Regional-level analysis of housing price dynamics in the United Kingdom: a multivariate causality approach

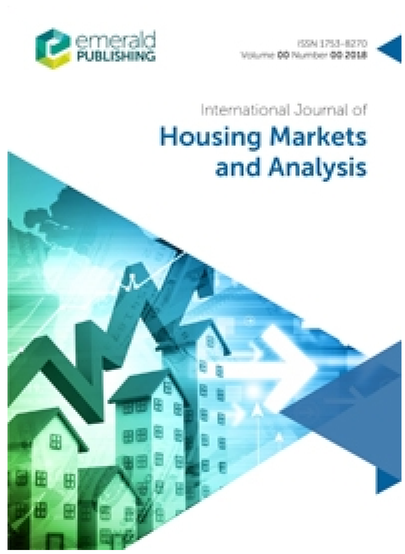
Article

Accepted Version

Daniel, I. D. ORCID: https://orcid.org/0000-0003-0749-3111, Fateye, T. B. and Abanda, F. H. (2025) Regional-level analysis of housing price dynamics in the United Kingdom: a multivariate causality approach. International Journal of Housing Markets and Analysis. ISSN 1753-8289 doi: 10.1108/IJHMA-08-2025-0186 Available at https://centaur.reading.ac.uk/124830/

To link to this article DOI: http://dx.doi.org/10.1108/IJHMA-08-2025-0186

Publisher: Emerald



Regional-Level Analysis of Housing Price Dynamics in the United Kingdom: A Multivariate Causality Approach

Journal:	*International Journal of Housing Markets and Analysis*
Manuscript ID	IJHMA-08-2025-0186.R1
Manuscript Type:	Research Paper
Keywords:	Housing Market Segmentation, Housing Price Dynamics, Regional Market Integration, Spatial Spillovers, Signal Transmission, Real Estate

Regional-Level Analysis of Housing Price Dynamics in the United Kingdom: A Multivariate Causality Approach

Abstract

This paper investigates the dynamic causal relationships between regional housing markets and the national house price index in the United Kingdom from 2005 to 2024, capturing periods of economic expansion, financial crisis, post-Brexit uncertainty, COVID-19 disruption, and inflationary volatility. Drawing on a dual spatial framework, disaggregating the devolved nations and England's NUTS1 regions, this study employs Granger causality testing alongside a triad of robust regression estimators (M-estimator, S-estimator, and MM-estimator) to detect persistent and directional price leadership patterns. Empirical results identify three English sub-regions (the North East, North West, and South West) as consistent 'signal transmitters' whose house price innovations significantly Granger-cause movements in the national index. In contrast, London and the South East exhibit diminishing bidirectional influence, suggesting post-pandemic price decoupling and weakening spatial arbitrage. These findings contradict classical ripple-effect assumptions and indicate increasing segmentation within the UK housing system. The analysis is further strengthened by a series of robustness checks that accounts for structural breaks, heteroskedasticity, and outlier bias, thereby increasing confidence in the model's validity across the complex macro-financial cycles under investigation. The results carry material implications for policymakers, particularly the Bank of England, HM Treasury, and the Office for Budget Responsibility, as early-warning signals from peripheral regions could enhance macroprudential risk forecasting and affordability targeting. This paper contributes to the theoretical discourse on regional integration and market segmentation, offering a multi-scalar, statistically robust framework for assessing housing market dynamics in advanced economies. It also opens new directions for incorporating time-varying causality and spatial dependency into national housing policy design.

Keywords: Housing Market Segmentation, Housing Price Dynamics, Regional Market Integration, Spatial Spillovers, Signal Transmission

1. Introduction

The spatial dynamics of housing markets have emerged as a critical axis of scholarly enquiry and policy concern worldwide, especially in advanced economies where housing systems operate as both investment platforms and social infrastructure. In the United Kingdom (UK) in particular (which is also a reflection of many countries across the globe), the housing market is characterised by acute spatial heterogeneity, manifesting in divergent regional cycles, uneven affordability, and locally contingent demand-supply conditions. This divergence is further complicated by the centralised orientation of UK macroeconomic and regulatory policy, which often operates on national aggregates, despite increasing recognition that housing markets do not move in lockstep. The aftermath of the Global Financial Crisis (GFC), the economic ambiguities surrounding Brexit, the systemic shock of the COVID-19 pandemic, and the inflationary volatility of the post-2021 period have collectively intensified spatial disparities in housing outcomes (Blakeley, 2021; Ojo, et al., 2022; Bailey et al., 2025; Tsai, 2024). In this context, conventional tools and assumptions underpinning housing market analysis, particularly those reliant on national indices, appear increasingly inadequate for guiding policy or understanding inter-regional market behaviour.

Indeed, while the UK House Price Index (HPI) remains a widely consulted indicator of national housing market conditions, its explanatory power has come under scrutiny. National-level aggregates risk concealing the complex interdependencies and temporal asymmetries that characterise regional housing markets. Empirical evidence increasingly suggests that distinct regions experience unique cyclical patterns and may exercise leadership or laggard roles at different times, depending on macroeconomic regime shifts, local policy interventions, or demographic realignments (Zhang et al., 2021; Oikarinen & Engblom, 2016). Traditional ripple-effect models, long predicated on the assumption of spatial price diffusion from London outward (Elias, 2006; Liao et al., 2015), may no longer offer a complete or accurate framework for explaining the evolving structure of UK housing dynamics. As London exhibits signs of decoupling from national trends (Tsai, 2024; Zhang & Hou, 2015), the analytical imperative shifts towards models that can accommodate decentralised sources of market leadership and capture time-varying spatial dependencies.

Despite a robust international literature on housing price interdependencies (Daly et al., 2003; Poon & Garratt, 2012; Carlos et al., 2015; Chiwuzie & Daniel, 2021; Tunstall, 2022; Mbah & Wasum, 2022; Cohen et al., 2023; Ogunba, et al., 2023; Osei et al., 2025; Ma & Zhang, 2025; Moreno-Foronda et al., 2025), the UK-specific evidence base remains partial and fragmented. Existing studies rarely adopt a multilevel spatial framework that includes both the devolved nations (Scotland, Wales, and Northern Ireland) and the nine English regions at the Nomenclature of Territorial Units for Statistics 1 (NUTS1) level. Moreover, relatively few empirical investigations integrate methodological tools capable of accounting for structural breaks and outlier distortions, which are increasingly common in the wake of major economic shocks such as the GFC, Brexit, and the COVID-19 crisis (Contat & Larson, 2024; Caporale & Gil-Alana, 2025). This methodological narrowness limits both the reliability of causal inference and the policy utility of empirical findings. This lacuna is particularly consequential for institutions such as the Bank of England (BoE), HM Treasury, and the Department for Levelling Up, Housing and Communities (DLUHC), which depend on stable and regionally attuned indicators for macroprudential regulation and housing strategy development.

In response to these theoretical, empirical, and policy gaps, this study offers a comprehensive regional-level analysis of housing price dynamics in the United Kingdom over the period 2005 to 2024. The analysis employs a multivariate approach combining Granger causality testing (Granger, 1969; Foresti, 2006; Mahdavi & Sohrabian, 1991), robust regression estimation techniques (M, S, and MM estimators), and structural break diagnostics to assess the nature and stability of interregional housing market linkages in an eclectic analysis. These techniques are particularly well-suited to the challenges posed by housing time series data, which are often characterised by non-normal distributions, heteroskedasticity, and episodic volatility (Susanti et al., 2014; Khotimah et al., 2019; Singgih & Fauzan, 2022; Trojanek et al., 2023; Tai, 2025). The selected timeframe covers multiple macroeconomic regimes including the pre-GFC expansion, the crisis and post-crisis adjustment, Brexit-related uncertainty, the COVID-19 pandemic, and the post-COVID inflationary landscape, thus allowing for a segmented understanding of spatial housing dynamics.

To capture the full breadth of the UK housing geography, the study disaggregates the market into twelve analytical units: nine English NUTS1 regions and the three devolved nations. This spatial granularity facilitates a more nuanced appreciation of political-economic heterogeneity and regional policy divergence. The study introduces the concept of "signal regions" defined as those regional markets whose price innovations Granger-cause movements in the national index over multiple sub-periods. Unlike the traditional ripple-effect theory, which assumes a singular spatial trajectory of influence, the signal region framework allows for multiple, possibly shifting, centres of market transmission. This conceptual innovation draws on and extends recent theoretical debates concerning spatial equilibrium, market segmentation, and regionally contingent housing regimes (Fingleton, 2008; Bressler & Seth, 2011; Gabrielli & French, 2021; Rahayu et al., 2023; Liu, 2024).

While this study is situated within the context of the United Kingdom, its analytical framework and empirical insights hold broader relevance for housing systems across advanced and emerging economies. Spatial asymmetries in housing price dynamics, manifesting through regional divergences, market segmentation, and shifting price leadership are increasingly global phenomena, particularly in nations experiencing rapid urbanisation, decentralisation of labour markets, or regionally uneven policy regimes. The conceptual innovation of identifying "signal regions" as systemic transmitters of price movements, combined with a robust, crisis-resilient empirical methodology, provides a transferable template for cross-national research. As policy institutions worldwide confront the challenge of balancing national financial stability with subnational market volatility, the study's findings offer a replicable and policy-relevant model for detecting early signals of systemic housing risk, designing spatially responsive macroprudential tools, and enriching global debates on housing market integration, resilience, and governance.

The study pursues four key research objectives. First, it assesses the degree of regional price integration by applying bivariate and multivariate Granger causality analysis, thereby determining the extent to which housing market shocks in one region anticipate movements in others or in the national index. Second, it identifies and examines persistent signal regions, those whose price movements serve as leading indicators for national market trends, thus contributing to the development of early-warning systems for macroprudential oversight. Third, it interrogates the robustness of empirical findings by employing a triangulated estimation strategy that includes M-estimation, S-estimation, and MM-estimation approaches. These estimators improve statistical reliability by mitigating the influence of outliers and structural irregularities common in long-run housing data. Fourth, the analysis conducts structural break testing across the five macroeconomic regimes noted earlier, to evaluate whether the causal roles of regions remain stable or shift over time in response to major exogenous shocks.

In synthesising these objectives, the study aims to make three interlocking contributions. Theoretically, it advances the debate on spatial housing market interdependence by introducing a flexible framework that accommodates both price leadership and temporal instability. Empirically, it provides a robust, granular, and temporally segmented analysis of UK housing market dynamics, addressing methodological weaknesses in prior literature. From a policy perspective, it generates actionable insights for spatially targeted housing and financial regulation, especially in the design of regionally differentiated mortgage instruments, credit allocation frameworks, and affordability metrics.

The remainder of this paper is structured as follows. Section 2 reviews theoretical and empirical literatures on spatial housing price dynamics, focusing on inter-regional causality, ripple effects, and market segmentation. Section 3 outlines the data sources and methodological framework, including unit root tests, Granger causality modelling, robust regression techniques, and structural break analysis. Section 4 presents the empirical results, identifying regional hierarchies, evolving price leadership roles, and the stability of causal patterns across macroeconomic regimes. Section 5 concludes with a summary of contributions, implications, and avenues for future research.

2. Theoretical Underpinnings and Literature Review

The theoretical foundation of this study is anchored in several interrelated frameworks that explain regional housing price dynamics, spatial interdependencies, and price leadership hierarchies. These frameworks include the spatial equilibrium theory, ripple effect hypothesis, market segmentation and integration theory, and housing market signalling mechanisms.

2.1 Theoretical Underpinnings

This study adopts a multidimensional theoretical framework that synthesises four interrelated paradigms: spatial equilibrium theory, the ripple effect hypothesis, the segmentation–integration dichotomy, and signal-based price leadership. These frameworks collectively underpin the investigation of how regional housing markets in the United Kingdom transmit, absorb, or resist price shocks across time and space.

At its core, this research draws upon spatial equilibrium theory as originally posited by Rosen (1979) and extended by Roback (1982), which asserts that households choose locations based on a trade-off among wages, housing costs, and local amenities. In long-run equilibrium, these trade-offs lead to utility equalisation across regions. However, persistent regional price differentials signal the presence of spatial frictions—including land use regulation, transaction costs, information asymmetries, and labour immobility—that inhibit arbitrage and delay convergence. These frictions are particularly acute in the UK, where centralised macroeconomic policies are layered upon regionally uneven planning regimes and divergent housing supply elasticities (Meen, 1999; Fingleton, 2008).

Superimposed on this spatial framework is the ripple effect hypothesis, which traditionally posits a unidirectional diffusion of housing market shocks from core urban centres—most notably London—towards peripheral regions (Meen, 1999; Oikarinen, 2004). This perspective has historically informed much of UK housing research and policy. However, emerging empirical evidence suggests that this mechanism has become increasingly episodic, nonlinear, and asymmetric, particularly following macroeconomic dislocations such as the Global Financial Crisis, Brexit, and the COVID-19 pandemic (Cook, 2003; Zhang et al., 2021). These systemic shocks have contributed to a decline in London's price leadership, driven by structural behavioural shifts—including the rise of remote working, increased demand for space, and the suburbanisation of affordability-seeking households—which have reshaped spatial preferences and investment patterns. The result is a weakening of the classic concentric diffusion paradigm and the emergence of multiple, context-specific sources of price volatility.

In tandem, the literature on housing market segmentation and integration offers a critical lens to interpret these spatial asymmetries. In an integrated market, housing prices co-move in response to shared macroeconomic fundamentals, such as monetary policy, credit conditions, and national income trends. In contrast, segmented markets exhibit independent trajectories due to localised demand drivers, policy divergence, or institutional barriers (Goodman & Thibodeau, 1998; Case & Shiller, 1989). The UK's post-2016 housing dynamics increasingly reflect such structural segmentation, as regional affordability pressures, credit availability, and household formation diverge. Recent studies demonstrate similar tendencies in other advanced housing systems—including the United States, Germany, and Canada—where national indices obscure pronounced regional disparities and local frictions decouple regional prices from aggregate trends (Zhang et al., 2021; Gabrielli & French, 2021). These global parallels highlight the limits of treating national housing markets as homogenous entities, reinforcing the need for multi-scalar analysis.

