property. Accordingly, the matches are geographically constrained, as home buyers typically search within specific target geographic areas. Here, the travel to work areas are used as proxy for local market boundaries. And they are used as a geographic constraint for the matches.

3. Summary of results and discussions

Results suggest an increase in the EPC premium from 2021 to 2023. And this effect is more pronounced in the transaction of flats than houses (**Table 1,** Column 1, EPC_rank coefficient). This can be interpreted as an increase in UK home buyers' awareness of the value of energy efficient homes. The finding has significant policy relevance in relation to the green transition of the economy. Also, the spatial matching approach easily extends to similar settings involving exogenous shocks and geo-referenced observational data, and it could be useful in assessing structural changes under volatile market conditions today.

Table 1 Equation (4) estimated with spatially matched pairs.

	Flat	House	All
	(1)	(2)	(3)
Δfloor_area	0.012***	0.006***	0.008***
	(0.0002)	(0.0001)	(0.0001)
…	…	…	…
ΔGP	0.004*	0.002	0.003*
	(0.002)	(0.002)	(0.001)
Δoutdoor_area	0.0002***	0.0003***	0.0002***
	(0.0001)	(0.0001)	(0.00004)
Δbuilding_age	0.0004***	-0.002***	-0.001***
	(0.0002)	(0.0002)	(0.0001)
ΔEPC_rank	0.018*	0.003	0.008
	(0.010)	(0.009)	(0.006)
Adjusted R2	0.464	0.569	0.474

Note: *p<0.1; **p<0.05; ***p<0.01

To follow up from the analysis: First, in terms of empirical analysis, the geographic variation in the inferred EPC premium change can be systematically explored. This would contribute to our understanding of the impact of the uneven capitalisation of green building technology and how it interacts with existing economic inequalities across the UK. Second, in terms of methodology, different variations in the implementation of spatial matching can be tested and analysed. For example, if supported by theoretical believes, different weights can be assigned to either the spatial proximity or the similarity of a certain feature when calculating the matching score. This leads to interesting challenges of sensitivity analysis and uncertain quantification regarding model uncertainty.

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Biographies

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