Finally, this framework integrates the concept of price leadership and signal transmission, which challenges the traditional ripple effect by identifying "signal regions"—local housing markets whose price innovations Granger-cause movements in the national index (Zhang et al., 2021; Cohen et al., 2023). Unlike ripple-based diffusion, signal transmission recognises that leadership in housing markets can be discontinuous, multi-nodal, and time-varying, with certain regions emerging as bellwethers under specific macroeconomic regimes. These regions often reflect underlying investor sentiment, institutional adjustments, or policy inflections that anticipate broader systemic changes. By focusing on dynamic causality and leadership asymmetries, this approach aligns more closely with how housing markets behave under uncertainty and decentralised demand structures.

In summary, the theoretical architecture of this research weaves together spatial equilibrium logic, ripple diffusion critique, segmentation–integration analysis, and dynamic signal theory to reflect the complex, uneven, and evolving structure of UK housing markets. It conceptualises regional housing systems not as passive recipients of national trends but as active participants in a fragmented housing network, with the capacity to influence national aggregates under specific structural and behavioural conditions. This composite framework informs the study's empirical design, which seeks to detect not only directionality of price influence but also the temporal stability and robustness of interregional linkages.

2.2. Literature Review

Understanding housing price dynamics within a multiregional context has long occupied scholars of urban economics, real estate finance, and regional planning. The literature spans conceptual, empirical, and policy-oriented dimensions, yet key gaps remain concerning the causal linkages between regions, temporal stability of interdependencies, and robustness of methods in the presence of structural shocks. This review addresses four major themes: (i) regional price interdependence and the ripple effect; (ii) market segmentation and integration in the UK housing market; (iii) methodological approaches to causality and robustness; and (iv) structural shocks and recent empirical advances.

2.2.1 Regional Price Interdependence and the Ripple Effect

Much of the early and mid-2000s literature on regional house price dynamics builds on the ripple effect hypothesis, which posits that price changes in dominant urban centres propagate outward over time (Oikarinen, 2004; Elias, 2006; Chuang, et al., 2018; Daniel et al., 2022; Osei et al., 2025). In the UK, London has traditionally been viewed as the epicentre of such ripples. However, the strength and direction of diffusion vary across cycles and subregions. Oikarinen and Engblom (2016) demonstrate that spatial diffusion is not uniform and may be conditioned by demographic, institutional, and policy differences across regions. Liao et al. (2015) further showed that capital inflows and foreign liquidity can amplify ripple effects in high-end markets but do not necessarily transmit to secondary cities.

More recent work challenges the linearity and stability of this effect. Zhang et al. (2021), using a dynamic network approach, identify evolving price leadership patterns, with northern and western regions occasionally leading, especially during the COVID-19 era. Similarly, Tsai (2024) documents a "flattening" of the traditional ripple pattern in post-pandemic UK, as hybrid work and affordability constraints shifted demand away from London to peripheral regions. These studies suggest a need to reconceptualise spatial interdependence beyond simple concentric diffusion models.

2.2.2 Market Segmentation and Integration in the UK

Closely related is the debate on housing market segmentation versus integration. In an integrated market, regional price movements co-move strongly due to arbitrage mechanisms, investor mobility, and common macroeconomic exposures. Conversely, segmented markets exhibit idiosyncratic trends, often reflecting local demand-supply imbalances, policy divergence, or structural barriers (Gabrielli & French, 2021; Czischke & Van Bortel, 2023; Pani, 2024; Daniel et al., 2024; Petris et al., 2025).

Evidence from UK studies remains mixed. Zhang et al. (2021) find increasing market segmentation post-2016, coinciding with Brexit and a weakening of London's price influence. Meen (2018) suggests affordability disparities across regions reflect structural segmentation, while Fingleton (2008) argues that housing supply rigidities reinforce localised market dynamics. Liu (2024) extends this argument by highlighting behavioural and credit-market frictions that limit arbitrage across regions.

The literature remains underdeveloped in identifying which regions act as consistent leaders or laggards, and few studies explicitly consider how price signals from some markets predict national trends. This paper addresses that gap by introducing the concept of "signal regions" and testing it empirically over a long temporal horizon.

2.2.3 Methodological Approaches to Causality and Robustness

Methodologically, many existing studies use bivariate or multivariate vector autoregressive (VAR) models to test for Granger causality or cointegration among regional housing markets (Shukur & Mantalos, 2000; Perez-Molina, 2021; Cohen et al., 2023;). While useful, these methods are often sensitive to violations of normality, structural breaks, and outliers common features in housing data due to policy shocks, market cycles, and transaction lags.

Recent contributions have advanced methodological approaches for analysing housing market dynamics. Caporale and Gil-Alana (2025) apply long-memory models to U.S. housing cycles, while Cohen et al. (2023) use Markov-switching frameworks to capture regime-dependent comovements. In the UK, Contat and Larson (2024) propose repeat-sales aggregation techniques to address transaction heterogeneity, and Zhang et al. (2021) employ dynamic network modelling to examine time-varying causality. Together, these studies reflect a shift toward frameworks that explicitly recognise persistence, heterogeneity, and regime changes in housing markets.

Beyond classical Johansen (1988, 1991) cointegration, which provides a likelihood-based framework for identifying and testing multiple cointegrating relationships in vector autoregressive models, this study extends the analysis to account for structural breaks and regime-dependent volatility. Johansen's methodology is particularly relevant here because it allows us to assess whether regional housing markets and the national index share long-run equilibria, a crucial step in determining whether "signal regions" persist beyond short-term causal dynamics. Subsequent advances beyond Johansen's methodology emphasise the importance of endogenously determined structural breaks. Gregory and Hansen (1996) introduced cointegration models with regime shifts, while Bai and Perron (2003) developed multiple-breakpoint tests for long time series. More recent applications by Caporale & Gil-Alana (2025) show that ignoring structural breaks can bias inference, particularly during disruptive events such as the Global Financial Crisis, Brexit, and COVID-19. To align with these developments, this study integrates Johansen cointegration analysis with structural break diagnostics, ensuring a robust assessment of both short-run adjustments and long-run equilibrium dynamics in UK housing markets.

At the same time, robust regression estimators remain underutilised in this domain, despite their advantages in addressing non-normality and volatility. MM-estimators, for instance, resist the influence of leverage points and heavy-tailed distributions (Khotimah et al., 2019; Rahayu et al., 2023). Similarly, Susanti et al. (2014) and Singgih and Fauzan (2022) demonstrate that M-, S-, and MM-estimators yield more reliable coefficients in crisis-prone datasets. This study therefore adopts a robust estimation framework to enhance the validity of causal inferences and ensure resilience against structural irregularities.

2.2.4 Structural Shocks and Empirical Advances

A final body of literature examines how macroeconomic shocks including financial crises, pandemics, geopolitical tensions—reshape regional housing markets. Pitros and Arayici (2017) show that housing cycles in the UK are punctuated by regime changes, suggesting a need for structural break modelling. Blakeley (2021) and Tunstall (2022) trace the COVID-19 pandemic's disruptions to housing consumption patterns, while Bailey et al. (2025) document the suburbanisation of poverty and uneven affordability shocks across UK cities.

More recent contributions incorporate uncertainty and volatility indices. Durmaz et al. (2025) demonstrate that economic policy uncertainty significantly alters housing price volatility in Southern Europe. Zhang et al. (2021) find that London's price influence diminished during periods of systemic uncertainty, reinforcing the need for time-varying analytical techniques.

These studies suggest that regional price causality is unlikely to be stable over time and must be empirically re-evaluated in light of recent shocks. This paper responds by conducting structural break tests and dividing the sample into key macroeconomic phases to assess the stability of interregional dynamics.

Despite the extensive body of literature on regional housing dynamics, much of the existing work remains fragmented, either constrained by pre-2020 data horizons, focused narrowly on London-centric ripple effects, or methodologically reliant on estimators sensitive to structural shocks and outliers. While spatial equilibrium theory, ripple diffusion models, and segmentation-integration paradigms have individually advanced our understanding of regional price behaviour, they have not been fully integrated into a unified empirical strategy that captures both the directionality and robustness of interregional price relationships. Recent macroeconomic disruptions including Brexit, the COVID-19 pandemic, and subsequent inflationary pressures have further destabilised traditional spatial hierarchies, raising fundamental questions about which regions now serve as price leaders or systemic signal transmitters. This study is motivated by the need to close this empirical and conceptual gap by applying a multivariate, robustness-enhanced framework to assess UK regional housing price dynamics across devolved nations and English NUTS1 regions from 2005 to 2024. In doing so, it leverages spatial equilibrium logic to assess convergence, ripple-effect logic to evaluate price diffusion, segmentation theory to interpret causal asymmetries, and leadership theory to identify signal regions. By unifying these strands and deploying Granger causality testing with M/S/MM robust estimation and structural break analysis, this research delivers a temporally sensitive and theoretically grounded assessment of UK housing market interdependencies. The findings not only refine the theoretical map of spatial housing dynamics but also respond directly to policy demands for more accurate, regionally disaggregated market signals to support macroprudential surveillance and spatially targeted housing interventions.

3. Methods

Variable Description and Study Area

This study employs monthly time-series data on housing price indices to examine housing price dynamics in the UK housing market over the past two decades, from January 2005 to December 2024. During this period, the global economy experienced several major disruptions, including the Global Financial Crisis (2007/2008), the COVID-19 pandemic (2019/2020), and the ongoing Russia-Ukraine war, each exacerbating tensions in housing price trends in the region.

All housing price indices were sourced from the UK House Price Index (HPI), published by HM Land Registry and available on GOV.UK (https://www.gov.uk). The HPI database categorizes UK housing prices into two main groups. The first category covers the four constituent nations of the UK (England, Northern Ireland, Scotland, and Wales) referred to in this study as the UK sub-regions. The second category breaks down England into nine regions: East, East Midlands, London, North East, North West, South East, South West, West Midlands, and Yorkshire and The Humber, collectively referred to as the England sub-regions in this study (*Figure 1*). A detailed description of the variables used, their sources, and data manipulation is provided in Table 1.

Table 1: Variable Description

Category	**Acronyms**	**Descriptions**
UK sub-Regions (Model 1)		
England	ENGL	Housing price index for the respective continent nations generated from HM Land Registry at GOV.UK, monthly data, unit £, 2005 Jan.-2024 Dec., 277 observations, not seasoned, log transformed, independent variable.
Northern Ireland	NORI	
Scotland	SCOT	
Wales	WALS	
England sub-Regions (Model 2)		
East	EAST	Housing price index for the respective region in England generated from HM Land Registry at GOV.UK, unit £, monthly data, 2005 Jan.-2024 Dec., 277 observations, not seasoned, log transformed, independent variable.
East Midlands	EASM	
London	LOND	
North East	NORE	
North West	NORW	
South East	SOUE	
South West	SOUW	
West Midlands	WESM	
Yorkshire and The Humber	YORH	
UK Average House Price	AVHP	UK housing price index generated from HM Land Registry at GOV.UK, monthly data, unit £, 2005 Jan.-2024 Dec., 277 observations, not seasoned, log transformed, Dependent variable.

The terms 'UK sub-Regions' and 'England sub-Regions' are acronyms used in this study to group the housing price data for analytical purposes. 'UK sub-Regions' refers to the four constituent nations of the United Kingdom (England, Scotland, Wales, and Northern Ireland) while 'England sub-Regions' denotes the nine official regions within England.

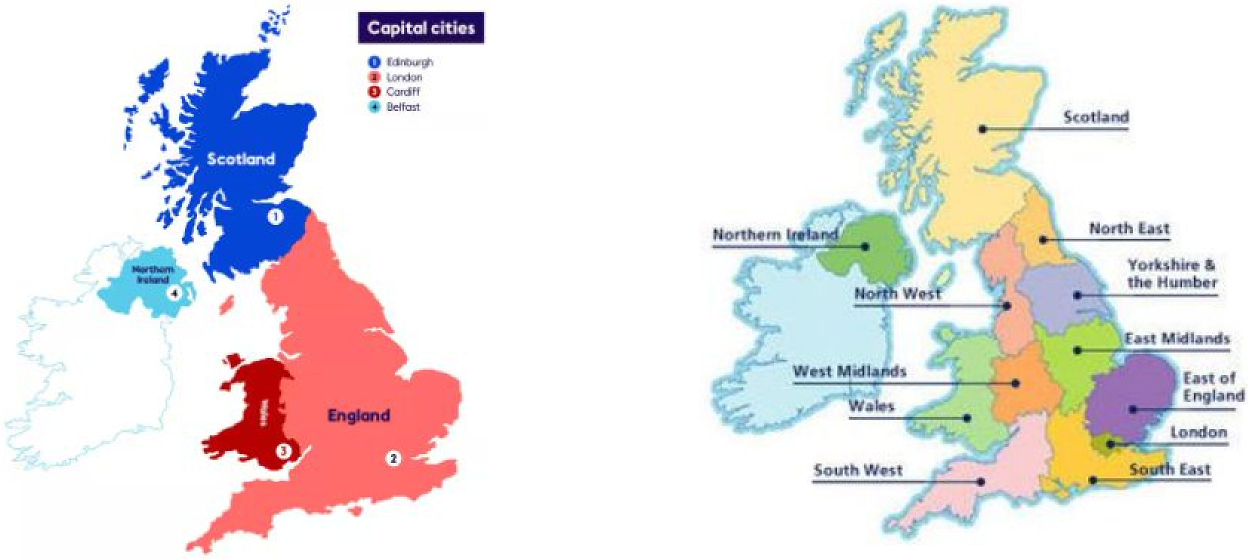


Figure 1 showing the UK sub-Regions and the England sub-Regions

Normal Distribution and Unit Root Tests

Preliminary tests, including normality and unit root assessments, were conducted to evaluate the model's fitness and the precision of the time-series data. To assess the data distribution pattern, the Quantile-Quantile (Q-Q) plot technique was employed. Unit root testing, a crucial step for analysing time-series data, was conducted to determine the stationarity of the dataset. The study applied both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to enhance robustness. Evidence of stationarity is confirmed when the null hypothesis of a unit root is rejected at a significance level of 5% ($p < 0.05$). These tests were performed at level I(0) and first difference I(1), using a model specification that includes an intercept and the Schwarz Information Criterion. Ensuring stationarity and structural stability is essential for reliable econometric modelling and confidence in the resulting estimates.

Main Analysis: Bivariate Analysis

The bivariate analysis employed in this study utilizes the pairwise Granger causality test, originally conceptualized by Norbert Wiener (Wiener, 1956) and later formalized by Clive Granger (Granger, 1968). This test is a feedback-based stochastic technique used to measure causal relationships between two time-varying series over a specified review period. As explained by Bressler and Seth (2011), consider two variables, A and B. If we attempt to predict A_{t+1} using only the historical values of A, and then compare this with a prediction of A_{t+1} using both the past values of A and B, a significant improvement in prediction in the latter case implies that B contains useful information for predicting A_{t+1} that is not in the past of A for forecasting A. Causality is established by *rejecting* the null hypothesis, which states that *"B does not Granger-cause A,"* at a probability value less than the 5% significance level ($p < 0.05$). In such a case, B is said to *Granger-cause A*. Following Foresti (2006), the causal relationship between A and B may be *unidirectional* or *reciprocal.*

In the context of this study, for instance, we explore the directional causal relationship between the UK average house price index (($AVHP_i$) and the London house price index *($LOND_i$)* in a VAR environment. As discussed by Mahdavi and Sohrabian (1989), this interaction can be expressed using two equations, with the first equation presented in Eqn 1

$$AVHP_t = \alpha + \sum_{i=1}^{p} \beta_i (AVHP)_{t-1} + \sum_{j-1}^{q} \tau_t (LOND)_{t-j} + \varepsilon_t - - - - - Eqn.1$$

Where α is a constant and ε_t represents the residual error term. In this model, $AVHP_t$ is the dependent variable, explained by its own lagged values $AVHP_{t-1}$ through the coefficients (β_i) and by the lagged values of the London house price index ($LOND_{i-j}$). If the inclusion of past values of ($LOND_{i-j}$) leads to a statistically significant improvement in the prediction of $AVHP_{t-1}$, then it can be concluded that ($LOND_{i-j}$) *Granger-causes*$AVHP_{t-1}$.

In the second equation presented in Eqn 2, the dependent variable is London house price index ($LOND$) while the UK average house price index ($AVHP$). Thus $AVHP_{t-1}$ granger cause $LOND_t$, If the knowledge of past information contains $AVHP_{t-1}$ leads to significant improvement in the prediction of $LOND_t$

$$LOND_t = \alpha + \sum_{i=1}^{p} \tau_i (LOND)_{t-1} + \sum_{j-1}^{q} \beta_t (AVHP)_{t-j} + \varepsilon_t - - - - - Eqn.2$$

From the g-causality analysis in $Eqn.1$ and $Eqn.2$, hypotheses of four cases can be identified and tested (Foresti, 2006). They are:

a) UK average house price index *($AVHP_{t-i}$)* can *granger-cause* London house price index *($LOND_{t-j}$)* but not vice versa (Unidirectional) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} = 0 \; and \; \sum_{t=j}^{q} \tau_t (LOND)_{t-j} \neq 0 - - - - - Eqn\ 3$$

b) London house price index *($LOND_{t-j}$)* can *granger-cause* UK average house price index *($AVHP_{t-i}$)* but not vice versa (Unidirectional) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} \neq 0 \; and \; \sum_{t=j}^{q} \tau_t (LOND)_{t-j} = 0 - - - - - Eqn\ 4$$

c) UK average house price index *($AVHP_{t-i}$)* can *granger-cause* London house price index *($LOND_{t-j}$)* and vice versa (Bidirectional) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} = 0 \; and \; \sum_{t=j}^{q} \tau_t (LOND)_{t-j} = 0 - - - - - Eqn\ 5$$

d) UK average house price index $(AVHP_{t-i})$ cannot *granger-cause* London house price index $(LOND_{t-j})$ and vice versa (Independent) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} \neq 0 \; and \; \sum_{t=j}^{q} \tau_t (LOND)_{t-j} \neq 0 \; ------ Eqn\ 6$$

The lag length was varied from order 1 to 5 to account for the model's sensitivity to lag structure. The bivariate Granger causality test was conducted between the UK average housing price index and the housing prices of both UK national regions and England counties.

Optimal lag lengths for the VAR and VECM specifications were determined using the Akaike Information Criterion (AIC), ensuring both statistical adequacy and model parsimony. The analysis is conducted at the NUTS1 regional level, encompassing the devolved nations (Scotland, Wales, Northern Ireland) and the nine English regions, as published in the UK House Price Index by HM Land Registry. County-level data were not employed, as they are not consistently available in monthly frequency over the study period, and the regional scale aligns with macroprudential policy frameworks. Structural break tests were implemented which identifies regime shifts endogenously. The detected breakpoints coincide closely with major macroeconomic disruptions namely the Global Financial Crisis (2008), Brexit referendum (2016), the onset of the COVID-19 pandemic (2020), and post-pandemic inflationary pressures (2021), thereby enhancing the robustness of the causality and cointegration results.

For the multivariate model estimation, a Granger Causality Wald Test statistic (see *Eqn. 7*) was employed. The test uses a chi-square distribution to evaluate joint hypotheses about the coefficients of time-varying series within a VAR framework. To clarify the econometric framework, Granger causality is employed to test whether lagged values of one regional housing price series contain predictive information about another series beyond its own history. In this context, the null hypothesis states that regional prices do not Granger-cause movements in the national index, while rejection of the null indicates predictive or directional influence. This approach is operationalised within a vector autoregressive (VAR) setting, with optimal lag lengths determined by information criteria. By summarising these hypotheses and their application, we ensure transparency in how Granger causality is used to identify "signal regions" within the UK housing market.

$$W = \; (R\acute{\beta} - r)'\left[R(\widehat{Var}(\hat{\beta}))\acute{R}\right]^{-1}(R\hat{\beta} - \acute{r}) \; ------ Eqn\ 7$$

$\hat{\beta}$ represents the estimated coefficients from the unrestricted regression. RRR is the matrix that selects the relevant coefficients for testing, while R is the vector of hypothesized values under the null hypothesis. The null hypothesis that *"X does not Granger-cause Y"* is rejected if the probability value is less than the 5% significance level ($p < 0.05$), indicating that past values of X significantly improve the prediction of Y.

Cointegration Equation (CE)

The cointegration equation is employed to determine whether a long-run relationship exists between the exogenous variable (UK national housing prices) and the explanatory variables: UK sub-national housing prices (Model 1) and England sub-national housing prices (Model 2). Given the multivariate nature of the analysis, this study adopts the Johansen cointegration technique. The Johansen approach produces two key test statistics: the Trace Statistic and the Maximum Eigenvalue Statistic. The conventional equations for the Trace and Max-Eigen statistics are presented in $Eqn.$ 8 and $Eqn.$ 9, respectively.

i) Trace Statistic (r)

$$r = -T \sum_{i=r+1}^{n} ln(1 - \pi_i) - - - - - - - - - - - - - Eqn. 8$$

ii) Maximum Eigenvalue Statistic *(r, r+1)*

$$r = -T\, ln(1 - \pi_{r+1}) - - - - - - - - - - - - - Eqn. 9$$

Based on the Johansen cointegration test, the null hypothesis of no cointegrating vector is rejected at the 5% significance level

Vector Error Correction Model (VECM)

The presence of cointegration implies that both immediate (short-run) and long-term relationships exist among the time-varying series. In such cases, the Vector Error Correction Model (VECM) is an appropriate modelling approach within the Vector Autoregression (VAR) framework. The VECM not only captures the short-run dynamics and long-run equilibrium relationships but also accounts for deviations from the long-run path, indicating the speed at which the system adjusts back to equilibrium following a shock. The conventional specification of the Vector Error Correction Model (VECM) is provided in $Eqn.$ 10.

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + \epsilon_t - - - - - - - - - - - - - Eqn. 10$$

Where Δ denotes the first-difference operator applied to an (n x 1) vector of variables; Π and Γ_i capture information about the long-run relationships and short-run dynamics, respectively. The parameter k represents the lag length corresponding to the integration order of the VAR model. μ denotes the constant or deterministic component, ϵ_t is the vector of error terms. A 5% significance level is adopted as the threshold for determining statistical significance in the model.

Robustness Checks.

For the robustness check, we employed robust least squares techniques namely M-estimation, S-estimation, and MM-estimation. These methods are particularly effective in addressing key econometric challenges such as the influence of outliers, variability in estimates, heteroscedasticity, and the non-normal distribution of time series data. Their application enhances the reliability and precision of model estimates, especially when standard ordinary least squares (OLS) assumptions are violated.

These techniques have been widely endorsed in the literature where applied robust least squares methods in real estate valuation analysis have demonstrated their effectiveness in managing outlier-influenced datasets (Rahayu et al., 2023; Singgih & Fauzan, 2022; Khotimah et al., 2019; Susanti et al., 2014). The study found that these estimators provided more stable and reliable parameter estimates compared to conventional OLS, thereby improving the overall robustness of empirical findings.

The conventional equation function of for the M-estimation, S-estimation, and MM-estimation is expressed in *Eqn. 11*, *Eqn. 12* and *Eqn. 13*.

i) M-estimator minimize influence of outlier

$$\widehat{\beta_s} = \arg_\beta \min \sum_{i=1}^{n} \rho \left(\frac{y_i - x_i{}^T \beta}{\hat{\sigma}} \right) ------ Eqn\ 11$$

ii) S-estimators minimize residual error

$$\widehat{\beta_s} = \arg_\beta\, min\ \ s(r_1(\beta), r_2(\beta), \ldots, r_n(\beta)) ------ Eqn\ 12$$

iii) MM-estimators refine M-estimators to provide high statistical efficiency

$$\widehat{\beta_{MM}} = \arg_\beta \min \sum_{i=1}^{n} \rho \left(\frac{y_i - x_i{}^T \beta}{\hat{\sigma}} \right) ------ Eqn\ 13$$

While Granger causality techniques were employed to test predictive precedence between variables within a VAR framework, robust least squares methods (specifically M-estimators, S-estimators, and MM-estimators) were used to enhance the accuracy and reliability of parameter estimates in the presence of data irregularities such as outliers and high-leverage points. Unlike traditional Ordinary Least Squares (OLS), which is highly sensitive to such anomalies, these robust techniques are designed to minimize the influence of outliers and maintain model stability even when classical regression assumptions (e.g., homoscedasticity and normality) are violated, thereby improving the overall precision and validity of the model.

4. Findings

Preliminary Result

The summary descriptive statistics of the average housing price index for the UK, both at the UK sub-regions and England sub-regions are presented in Table 2 and Table 3. Empirical evidence indicates that among the UK's sub-regions, only England exhibits mean and median housing price index values that exceed the national average. In contrast, other sub-regions namely Northern Ireland, Scotland, and Wales, have housing price indices below the national average. This finding underscores the significantly higher housing prices in England, which are strongly linked to an intensifying affordability crisis, particularly affecting vulnerable and urban-poor populations.

The elevated housing prices in England are largely attributed to the competitiveness of its housing market and the cosmopolitan nature of its urban centres. These factors have drawn substantial internal and external migration, contributing to rapid population growth and increasing demand, thereby putting upward pressure on housing prices. On the other hand, the lower housing price indices recorded in regions such as Northern Ireland reflect relatively more affordable housing markets. However, these regions are characterized by less competitive markets and lower population pressures.

Table 2: Summary Descriptive Statistics for Average UK housing Price index and UK sub-Nationals

	AVHP	ENGL	NORI	SCOT	WALE
Mean	203812.5	215491.7	139377.0	141989.1	151066.2
Median	190032.0	200825.0	134619.0	136891.0	141503.0
Max.	291716.0	311059.0	224670.0	193673.0	220878.0
Min.	150488.0	158609.0	97428.00	93554.00	121070.0
Std. Dev.	40035.22	44518.62	29529.32	21255.62	27079.12
Skew	0.726806	0.657041	0.889624	0.804637	1.270024
Kurt	2.371791	2.214117	3.342634	3.242591	3.479008
Jarque-Bera	23.71805	22.17436	31.05287	25.05147	63.19392
Prob	0.000007	0.000015	0.000000	0.000004	0.000000
Obs.	227	227	227	227	227

Note: Average UK Housing price (AVHP), England (ENGL), North Ireland (MORI), Scotland (SCOT), and Wales (WALS), Maximum (Max.), Minimum (Min.), Standard Deviation (Std. Dev.), Probability (Prob), No of observations (Obs.)

Significantly higher variability in England's housing price index is observed, with price index extremes ranging from 158609.00 to 311059.00 and a standard deviation of 44518.62. This variability is expected due to sub-regional disparities, where housing prices in central urban areas are markedly higher than in peripheral zones. These urban centers tend to attract private investment due to their profitability and strategic location. Similarly, the average UK housing price index demonstrates fluctuations between 150488.00 (minimum) and 291716.00 (maximum), with a standard deviation of 40035.22.

In contrast, the housing price indices for other UK sub-regions show lower levels of variability, indicating more stable housing markets with less volatility and uncertainty. Nevertheless, the price indices for all UK regions, including the national average, follow a relatively none-normal distribution (see Figure 2). Notably, Scotland and Wales exhibit leptokurtic distributions, as evidenced by skewness and kurtosis statistics. The statistically significant Jarque-Bera test further confirms the dispersion and non-linear distribution patterns of the housing price index time-series data.

Table 3: Summary Descriptive Statistics for England sub-Regions

	EAST	EASM	LOND	NORE	NORW	SOUE	SOUW	WESM	YORH
Mean	242990.4	170315.3	383049.9	128648.1	152168.4	274479.3	227925.4	176050.4	151537.9
Median	221817.0	155033.0	398737.0	124799.0	143009.0	257701.0	211576.0	161813.0	144594.0
Max.	358418.0	251161.0	543572.0	163100.0	218353.0	397696.0	333922.0	253854.0	211911.0
Min.	168263.0	129876.0	231263.0	110454.0	117630.0	191156.0	171356.0	136966.0	120419.0
Std. Dev.	57902.22	35056.31	103265.4	12307.21	26301.13	61953.20	45203.04	33419.64	24307.82
Skew	0.489006	0.940111	0.000207	1.185688	1.159698	0.441651	0.859407	0.959391	1.095189
Kurt	1.830649	2.720011	1.339929	3.669093	3.288690	1.852596	2.638989	2.756208	3.172200
Jarque-Bera	21.98012	34.17890	26.06560	57.42256	51.67031	19.83182	29.17564	35.38512	45.65928
Prob	0.000017	0.000000	0.000002	0.000000	0.000000	0.000049	0.000000	0.000000	0.000000
Obs.	227	227	227	227	227	227	227	227	227

Note: East (EAST), East Midlands (EASM), London (LOND), North-east (NORE) North-west (NORW), South-east (SOUE), South-west (SOUW), West Midlands (WESM), Yorkshire and The Humber (YORH)

An analysis of the housing price index across regions in England reveals that London has the highest mean price index (383,049.9) and median value (398,737.0), significantly surpassing the national average. London also exhibits the greatest variability, with a standard deviation of 543572.0 and a wide range between the highest (543572.0) and lowest (231263.0) values. This suggests that housing prices in London do not reflect the overall UK housing market. Beyond London, higher-than-average price indices are observed in the East (242990.0), South East (274479.3), and South West (227925.4), all showing relatively greater price fluctuations over the review period. In contrast, other regions in England recorded housing price indices below the national average, with the lowest observed in Yorkshire and the Humber (YORH). The distribution of the housing price index data follows a non-linear pattern, as evidenced by skewness and kurtosis statistics and a statistically significant Jarque-Bera test ($p < 0.05$).

In addition, *Figure 2* illustrates the non-linear distribution patterns of housing price indices across the UK and its sub-regions, including those within England using Quantile-Quantile plot (Q-Q) techniques. Notably, *Figure 3* highlights the overall trajectory of housing price indices, reflecting long-term trends and regional disparities within the broader UK housing market.

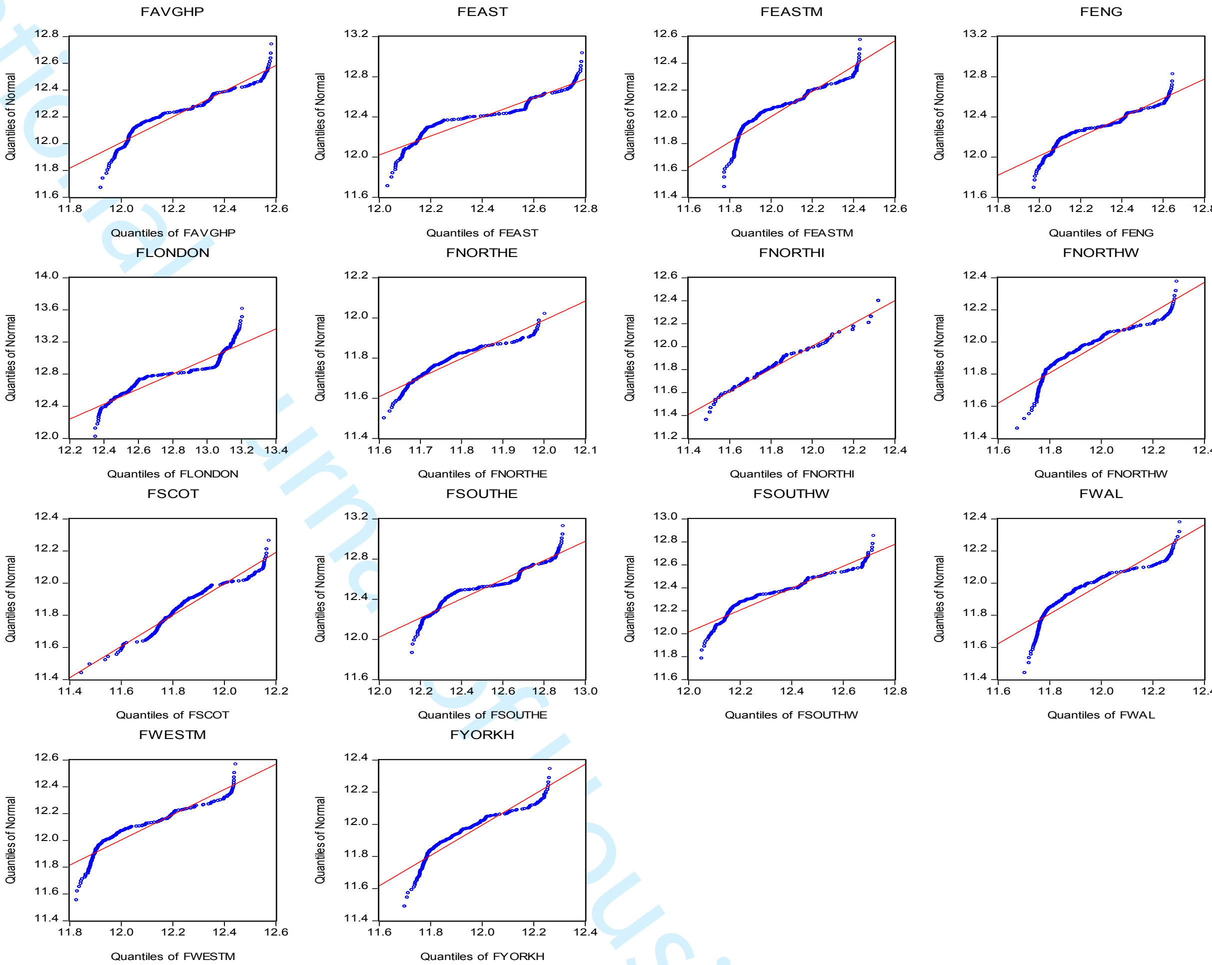


Figure 2 illustrates the normal distribution pattern of the variables using a Q-Q (quantile-quantile) plot.

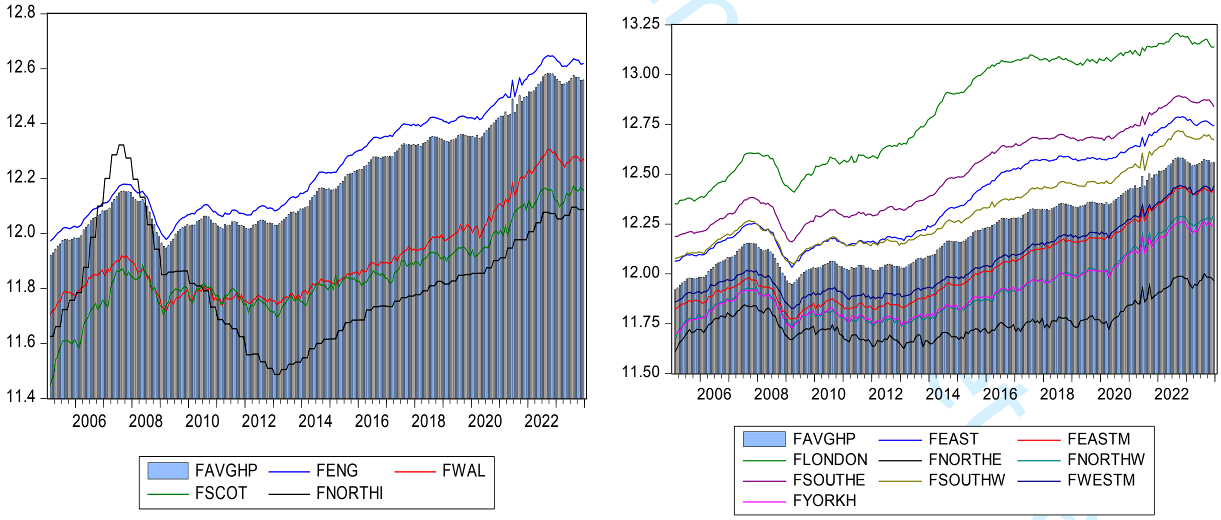


Figure 3 displays the trends in the Housing Price Index (HPI) for the UK average national housing prices, the devolved UK regions (England, Scotland, Wales, and Northern Ireland), as well as the regions within England.

In addition to the descriptive statistics (Table 3), which indicate deviations from normality through skewness, excess kurtosis, and the Jarque–Bera test, the unit root tests (Table 4) further confirm that the regional housing price series are non-stationary in levels. Taken together, the evidence of non-normality and non-stationarity justifies the modelling approach adopted in this study. Specifically, differencing the series ensures valid inference in the time-series framework, while the application of robust estimation techniques mitigates the influence of heavy-tailed distributions and volatility clustering that are characteristic of housing price dynamics, particularly during crisis periods.

The stationarity tests for the variables were conducted using the Augmented Dickey-Fuller (ADF). Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) techniques for the UK average housing price index, UK sub-regions, and England sub-regions. The results presented in Table 4 indicate that all data series become stationary at their first differences, i.e., they are integrated of order one [I(1)]. This finding is consistent with previous studies, which frequently report that economic indicators typically achieve stationarity at the I(1) level (Fateye et al., 2024; Olanrele et al., 2021). To ensure the robustness of the unit root testing, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was employed as a complementary approach. The KPSS test results were consistent with those of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, confirming the stationarity of the variables at first difference lag length order (I(1)). The stationarity characteristics of the time series data confirm the appropriateness of the dataset for econometric analysis, ensuring the reliability, validity, and accuracy of subsequent estimations.

Table 4: Unit Root tests

Variable	**ADF**			**PP**			**KPSS LM-Stat (critical value @5%)**		
	@ Level	**@1st Diff.**	**Stat.**	**@ Level**	**@1st Diff.**	**Stat.**	**@ Level**	**@1st Diff.**	**Stat.**
Model 1: UK sub-Regions									
AVHP	0.2051	-4.6061	*I[1]*	-0.1274	-13.129	*I[1]*	1.7855	0.1193	I[1]
	(0.9724)	*(0.0002)**		(0.9438)	*(0.0000)**		(0.463)	(0.463)	
ENGL	0.1042	-6.0931	*I[1]*	-0.0650	-14.601	*I[1]*	1.8277	0.1165	I[1]
	(0.9654)	*(0.0000)**		(0.9505)	*(0.0000)**		(0.463)	(0.463)	
NORI	-2.3625	-3.0994	*I[1]*	-1.3612	-17.031	*I[1]*	0.3439	0.1574	I[1]
	(0.1537)	*(0.0280)**		(0.6008)	*(0.0000)**		(0.463)	(0.463)	
SCOT	-0.8671	-2.5282	-	-1.9090	-14.464	*I[1]*	1.5702	0.1641	I[1]
	(0.7971)	*(0.1102)*		(0.3278)	*(0.0000)**		(0.463)	(0.463)	
WALS	1.00152	-18.341	*I[1]*	(0.5089)	-17.971	*I[1]*	1.4781	0.3034	I[1]
	(0.9966)	*(0.0000)**		(0.9867)	*(0.0000)**		(0.463)	(0.463)	
Model 2: England sub-Regions									
EAST	-0.5387	-4.6056	*I[1]*	-0.1965	-14.744	*I[1]*	1.8539	0.1124	I[1]
	(0.8798)	*(0.0002)**		*(0.9356)*	*(0.0000)**		(0.463)	(0.463)	
EASM	0.4855	-5.6126	*I[1]*	0.8582	-16.453	*I[1]*	1.6807	0.3575	I[1]
	(0.9859)	*(0.0000)**		*(0.9948)*	*(0.0000)**		(0.463)	(0.463)	
LOND	-1.2477	-5.4448	*I[1]*	-1.2364	-13.787	*I[1]*	1.9044	0.1648	I[1]
	(0.6538)	*(0.0000)**		*(0.6589)*	*(0.0000)**		(0.463)	(0.463)	
NORE	-0.5639	-19.181	*I[1]*	-0.9647	-18.912	*I[1]*	0.9093	0.1457	I[1]
	(0.8746)	*(0.0000)**		*(0.7658)*	*(0.0000)**		(0.463)	(0.463)	
NORW	0.5448	-6.4416	*I[1]*	0.3478	-18.376	*I[1]*	1.4917	0.2665	I[1]
	(0.9879)	*(0.0000*)*		*(0.9803)*	*(0.0000)**		(0.463)	(0.463)	
SOUE	-0.8886	-4.4885	*I[1]*	-0.4060	-12.788	*I[1]*	1.8761	0.0776	I[1]
	(0.7906)	*(0.0003)**		*(0.9046)*	*(0.0000)**		(0.463)	(0.463)	

SOUW	-0.3747	-5.1886	*I[1]*	0.1389	-16.910	*I[1]*	1.7641	0.1564	I[1]
	(0.9099)	*(0.0000)**		*(0.9680)*	*(0.0000)**		(0.463)	(0.463)	
WESM	0.4507	-5.8935	*I[1]*	0.8179	-17.693	*I[1]*	1.6732	0.3274	I[1]
	(0.9847)	*(0.0000)**		*(0.9942)*	*(0.0000)**		(0.463)	(0.463)	
YORH	-0.0133	-6.3794	*I[1]*	0.0936	-18.176	*I[1]*	1.5405	0.2022	I[1]
	(0.9555)	*(0.0000)**		*(0.9647)*	*(0.0000)**		(0.463)	(0.463)	

This table presents the stationarity characteristics of the time-varying data series used in the analysis, based on unit root test statistics: the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The tests are conducted at both the level form (I(0)) and the first-differenced form (I(1)). For the ADF and PP tests, the null hypothesis of a unit root (i.e., non-stationarity) is rejected at the 5% significance level when the p-value is less than 0.05. In contrast, for the KPSS test, the null hypothesis assumes stationarity, and it is not rejected if the test statistic is below the 5% critical value. This study adopts the 5% threshold to evaluate statistical significance and determine the integration order of each series.

The strength of stationarity at first difference also varies across regions, and this variation has an important economic context. Regions such as Wales (WALS) and Northern Ireland (NORI) record larger negative ADF statistics at the first-difference level, indicating sharper price adjustments and stronger mean-reverting behaviour. This can be explained by their relatively smaller and less diversified economies, which render housing markets more sensitive to national credit cycles and policy shocks. By contrast, regions with more diversified and internationally exposed housing demand, such as London, display slower adjustment dynamics and correspondingly weaker test statistics. These differences highlight how structural and economic characteristics condition the speed and strength of adjustment in regional housing markets, adding depth to the interpretation of the unit root results.

Main Result

The volatility of housing price indexes across UK sub-regions and England sub-regions is further highlighted by the Cholesky factor analysis presented in Figure 4. The national housing price index exhibited relatively mild fluctuations in its structural response to external shocks, with a notable structural break occurring around 2021 coinciding with the period of economic recovery following the COVID-19 disruptions.

In contrast, Northern Ireland experienced higher volatility in housing prices during the early part of the review period (2006–2008), while regions such as England showed greater turbulence in the later years (2020–2022). These differences in structural adjustment to external forces across UK regions suggest that housing price dynamics are more locally driven rather than being determined by national trends. Similar volatility patterns were also observed in housing price indexes within England, with certain areas such as Yorkshire experiencing marked fluctuations during specific periods. These results are consistent with Meen's (1999) argument that housing markets exhibit sluggish adjustment to shocks, and with Oikarinen's (2004) findings of persistence in regional price dynamics. The weaker evidence for Scotland reflects institutional and policy differences in devolved housing systems, which often lead to distinctive adjustment speeds.


VAR Structural Residuals using Cholesky (d.f. adjusted) Factors
FAVGHP Structural Residuals
FENG Structural Residuals
FNORTHI Structural Residuals
FSCOT Structural Residuals
FWAL Structural Residuals

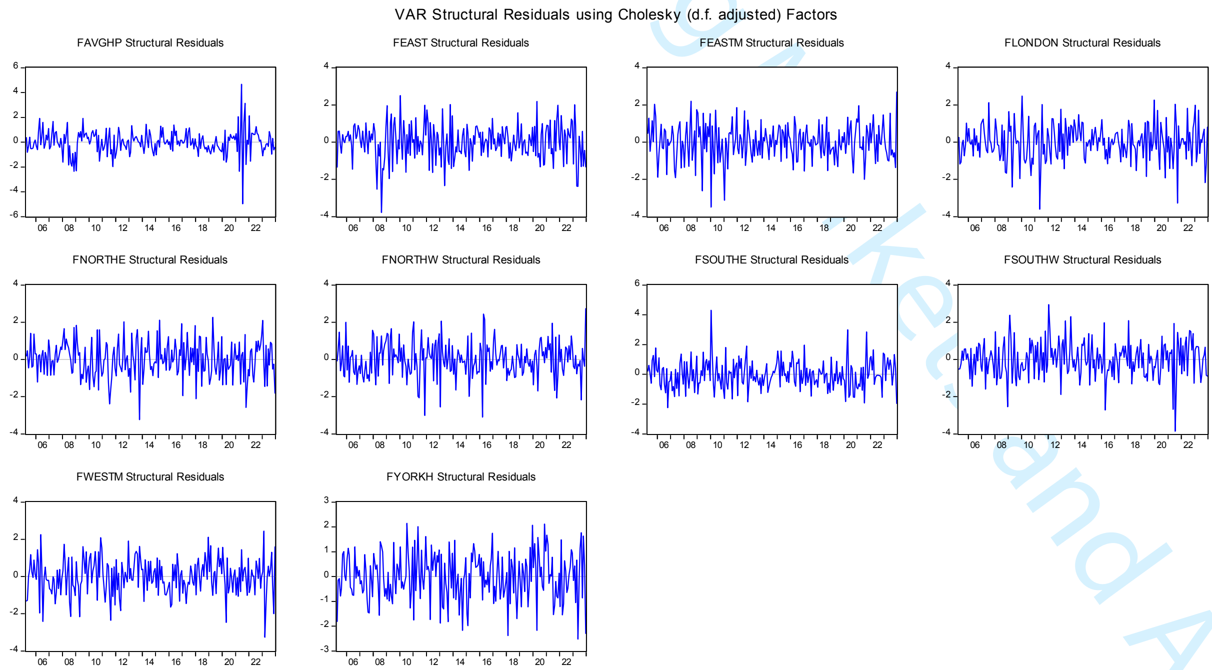

VAR Structural Residuals using Cholesky (d.f. adjusted) Factors
FAVGHP Structural Residuals
FEAST Structural Residuals
FEASTM Structural Residuals
FLONDON Structural Residuals
FNORTHE Structural Residuals
FNORTHW Structural Residuals
FSOUTHE Structural Residuals
FSOUTHW Structural Residuals
FWESTM Structural Residuals
FYORKH Structural Residuals

Figure 4 present the structural response of the UK sub-regions and England sub-regions to national housing index over the review period (2005-2024) in the VAR framework. The housing price index experienced fluctuations across the study areas at varying levels, with highest volatility regime in England at National level and Yorkshire at England counties. The depict the spatial differences in the housing prices across UK indicating more segregated housing market

The correlation matrices presented in Table 5a and Table 5b summarize the strength of association among the variables included in Model 1 and Model 2, respectively. In Model 1, which examines the relationship between the average UK housing price index and regional housing markets, all sub-regions exhibit strong positive correlations with the national average, with the exception of Northern Ireland (r = 0.4067), which shows a relatively weaker degree of association. In Model 2, the England sub-regions exhibit stronger correlations with the national housing price trends. Notably, the South West (r = 0.7978), East Midlands (r = 0.7897), and East of England (r = 0.7896) demonstrate the highest degrees of association, indicating a more pronounced alignment with the overall UK housing market dynamics. Nevertheless, the overall positive correlations suggest a degree of co-movement between regional housing prices and national housing trends, albeit with varying strengths across regions.

Table 5a: Correlation Matrix for Model 1: UK sub-Regions

	X_1	X_2	X_3	X_4	X_5
X_1	1				
X_2	0.7984	1			
X_3	0.4067	0.3608	1		
X_4	0.7393	0.7254	0.5103	1	
X_5	0.7567	0.7422	0.5653	0.7361	1

X_1-AVGHP, X_2-ENG, X_3-NORTHI, X_4-SCOT, X_5-WAL

Table 5b: Correlation Matrix for Model 2: England sub-Regions

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	1									
X_2	0.7896	1								
X_3	0.7897	0.7704	1							
X_4	0.7252	0.7611	0.6729	1						
X_5	0.6111	0.5283	0.6501	0.5483	1					
X_6	0.7632	0.7193	0.7815	0.7914	0.8262	1				
X_7	0.7865	0.7981	0.7611	0.7116	0.7126	0.8075	1			
X_8	0.7978	0.7848	0.7932	0.7109	0.8209	0.7685	0.7809	1		
X_9	0.7890	0.7669	0.7989	0.6665	0.8595	0.7855	0.7574	0.6926	1	
X_{10}	0.7729	0.7331	0.7858	0.6153	0.7158	0.7981	0.7233	0.67701	0.7893	1

X_1-AVGHP, X_2-EAST, X_3-EASTM, X_4-LONDON, X_5-NORTHE, X_6-NORTHW, X_7-SOUTHE, X_8-SOUTHW, X_9-WESTM, X_{10}-YORKH

The study conducted a bivariate causality test to determine the direction of causal relationships between the average UK housing price and the housing prices in UK sub-regions and England sub-regions. The test was performed across lags 1 to 5 to account for the sensitivity of the method to changes in lag order. As presented in Table 6, the p-values indicate statistically significant causal relationships ($p < 0.05$) between the average housing price index and all the UK sub-regions namely, England, Northern Ireland, and Scotland, suggesting a bidirectional causal effect across all lags. For example, changes in the national average housing price strongly influence housing price dynamics in England, and conversely, fluctuations in England's housing prices significantly affect the national index. Similar bidirectional causality is observed in the relationships with Northern Ireland and Scotland.

At the regions level within England, bidirectional causality is evident between the UK national average housing price and England sub-regions such as the North-East, North-West, and South-East, implying mutual influence. However, other counties including the East, East Midlands, London, South West, and West Midlands. exhibit a unidirectional causal relationship. In these cases, changes in the UK national average housing price significantly influence regional housing prices, but the reverse effect is not statistically supported across the tested lags.

Table 6: Bivariate Granger Causality Test

Null Hypothesis	X_{-1}	X_{-2}	X_{-3}	X_{-4}	X_{-5}	**Decision**
Model 1: UK sub-Regions						
ENGL ≠ AVHP	2.6757	19.453	11.780	8.7763	7.8906	
	(0.1033)	*(2.E-08)**	*(4.E-07)**	*(1.E-06)**	*(8.E-07)**	*Bidirectional*
AVHP ≠ ENGL	1.9454	24.666	15.695	10.988	10.751	
	(0.1645)	*(2.E-10)**	*(3.E-09)**	*(4.E-08)**	*(3.E-09)**	
NOR1 ≠ AVHP	2.7148	8.0396	8.78054	5.23214	4.5702	
	(0.1008)	*(0.001)**	*(2.E-05)**	*(0.0005)**	*(0.0006)**	*Bidirectional*
AVHP ≠ NORI	1.6165	10.810	12.169	2.0739	2.7170	
	(0.2049)	*(3.E-05)**	*(2.E-07)**	*(0.0853)**	*(0.0211)**	
SCOT ≠ AVHP	6.0588	15.005	8.5276	7.4272	6.4574	
	*(0.0146)***	*(8.E-07)**	*(2.E-05)**	*(1.E-05)**	*(1.E-05)**	*Bidirectional*
AVHP ≠ SCOT	18.335	11.530	5.1133	3.9467	4.0085	
	*(3.E-05)**	*(2.E-05)**	*(0.0019)**	*(0.0041)**	*(0.0017)**	
WALS ≠ AVHP	0.4334	0.1972	0.3955	0.5097	0.5686	
	(0.5110)	*(0.8211)**	*(0.7563)**	*(0.7287)**	*(0.7240)**	*Bidirectional*
AVHP ≠ WALS	3.5883	15.89	18.995	13.999	10.469	
	*(0.0595)***	*(4.E-07)**	*(6.E-11)**	*(4.E-10)**	*(5.E-09)**	
Model 2: England sub-Regions						
EAST ≠ AVHP	3.0375	1.4943	1.0454	1.3639	0.8126	
	(0.0827)	*(0.2267)*	*(0.3733)*	*(0.2475)*	*(0.5418)*	*Unidirectional*
AVHP ≠ EAST	1.2931	9.5422	0.3733	8.7193	8.9124	
	(0.2567)	*(0.0001)**	*(3.E-05)**	*(2.E-06)**	*(1.E-07)**	
ESTM ≠ AVHP	0.7815	1.6014	0.8609	1.2486	1.0664	
	(0.3776)	*(0.2040)*	*(0.4622)*	*(0.2914)*	*(0.3800)*	*Unidirectional*
AVHP ≠ ESTM	1.1582	19.1784	12.9295	12.4266	9.8559	
	(0.2830)	*(2.E-08)**	*(8.E-08)**	*(4.E-09)**	*(2.E-08)**	
LOND ≠ AVHP	1.7168	1.6759	0.8106	1.0730	1.0601	
	(0.1915)	*(0.1895)*	*(0.4892)*	*(0.3708)*	*(0.3835)*	*Unidirectional*
AVHP ≠ LOND	4.3566	7.1545	10.1521	6.5625	6.2651	
	*(0.0380)**	*(0.0010)**	*(3.E-06)**	*(5.E-05)**	(2.E-05)*	
NORE ≠ AVHP	5.4826	4.9733	3.1069	2.3975	2.1616	
	*(0.0201)**	*(0.0077)**	*(0.0274)***	*(0.0513)**	*(0.0596)**	*Bidirectional*
AVHP ≠ NORE	4.3063	11.9176	9.4531	8.0354	7.1453	
	*(0.0391)**	*(1.E-05)**	*(7.E-06)**	(5.E-06)*	*(3.E-06)**	
NORW ≠ AVHP	3.9149	9.5262	7.5119	3.9430	3.8537	
	*(0.0491)***	*(0.0001)**	*(8.E-05)**	*(0.0041)**	*(0.0023)**	*Bidirectional*
AVHP ≠ NORW	3.7804	24.007	21.088	14.016	13.748	
	*(0.0531)**	*(4.E-10)**	*(5.E-12)**	*(4.E-10)**	*(1.E-11)**	
SOUE ≠ AVHP	2.6727	1.68825	1.44187	0.72922	0.93611	
	(0.1035)	*(0.1872)*	*(0.2315)*	*(0.5729)*	*(0.4585)*	*Unidirectional*
AVHP ≠ SOUE	2.0313	5.56034	4.13871	4.41998	5.34347	
	(0.1555)	*(0.0044)**	*(0.0070)**	*(0.0019)**	*(0.0001)**	
SOUW ≠AVHP	0.0111	4.1088	3.2347	2.3295	1.4026	

	(0.9161)	*(0.0177)**	*(0.0232)***	*(0.0571)**	*(0.2246)*	*Bidirectional*
AVHP ≠ SOUW	8.9969	15.864	17.172	11.611	9.5829	
	*(0.0030)**	*(4.E-07)**	*(5.E-10)**	*(1.E-08)**	*(3.E-08)**	
WESM ≠ AVHP	0.0505	1.9574	1.1841	1.6399	1.4091	
	(0.8223)	*(0.1437)*	*(0.3167)*	*(0.1653)*	*(0.2222)*	*Unidirectional*
AVHP ≠ WESM	3.3907	18.059	17.647	17.253	13.454	
	(0.0669)	*(5.E-08)**	*(3.E-10)**	*(3.E-12)**	*(2.E-11)**	
YORH ≠ AVHP	3.9025	6.2867	3.3520	2.2724	2.5818	
	*(0.0494)**	*(0.0022)**	*(0.0199)**	*(0.0625)*	*(0.0272)**	*Bidirectional*
AVHP ≠ YORH	5.2355	15.768	14.317	9.0417	8.9751	
	*(0.0231)***	*(4.E-07)**	*(2.E-08)**	*(9.E-07)**	*(1.E-07)**	

The table presents the results of the bivariate analysis examining the causal relationship between the average UK housing price index (AVHP) and housing prices (HP) across UK sub-regions and England sub-regions. The Granger causality test was conducted across lags 1 to 5. The direction of causality may be: (i) unidirectional, where AVHP Granger-causes HP but not vice versa (AVHP → HP, HP ≠ AVHP); (ii) bidirectional, where both variables Granger-cause each other (AVHP ↔ HP); or (iii) no causal effect, where neither variable Granger-causes the other (AVHP ≠ HP, HP ≠ AVHP). The reported values are F-statistics, with corresponding probabilities in parentheses. The null hypothesis of no causal relationship is rejected at the 5% significance level ($p < 0.05$).

The study presents mixed results regarding the diffusion of national housing prices to regional housing markets. On one hand, the observed bidirectional influences between UK national housing prices and the national housing market contradict the ripple effect and spatial equilibrium theories, which emphasize price divergence across regions (Zhang et al., 2021; Fingleton, 2008). This mutual influence suggests a price synergy between national housing prices and overall market dynamics, indicating a degree of market integration. On the other hand, at the sub-national level within England, the majority of regions exhibit a unidirectional influence, where local housing prices contribute to national housing price movements. Notably, the North East, North West, and South East regions display bidirectional causal relationships with national housing price trends. These disparities in causal effects imply that national housing prices do not fully reflect regional price dynamics, supporting the ripple effect hypothesis, which is based on the assumption of segmented market behaviour, particularly at regional levels (Zhang et al., 2021; Cohen et al., 2023). The presence of bidirectional causality in this study reflects the interdependence of regional housing and labour markets, consistent with Rosen's (1979) and Roback's (1982) spatial equilibrium models, and with Goodman and Thibodeau's (1998) evidence of feedback effects between regional price shocks

In Table 7, the Granger Causality Wald Test was conducted, and two models were developed. Model 1 comprises the UK sub-regions (England, Northern Ireland, Scotland, and Wales) while Model 2 includes the England sub-regions: East, East Midlands, London, North East, North West, South West, West Midlands, and Yorkshire and the Humber (YORH). The test was conducted across multiple lag structures (lag 1 to lag 5).

In Model 1, the average UK national housing price is statistically significantly influenced ($p < 0.05$) by all the UK sub-regions at lag 1, including by the historical values of their housing prices at lags 4 and 5 except for Wales, which shows no statistically significant effect ($p > 0.05$) across all lags showing higher housing market price integration with the national housing trends. For Model 2, which examines the England sub-regions, the explanatory power of regional housing prices on the national housing price index is generally less statistically significant ($p > 0.05$), suggesting that national housing price dynamics are less dependent on fluctuations in these sub-regional markets. However, at lag 1, several regions including the East, East Midlands, London, North East, North West, and South West, exert a statistically significant influence on national housing price trends. Notably, the historical housing price movements in regions such as the North East, North West, and South West display statistical significance at various levels (10%, 5%, and 1%). The findings showcase prominent local factor such as economy, political and sociocultural factors to drive sub-regional housing prices compared to national housing price index (Gabrielli & French, 2021; Czischke & Van Bortel, 2023).

Specifically, the West Midlands shows a statistically significant effect that increases with lag length, indicating a stronger predictive potential of its housing price trends on the national index. A similar pattern is observed for London, particularly up to lag 3. Overall, the results reveal heterogeneous effects among the England sub-regions, with some exhibiting stronger and more consistent predictive power on national housing price movements, while others demonstrate weaker or statistically insignificant influence.

Table 7: Granger Causality Wald Test

Variable	X_{-1}	X_{-2}	X_{-3}	X_{-4}	X_{-5}
Model 1: Uk National					
ENGL	3.3692	1.0130	1.5665	8.1949	11.322
	*(0.0664)****	*(0.6026)*	*(0.6670)*	*(0.0847)****	*(0.0453)***
NORI	4.4122	2.7249	7.4445	12.744	13.944
	*(0.0357)***	*(0.2560)*	*(0.0590)****	*(0.0126)***	*(0.0160)***
SCOT	6.6742	2.3055	3.0361	11.797	10.122
	*(0.0098)**	*(0.3158)*	*(0.3861)*	*(0.0189)***	*(0.0718)****
WALE	1.2420	(0.1556	2.0957	7.0285	6.5156
	(0.2651)	*(0.9251)*	*(0.5528)*	*(0.1344)*	*(0.2592)*
Model 2: England sub-Regions					
EAST	6.6224	1.2389	1.1466	2.3992	3.5790
	*(0.0101)***	*(0.5382)*	*(0.7658)*	*(0.6628)*	*(0.6115)*
EASM	9.0567	6.2151	4.8702	6.2411	6.7687
	*(0.0026)**	*(0.0447)***	*(0.1815)*	*(0.1818)*	*(0.2384)*
LOND	7.6288	6.8428	6.8026	3.7633	4.2244
	*(0.0057)**	*(0.0327)***	*(0.0785)****	*(0.4390)*	*(0.5176)*
NORE	3.3344	7.5221	6.0505	10.015	14.882
	*(0.0678)****	*(0.0233)***	*(0.1092)*	*(0.0402)***	*(0.0109)***
NORW	7.7171	11.742	19.367	27.175	28.212
	*(0.0055)**	*(0.0028)**	*(0.0002)**	*(0.0000)**	*(0.0000)**
SOUE	0.3111	1.3469	3.7154	4.0228	5.8475
	(0.5770)	*(0.5099)*	*(0.2939)*	*(0.4029)*	*(0.3213)*
SOUW	4.9277	16.423	19.383	14.3078	16.290
	*(0.0264)***	*(0.0003)**	*(0.0002)**	*(0.0064)**	*(0.0061)**
WESM	1.2244	4.8162	4.2531	11.4521	11.169
	(0.2685)	*(0.0900)****	*(0.2354)*	*(0.0219)***	*(0.0481)***
YORH	0.3523	5.3194	3.4290	6.6016	9.1225
	(0.5528)	*(0.0700)****	*(0.3301)*	*(0.1585)*	*(0.1043)*

The table presents the results of the multivariate analysis using the Granger Causality Wald Test for model estimation. The coefficients are reported as Chi-square values, with corresponding probability values in parentheses. The analysis was conducted across varying lag structures, from lag 1 (X_{-1}) to lag 5 (X_{-5}), to account for the sensitivity of the technique to different lag lengths. The tests were applied to both Model 1 and Model 2. Statistical significance is indicated at the 10% (***), 5% (**), and 1% (*) levels.

The emergence of the North East, North West, and South West as persistent signal transmitters, despite their relatively modest price levels and populations compared to London or the South East, can be understood through their structural and behavioural housing market dynamics. The North East and North West function as affordability frontiers, where shifts in national credit conditions or macroeconomic uncertainty are reflected most rapidly in local housing demand. These regions are often the first to register changes in mortgage accessibility, household income shocks, or migration flows, making them early indicators of broader market adjustments. Similarly, the South West's role as a signal transmitter is shaped by its dual function as both a primary residence and second-home/retirement market. Demand pressures in this region are sensitive to macroeconomic cycles, particularly interest rate changes, which in turn propagate into national housing trends.

In contrast, London and the South East, while larger in scale, exhibit dynamics increasingly shaped by international capital flows, investor behaviour, and global financial linkages. These factors decouple them from domestic affordability constraints, weakening their role as consistent signal regions. Taken together, the results suggest that regional housing markets with affordability-driven demand, credit sensitivity, and structurally elastic supply responses may act as early warning transmitters of systemic change, even when they do not dominate in size or price levels.

To capture the causal relationship between national housing prices over time—particularly in response to major economic disruptions such as the Global Financial Crisis (GFC), the post-COVID-19 recovery, and periods of economic expansion, the review period (2005–2024) was divided into four sub-periods: 2005–2009, 2010–2014, 2015–2019, and 2020–2024. This segmentation allows for a more nuanced analysis of how these events influenced regional disparities in housing prices across the UK and the result is presented in Table 8.

The results of the Wald tests, presented in Table 8, reveal that the causal effects of the UK sub-national regions became significantly more pronounced during the post-COVID economic recovery period (2020–2024). This suggests that earlier economic shocks, such as the GFC and the Brexit crisis, had comparatively minimal and statistically insignificant effects on national housing prices.

However, over the entire review period (2005–2024), the cumulative contribution of regional housing markets to national price dynamics was found to be significant. This highlights the long-term predictive power of regional housing trends on national price movements. The significance of these regional contributions indicates that each region exhibits a distinct, long-memory causal effect on national housing price behaviour.

The observed bidirectional causality between the average UK housing price index (AVHP) and the devolved nations (England, Northern Ireland, and Scotland) reflects their strong integration with the national housing market and the broader credit cycle. In particular, Northern Ireland and Scotland, while smaller in scale, are highly sensitive to UK-wide macroeconomic policies and interest rate changes, leading to reciprocal price movements with the national index. The mixed results for English sub-regions also carry important economic implications. The bidirectional causality for the North East (NORE), North West (NORW), and South West (SOUW) is consistent with their role as affordability-driven regions where shifts in credit conditions and household migration pressures are quickly reflected in prices. By contrast, the unidirectional causality observed for the East (EAST, EASM), London (LOND), South East

(SOUE), and West Midlands (WESM) suggests that these markets are more influenced by national or global dynamics than they are in transmitting signals back to the wider market.

This pattern aligns with existing literature on ripple effects and regional heterogeneity. For example, Cook (2003) and Meen (1999) show that ripple effects are not uniform across all regions, and may be weaker where international capital flows (e.g., London) or strong labour market links (e.g., South East, West Midlands) dominate local housing demand. Similarly, Zhang et al. (2021) demonstrate that time-varying causality networks emerge where affordability pressures and migration dynamics drive regional spillovers. Situating these findings within such frameworks underscores that causality patterns are not merely statistical artefacts but reflect underlying institutional, demographic, and spatial-economic conditions.

These findings align with and extend insights from the wider housing literature. For instance, Zhang et al. (2021) show through dynamic network modelling that regional house price causality is time-varying and often led by affordability-driven markets rather than globalised hubs such as London. Similarly, Cohen et al. (2023) demonstrate that regime-dependent comovements emerge during macroeconomic transitions, which helps explain why the North East and North West act as affordability-sensitive transmitters during periods of credit expansion or contraction. The South West's persistent transmitter role can also be linked to its dual market function as both a primary residence and a second-home/retirement destination, consistent with literature highlighting the role of demographic and lifestyle drivers in shaping housing dynamics. Moreover, recent methodological contributions by Caporale and Gil-Alana (2025) and Contat and Larson (2024) underscore the importance of accounting for long-run equilibria and structural breaks, which is consistent with the cointegration and VECM results presented here. By integrating these strands of literature, the results suggest that peripheral affordability-driven markets act as early indicators of systemic adjustment, whereas London and the South East (though large in scale) are increasingly decoupled due to international investment flows.

Table 8: 5-year sub-Sample Tests

Variable	**2005-2009**	**2010-2014**	**2015-2020**	**2021-2024**	**Full Sample**
Model 1: Uk Sub-National					
ENGL	1.5976	1.3579	1.3331	5.2627	8.1414
	(0.4499)	*(0.5071)*	*(0.5135)*	*(0.0720)****	*(0.0043)**
NORI	3.6593	1.5969	0.1199	7.9441	8.8956
	(0.1605)	*(0.4500)*	*(0.9418)*	*(0.0188)***	*(0.0029)**
SCOT	1.0967	8.7814	1.3839	6.6807	8.4920
	(0.5779)	*(0.0124)***	*(0.5006)*	*(0.0354)***	*(0.0036)**
WALE	1.1806	1.9668	3.5395	6.6791	5.947574

	(0.5542)	(0.3740)	(0.1704)	(0.0355)**	(0.0147)**
Model 2: England Sub-sub-Regions					
EAST	1.5071	0.7259	0.8102	1.2858	4.7408
	(0.2196)	(0.6956)	(0.3680)	(0.5258)	(0.0295)**
EASM	0.9021	0.9865	0.2003	0.6037	10.405
	(0.3422)	(0.6106)	(0.6544)	(0.7394)	(0.0013)*
LOND	5.5681	0.9051	1.5742	3.7223	10.837
	(0.0183)**	(0.6360)	(0.2096)	(0.1555)	(0.0010)*
NORE	0.7488	0.5324	2.9393	13.536	2.2443
	(0.3868)	(0.7663)	(0.0864)***	(0.0011)*	(0.1341)
NORW	2.7890	1.3382	3.7519	3.0032	6.5121
	(0.0949)***	(0.5122)	(0.0527)***	(0.2228)	(0.0107)**
SOUE	0.2091	0.5562	0.4548	8.2142	0.1503
	(0.6474)	(0.7572)	(0.5000)	(0.0165)**	(0.6982)
SOUW	4.1991	0.4758	7.7169	11.655	13.633
	(0.0404)**	(0.7883)	(0.0055)*	(0.0029)*	(0.0002)*
WESM	1.8241	0.2321	0.5307	0.2356	2.1988
	(0.1768)	(0.8904)	(0.4663)	(0.8888)	(0.1381)
YORH	0.4721	1.6339	0.4157	1.7613	1.2564
	(0.4920)	(0.4418)	(0.5191)	(0.4145)	(0.2623)

In this table, the reviewed period is divided 5-year sample period i.e. 2005-2009 (GCF crisis), 2010-2014 (Brexit), 2015-2019 (Brexit/COVID 19), and 2020-2024 (post-COVID 19/Economy Recovery). The causal effect is captured using Granger Causality Wald Test for model estimation. The coefficients are reported as Chi-square values, with corresponding probability values in parentheses. The independent variables is UK average housing price index (AVGPH), the independent variables are the UK sub-regions (England, Scotland, Wales, and Northern Ireland), and the England sub-nationals. The tests were applied to both Model 1 and Model 2. Statistical significance is indicated at the 10% (***), 5% (**), and 1% (*) levels

An analysis of county-level housing prices in England reveals distinct regional influences on national housing price trends during major economic events. During the Global Financial Crisis (2005–2009), London, the North West, and the South West exhibited a noticeable causal impact on national housing price movements. In contrast, during the COVID-19 period, the North East and South East regions played a more prominent role, indicating that changes in housing prices within these regions were more reflective of national trends, while other regions showed less alignment. Over the full sample period, sub-regions in the East, East Midlands, London, North West, and South West demonstrated significant influence on national housing prices, though the magnitude of their effects varied. These findings highlight the presence of regional ripple effects, underscoring the limitations of using national housing price movements to fully capture the dynamics occurring at sub-national levels.

The weaker or insignificant causal relationships observed in regions such as Wales (WALE) and the East of England (EAST) can be explained by structural and market-specific factors. Wales exhibits greater policy autonomy in housing, planning, and mortgage regulation, which can partially decouple its price dynamics from the rest of the UK. In contrast, the East of England, while economically significant, has strong commuting and investment linkages with London, making its dynamics more synchronised with the capital rather than acting as an independent transmitter. These institutional and locational features reduce the strength of detectable causal signals in the empirical tests.

The results are further reinforced by comparing outcomes across the M-, S-, and MM-estimation techniques. While minor differences in coefficient magnitude are observed, the identification of core signal regions (North East, North West, South West) remains consistent across all estimators. The MM-estimator, which provides the strongest resistance to both leverage points and heavy-tailed errors, yields particularly stable results during volatile periods such as the 2008 Global Financial Crisis and the 2020 pandemic shock. This consistency across estimators underscores the robustness of the main findings.

The regional-level, time-varying data series span multiple economic and business cycles, including major events such as the Global Financial Crisis (2007–2008) and the COVID-19 pandemic (2020–2021). The consistency of results across robust estimation methods in this study mirrors findings by Susanti et al. (2014) and Singgih and Fauzan (2022), who demonstrate the reliability of M-, S-, and MM-estimators under non-normality and volatility. This is particularly important in housing datasets, which often exhibit heavy tails and crisis-driven outliers (Khotimah et al., 2019; Rahayu et al., 2023). To investigate the presence of any structural breaks in the relationship between regional and national housing price trends, the regression estimates were subjected to the Chow Breakpoint Test, with results presented in Table 9.

Table 9: Chow Breakpoint Test

Statistic	**Model 1 (UK Sub-Nationals)**	**Model 2 (England Sub-Nationals)**
F-statistic	30.50557	1.967464
(p-value)	(0.0000)	(0.0103)
Log likelihood ratio	352.0881	41.33829
(p-value)	(0.0000)	(0.0034)
Wald Statistic	732.1336	39.34928
(p-value)	(0.0000)	(0.0060)

The p-values from the Chow Breakpoint Test were statistically significant ($p < 0.05$), which indicates evidence of a structural break in the relationship between national and regional housing prices over the study period. This finding suggests that the causal relationship between national housing price trends (dependent variable) and regional housing price variations across UK and England sub-national levels (independent variables) has not remained stable, and may have changed at one or more points during the review period.

The evidence of a structural break at an unknown point in the regression estimates prompted further investigation to identify the specific time at which significant changes occurred in the model's parameters over the study period. To determine the precise breakpoint, the Quandt-Andrews Unknown Breakpoint Test was conducted, and the results are presented in Table 10

Table 10: Quandt-Andrews unknown breakpoint test

Statistics	**Model 1 (UK Sub-Nationals)**		**Model 2 (England Sub-Nationals)**	
	Breakpoint	**Coefficient**	**Breakpoint**	**Coefficient**
Maximum LR F-statistic (p-value)	2015M01	89.63225 (0.0000)	2012M02	22.00054 (0.0000)
Maximum Wald F-statistic (p-value)	2015M01	537.7935 (0.0000)	2012M02	220.0054 (0.0000)
Exp LR F-statistic (p-value)		39.75438 (0.0000)		8.695010 (0.0000)
Exp Wald F-statistic (p-value)		263.8341 (0.0000)		104.9649 (0.0000)
Ave LR F-statistic (p-value)		32.79690 (0.0000)		16.43772 (0.0000)
Ave Wald F-statistic (p-value)		196.7814 (0.0000)		164.3772 (0.0000)

In Model 1, a structural breakpoint was identified in January 2015 (2015M01), while for Model 2, the breakpoint occurred in February 2012 (2012M02). These breakpoints are supported by statistically significant p-values ($p < 0.05$) associated with the Maximum Likelihood Ratio (LR) F-statistic and the Maximum Wald F-statistic. Furthermore, consistent results were obtained from their respective variants — the Exponential LR and Wald F-statistics, and the Average LR and Wald F-statistics — all of which also indicated statistically significant values at the 5% level. This provides strong and consistent evidence of structural changes in both models during the study period. The significant shifts observed in the relationship between the national housing price trend and the UK sub-regions (Model 1: 2015M01), as well as the England sub-national regions (Model 2: 2012M02), may be attributed to underlying macroeconomic changes, policy interventions, or market shocks, potentially arising from or in response to regional housing market reforms.

To detect the long memory effect between national housing price movements and regional housing price spikes at the UK and England sub-national levels, the cointegration results presented in Table 11 confirm the existence of two cointegrating relationships for the UK sub-national regions. Both the Trace and Maximum Eigenvalue tests reject the null hypothesis of *no cointegration* at the 5% significance level ($p < 0.05$) at the 'None' and 'At most 1' levels. For the England sub-national regions, seven cointegrating relationships were identified, also with p-values below the 5% threshold. These findings confirm the presence of long-run equilibrium relationships between the UK average housing price and its sub-national counterparts, indicating both short-term and long-term influences on national housing price dynamics

Table 11: Johansen Cointegration Test

Hypothesized No. of CE(s)	Trace Rank Test			Maxi-Eigen Rank Test		
	t-Stats	CV (0.05)	Prob-Value	M-E Stats	CV (0.05)	Prob-Value
Model 1: Uk Sub-National						
None*	97.04244	69.81889	0.0001	40.84389	33.87687	0.0063
At most 1*	56.19855	47.85613	0.0068	32.85967	27.58434	0.0095
At most 2	23.33889	29.79707	0.2298	14.37638	21.13162	0.3349
At most 3	8.962512	15.49471	0.3689	8.617270	14.26460	0.3194
At most 4	0.345242	3.841466	0.5568	0.345242	3.841466	0.5568
Model 2: England Sub-sub-Regions						
None *	357.6698	239.2354	0.0000	89.02644	64.50472	0.0001
At most 1 *	268.6433	197.3709	0.0000	63.39821	58.43354	0.0151
At most 2 *	205.2451	159.5297	0.0000	50.68869	52.36261	0.0735
At most 3 *	154.5564	125.6154	0.0003	42.71565	46.23142	0.1137
At most 4 *	111.8408	95.75366	0.0025	32.67304	40.07757	0.2676
At most 5 *	79.16773	69.81889	0.0074	26.94332	33.87687	0.2664
At most 6 *	52.22440	47.85613	0.0184	24.47478	27.58434	0.1190
At most 7	27.74963	29.79707	0.0846	13.89597	21.13162	0.3736
At most 8	13.85365	15.49471	0.0870	12.02490	14.26460	0.1097
At most 9	1.828749	3.841466	0.1763	1.828749	3.841466	0.1763

The table summarizes the results of the Johansen cointegration analysis using both the Trace and Maximum Eigenvalue (Max-Eigen) tests. A cointegrating relationship (indicating a long-run equilibrium) is confirmed when the test statistic exceeds the 5% critical value in both the Trace and Max-Eigen tests.

The identification of cointegrating relationships within the models informed the application of the Vector Error Correction Model (VECM) to effectively capture both long-run and short-run dynamics, as well as the speed of adjustment toward long-run equilibrium. The results of the VECM estimation are presented in Table 12. The cointegration equation has been normalized by reversing the signs of the coefficients, by transforming positive values to negative and vice versa, in line with established conventions for interpreting cointegration equations (Abdellah, 2025; Barma, 2025).

For Model 1 (UK Sub-National), the contribution of sub-national housing prices to national UK housing price trends is positive and statistically significant ($p < 0.05$), though the magnitude of influence varies across regions. Specifically, housing prices in England exert the strongest long-run impact, as indicated by a high t-statistic (125.14), followed by Scotland (t-statistic: 16.59). However, the short-run estimates present a more mixed picture, with most effects being statistically insignificant ($p > 0.05$). These results suggest that sub-national housing price movements significantly explain the long-run dynamics of national housing prices in the UK, while their short-run effects are comparatively weaker and less statistically robust.

Table 12: Vector Error Correction Model

	Long run			**Short run (Δ)**		
	Coeff.	**Std. Err**	**t-Stats**	**Coeff.**	**Std. Err**	**t-Stats**
Model 1: Uk Sub-National (normalize)						
ENG	0.8268	0.0066	125.14	0.8793	0.8599	1.0226
NORTHI	0.0222	0.0024	9.0268	-0.0852	0.0450	-1.8929
SCOT	0.1363	0.0082	16.597	-0.1026	0.0879	-1.1671
WAL	0.0211	0.0087	2.4166	0.0702	0.0738	0.9510
ect. (-1)				*-0.2069*	*0.1617*	*-2.2790*
Model 2: England Sub-sub-Regions (normalize)						
EAST	1.1113	0.2376	4.6755	0.0746	0.12787	0.5839
EASM	-1.1460	0.2727	-4.2020	0.1393	0.12125	1.1490
LOND	0.6534	0.0854	7.6435	0.1812	0.09177	1.9753
NORE	0.5738	0.1175	4.8803	0.3292	0.15299	2.1520
NORW	2.3260	0.3469	6.7040	0.6109	0.13423	4.5517
SOUE	-2.4368	0.4146	-5.8769	0.0776	0.06481	1.1974
SOUW	1.3278	0.2591	5.1247	0.3376	0.10931	3.0889
WESM	1.7410	0.3784	4.6002	-0.0020	0.12398	-0.0166
YORH	1.8684	0.3810	4.9031	0.0795	0.12144	0.6549
ect. (-1)				*-0.3160*	*0.1290*	*-2.4489*

The table presents the results of the Vector Error Correction Model (VECM), conducted due to the presence of cointegration relationships over the study period (2003–2024). The dependent variables is UK Average housing price and the independent variables are the housing prices from the UK sub-nationals (model1) and England sub-nationals (model 2) The VECM is employed to capture both the long-run equilibrium dynamics and the short-run (Δ) relationships among the variables, as well as the speed at which deviations from the long-run equilibrium are corrected, measured by the error correction term [ECT(-1)]. For interpretation purposes, the signs of the coefficients have been normalized—positive signs have been converted to negative and vice versa—following the standard convention for interpreting cointegration equations.

For Model 2, the long-run estimates indicate that, with the exception of the East Midlands (t-statistic: -4.2020) and the South East of England (t-statistic: -5.8769), which exhibit negative and statistically significant effects ($p < 0.05$), all other sub-national regions within England show positive and statistically significant contributions to national housing prices ($p < 0.05$). However, in the short run, the impact of housing prices from most English sub-national regions is statistically insignificant ($p > 0.05$), with the exception of the North East (t-statistic: -2.1520), North West (t-statistic: 4.5517), and South West (t-statistic: 3.0889), which show statistically significant short-run effects ($p < 0.05$). These findings suggest that while sub-national housing prices within the UK and England have limited immediate influence on national housing price trends, they contribute significantly to the long-run dynamics of national housing prices. Furthermore, the negative and statistically significant coefficients of the error correction terms in both Model 1 (t-statistic: -2.2790) and Model 2 (t-statistic: -2.4489) confirm the models' validity and indicate that deviations from the long-run equilibrium are corrected over time.

Robustness Test Results

To affirm the consistency, reliability, and validity of the model estimations, robust least squares tests namely M-estimation, S-estimation, and MM-estimation, were employed to examine the robustness of the model outputs. The dependent variable is the UK Average Housing Price (AVHP), while the independent variables comprise the sub-national components of the UK in Model 1, and those of England in Model 2. The results, presented in Table 13, show that all UK sub-regions, including England, Northern Ireland, Scotland, and Wales, exhibit statistically significant effects on the average UK national housing price. These results align with the Granger causality tests, with the exception of Wales, likely due to the influence of outliers and heteroscedasticity in the time series data, issues that are effectively addressed by the robust estimation techniques.

Furthermore, the weak statistical contributions from the East Midlands and South East are consistent with the findings from the Granger causality Wald test, reaffirming their limited predictive influence on national housing price dynamics. While the results for the North East remain inconclusive, other regions namely the East, London, North West, South West, West Midlands, and Yorkshire, demonstrate consistently significant impacts on national housing prices. The model summary statistics indicate that over 80% of the variation in national housing prices is explained by the model, with the statistically significant F-value ($p < 0.05$) confirming the strong joint explanatory power of the regional housing price dynamics over the review period. The negative sign of the constant coefficient across the M, S, and MM estimators in Model 2 indicates that when there are no changes in the housing prices of England's sub-national regions, the national housing price trend continues to decline. This suggests that the sub-national regions of England play a significant role in driving national housing prices upward

Table 13: Robust Least Squares Test Results

Var	**M-estimation**				**S-estimation**				**MM-estimation**			
	β_i	$\propto_i$	z_{stat}	p_{value}	β_i	$\propto_i$	z_{stat}	p_{value}	β_i	$\propto_i$	z_{stat}	p_{value}
Model: UK sub-Regions												
ENGL	0.8437	0.0018	448.93	0.0000	0.8398	0.0010	786.47	0.0000	0.8431	0.0018	450.49	0.0000
NORI	0.0281	0.0007	40.273	0.0000	0.0309	0.0003	77.795	0.0000	0.0284	0.0006	40.820	0.0000
SCOT	0.0597	0.0019	30.984	0.0000	0.0713	0.0011	65.091	0.0000	0.0603	0.0019	31.421	0.0000
WALE	0.0645	0.0023	26.912	0.0000	0.0569	0.0013	41.789	0.0000	0.0644	0.0023	26.989	0.0000
C	0.0516	0.0080	6.4080	0.0000	0.0196	0.0045	4.2858	0.0000	0.0492	0.0080	6.1292	0.0000
Model Summary												
R-sq		0.8339				0.9951				0.7986		
Adj. R		0.8309				0.9949				0.7950		
Prob_Rn		0.0000				0.0000				0.0000		
Model 2: England sub-Regions												
EAST	0.1277	0.0242	5.2582	0.0000	0.0897	0.0357	2.5144	0.0119	0.1287	0.0244	5.2754	0.0000
ESTM	0.0051	0.0251	0.2063	0.8365	-0.035	0.0370	-0.9512	0.3415	0.0038	0.0252	0.1512	0.8798
LOND	0.1652	0.0097	16.882	0.0000	0.1777	0.0143	12.3603	0.0000	0.1656	0.0098	16.846	0.0000
NORE	0.0546	0.0130	4.1993	0.0000	0.0109	0.0191	0.5723	0.5671	0.0545	0.0130	4.1719	0.0000
NORW	0.2431	0.0309	7.8635	0.0000	0.3051	0.0454	6.7128	0.0000	0.2427	0.0310	7.8114	0.0000
SOUE	0.0203	0.0383	0.5300	0.5961	0.0278	0.0563	0.4949	0.6206	0.0178	0.0385	0.4632	0.6432
SOUW	0.1786	0.0254	7.0262	0.0000	0.1604	0.0373	4.2945	0.0000	0.1801	0.0255	7.0501	0.0000
WESM	0.0330	0.0334	0.9878	0.3232	0.1057	0.0491	2.1497	0.0316	0.0342	0.0336	1.0176	0.3089

YORH	0.2021	0.0338	5.9663	0.0000	0.1780	0.0498	3.5748	0.0004	0.2024	0.0340	5.9449	0.0000
C	-0.356	0.0607	-5.875	0.0000	-0.247	0.0893	-2.7725	0.0056	-0.357	0.0610	-5.856	0.0000
Model Summary												
R-sq		0.8886				0.9856				0.8782		
Adj. R		0.8839				0.9345				0.8732		
Prob_Rn		0.0000				0.000				0.0000		

The results of the robustness checks are presented in the table, employing robust least squares methods, namely M-estimation, S-estimation, and MM-estimation. The dependent variable is the UK Average Housing Price (AVHP), while the independent variables comprise the sub-national components of the UK in Model 1, and those of England in Model 2. The regression coefficients are denoted by beta (β_i), and their significance is assessed using the corresponding z-statistics. Statistical significance is determined at the 5% level ($p < 0.05$). The model summary includes the R-squared (R^2), adjusted R-squared (Adj. R^2), and the F-statistical probability (F-stat.), which together assess the model's explanatory power and overall fit.

In addition, the summary statistics of Model 1 and Model 2 indicate a statistically significant contribution to model variance ($p < 0.05$), as reflected by the adjusted R-squared (Adj. R^2) values. These results suggest strong model fitness and substantial predictive power. For Model 1, the adjusted R^2 values for the M-, S-, and MM-estimators were 83.09%, 99.49%, and 79.50%, respectively. In Model 2, the adjusted R^2 values were 88.39% for M-estimation, 93.45% for S-estimation, and 87.32% for MM-estimation. These high values indicate that the models account for a large proportion of the total variance in the data, thereby reflecting a high level of precision and explanatory power achieved through the use of robust estimation techniques.

This study delivers a multifaceted contribution to the understanding of housing price dynamics in the United Kingdom by articulating both empirical innovation and theoretical advancement. First, the analysis introduces and operationalises the concept of "signal regions" those regional housing markets whose price innovations consistently Granger-cause movements in the national house price index (HPI). These regions act as systemic transmitters of price information, and their consistent causal influence challenges the traditional spatial diffusion logic embedded in the ripple-effect hypothesis. By revealing a persistent leadership role for non-core regions such as the North East, North West, and South West, the findings reframe conventional narratives that privilege London as the epicentre of housing market contagion. This nuanced spatial hierarchy contributes to a more differentiated theory of interregional housing interdependence (Zhang et al., 2021; Guan et al., 2021; Shen et al., 2024; Tang et al., 2025), and offers strategic foresight for macroprudential oversight. For central banks and fiscal authorities, such as the Bank of England and HM Treasury, early detection of market shifts in these "signal regions" could significantly enhance spatially targeted policy responses and systemic risk forecasting.

Second, this study advances methodological robustness by implementing a triangulated regression framework based on M-estimation, S-estimation, and MM-estimation techniques. These estimators are specifically designed to address the statistical limitations often encountered in housing time-series data, including non-normal residual distributions, heteroskedasticity, and extreme-value outliers, issues exacerbated during financial crises and pandemic-induced market turbulence. In contrast to conventional least squares methods, the use of robust estimation ensures that the causal relationships detected are not artefacts of episodic volatility or structural anomalies (Susanti et al., 2014; Khotimah et al., 2019; Singgih & Fauzan, 2022; Trojanek et al., 2023; Tai, 2025). This methodological pluralism strengthens the internal validity of the empirical results and establishes a best-practice template for housing market econometrics under high-volatility regimes.

Third, the study adds depth by subjecting the inter-regional causal structure to structural break tests across five macro-financial regimes: the pre-Global Financial Crisis (2005–2007), the post-crisis adjustment phase (2008–2012), the recovery and Brexit transition (2013–2019), the COVID-19 pandemic shock (2020–2021), and the inflationary volatility period following the pandemic (2022–2024). The evidence demonstrates that regional housing markets exhibit time-varying patterns of influence on the national index, with certain "signal regions" increasing in systemic importance during periods of macroeconomic upheaval. Such findings underscore the temporal instability of housing market integration, revealing that causal relationships are neither static nor uniformly distributed but rather contingent on evolving economic contexts (Poon & Garratt, 2012; Carlos et al., 2015; Tunstall, 2022; Mbah & Wasum, 2022; Moreno-Foronda et al., 2025). This insight challenges the assumptions of stationarity underlying many previous models and signals the need for more dynamic policy instruments and time-sensitive econometric designs.

Fourth, the study's findings are situated within an integrated theoretical schema that draws on spatial equilibrium theory, arbitrage theory, and segmented market behaviour. In this framework, the persistence of directional causality among regions is interpreted not merely as a statistical artefact, but as a reflection of deeper institutional, behavioural, and structural rigidities. The evidence suggests that while some degree of national market integration exists, the UK housing market remains fundamentally segmented, a condition reinforced by regional supply constraints, lending disparities, and localised behavioural heuristics (Gabrielli & French, 2021; Fingleton, 2008; Liu, 2024). These findings not only align with, but also extend, the international evidence base on partial market integration and regional decoupling (Tsatsaronis & Zhu, 2004), offering important implications for regionally calibrated mortgage policy, fiscal interventions, and affordability metrics.

Taken together, these findings affirm the theoretical and empirical proposition that the UK housing market operates as a complex, evolving spatial system in which national averages may obscure critical inter-regional dynamics. By unveiling the persistent and time-contingent leadership of signal regions, employing robust statistical techniques to withstand data irregularities, and offering a theoretically grounded explanation of market segmentation, the study contributes to the academic discourse on housing market structure and provides actionable intelligence for policy design at multiple spatial scales.

5. Conclusion and Policy Implications

This paper has examined the causal interrelationships between regional and national housing prices in the United Kingdom over the period 2005 to 2024, employing a multivariate framework that integrates Granger causality, robust regression estimation (M, S, and MM), and structural break analysis. By disaggregating the UK into twelve regions—including the three devolved nations and nine English NUTS1 regions. This study provided a detailed, temporally rich, and spatially nuanced understanding of how housing price dynamics evolve and interact across space and time.

The theoretical framework drew on spatial equilibrium theory, ripple effect dynamics, market segmentation versus integration models, and the concept of housing market signal transmission. Empirically, the results challenge the longstanding assumption that London unilaterally leads national price trends. Instead, regions such as the North East, North West, and South West consistently exhibit causal influence on the national index, particularly during periods of structural change and macroeconomic uncertainty. These findings were robust across multiple estimation techniques and sample partitions, underscoring their reliability and policy relevance.

The literature review revealed a significant gap in UK-focused studies that integrate both constitutional geography and robust econometric methodologies to assess regional housing interdependencies. This research fills that void by offering a unified and empirically validated model that captures both the directionality and temporal stability of regional price spillovers.

From a policy perspective, the identification of signal regions offers a practical tool for enhancing the predictive power of national housing market surveillance. The structural break evidence also underscores the need for time-varying models in both housing finance and planning policy. Internationally, the methodology and conceptual framing can be readily adapted to other jurisdictions grappling with spatial housing inequalities, financialisation, and post-crisis recovery strategies.

The findings of this research carry significant implications for housing and financial policymakers, both in the United Kingdom and internationally. Most notably, the identification of “signal regions” such as the North East, North West, and South West of England—regions that Granger-cause national house price movements across multiple estimation techniques—provides a vital early-warning mechanism for monetary authorities and regulatory institutions. For the Bank of England, such regions offer additional temporal lead time in monitoring overheating risks, assessing affordability erosion, and calibrating counter-cyclical macroprudential tools such as mortgage lending criteria or stress-testing scenarios.

Moreover, the demonstrated breakdown of London’s historical dominance as a consistent price leader suggests the need for re-evaluating spatial assumptions embedded in national policy models. Central government agencies, such as HM Treasury and DLUHC (Department of Levelling Up, Housing and Communities), could reconsider funding allocations, planning targets, and housing investment priorities that have historically been biased toward London and the South East. The weakening of ripple dynamics from the capital implies that interventions must be tailored to region-specific dynamics rather than assuming a homogeneous policy multiplier across geographies.

These results extend Case and Shiller’s (1989) and Cook’s (2003) insights on ripple effects, showing that London’s leading role has weakened, while peripheral affordability-driven regions now act as transmitters. This shift is consistent with Zhang et al. (2021) and Cohen et al. (2023), who emphasise time-varying and regime-dependent causal networks. The policy implication is that macroprudential monitoring should incorporate regional signals beyond London and the South East.

Globally, the study contributes to the growing body of international evidence, paralleled in markets such as Canada, Australia, and parts of Europe that national house price indices may fail to reflect the true heterogeneity of regional housing conditions. Policymakers in countries with similarly centralised monetary regimes but regionally varied housing markets can adapt this framework to identify their own “signal regions” and causal hierarchies, thus improving the responsiveness and granularity of policy responses. The application of robust estimators (M/S/MM) further suggests that regulatory stress tests, risk models, and affordability forecasts should incorporate estimation techniques resilient to crisis-period volatility, which is increasingly relevant in the context of post-COVID economic regimes and climate-related risks.

Finally, the structural break findings reinforce the importance of temporal sensitivity in housing policy evaluation. Institutions must move away from static regional models and instead incorporate time-varying dynamics into their spatial analysis frameworks. In sum, this study advocates for a more disaggregated, robust, and causally aware approach to housing and financial policy, an imperative not just for the UK, but for all economies facing rising spatial inequality and systemic housing challenges.

The causality and regression results have direct implications for housing market policy and macroprudential regulation. The identification of the North East, North West, and South West as signal transmitters suggests that systemic risks in the housing market may emerge first in affordability-driven, credit-sensitive regions rather than in London or the South East. This challenges conventional policy frameworks that disproportionately focus on London-centric ripple effects (Cook, 2003; Case & Shiller, 1989). For example, the Bank of England’s stress-testing and mortgage market interventions could be enhanced by incorporating early-warning signals from peripheral regions, where shifts in credit conditions and household affordability pressures are more rapidly reflected in prices.

Furthermore, the weaker causal role of devolved and London-adjacent regions, such as Wales and the East of England, highlights the importance of institutional and spatial heterogeneity. Devolved housing policies, differing planning regimes, and varying exposure to international capital flows all influence the speed and extent of price transmission. Policymakers should therefore tailor interventions to regional dynamics rather than adopting a uniform national approach. These findings demonstrate how econometric evidence of causal linkages and robust estimation results can inform the design of region-sensitive housing and credit policies.

In conclusion, this study advances the understanding of spatial housing dynamics by integrating theory, method, and policy in a manner that reflects the complex realities of a post-pandemic, inflation-sensitive, and regionally diverse housing system. The study is limited by its reliance on regional-level data, excluding household-level variations, and by focusing mainly on the UK. It calls for further research incorporating household-level data, cross-border comparisons, and the dynamic interaction between housing and broader macro-financial systems. By doing so, it lays the groundwork for more granular, evidence-driven, and resilient housing policy both in the UK and globally.

References

Abdellah, O. (2025). Modeling Non-Stationary Processes in Panel Data Econometrics: Cointegration Tests and Error Correction Mechanisms Applied to Macroeconomic Time Series Across Multiple Countries. *Journal of Experimental and Computational Methods in Applied Sciences*, *10*(5), 1-13.

Bai, J., & Perron, P. (2003). Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics, 18*(1), 1–22.

Bailey, N., Livingston, M., & Chi, B. (2025). Housing and welfare reform, and the suburbanization of poverty in UK cities 2011–20. *Housing Studies, 40*(1), 185–206. https://doi.org/10.1080/02673037.2022.2128815

Barma, S. C. (2025). Exploring the Dynamic Interdependencies of Exchange Rates, Exports, and Imports in Kazakhstan: Johansen Cointegration & A Vector Autoregression Analysis. *IJSAT-International Journal on Science and Technology*, *16*(3).

Blakeley, G. (2021). Financialization, real estate and COVID-19 in the UK. *Community Development Journal, 56*(1), 79–99. https://doi.org/10.1093/cdj/bsaa037

Bressler, S. L., & Seth, A. K. (2011). Wiener–Granger causality: A well-established methodology. *NeuroImage, 58*(2), 323–329.

Caporale, G. M., & Gil-Alana, L. A. (2025). Long-run trends and cycles in US house prices. *Computational Economics*, 1–15. https://doi.org/10.1007/s10614-024-10403-6

Carlos Pestana Barros, Gil-Alana, L. A., & Payne, J. E. (2015). Modeling the long memory behavior in U.S. housing price volatility. *Journal of Housing Research, 24*(1), 87–106.

Case, K. E., & Shiller, R. J. (1989). The efficiency of the market for single-family homes. *American Economic Review, 79*(1), 125–137.

Chiwuzie, A. & Daniel I. D. (2021). Construction costs and house rents fluctuations in an emerging property market: the case of Osogbo, Nigeria. *Property Management, 39*(4), 527-545

Chuang, M. C., Yang, W. R., Chen, M. C., & Lin, S. K. (2018). Pricing mortgage insurance contracts under housing price cycles with jump risk: Evidence from the UK housing market. *The European Journal of Finance, 24*(11), 909–943. https://doi.org/10.1080/1351847X.2017.1381082

Cohen, J., Coughlin, C., & Soques, D. (2023). Housing Price Cycle Interdependencies and Comovement: A Markov-Switching Approach. *Journal of Real Estate Research*, *46*(2), 159–188. https://doi.org/10.1080/08965803.2023.2247293

Contat, J., & Larson, W. D. (2024). A flexible method of housing price index construction using repeat-sales aggregates. *Real Estate Economics*, 52, 1551–1583. https://doi.org/10.1111/1540-6229.12474

Cook, S. (2003). The convergence of regional house prices in the UK. Urban Studies, 40(11), 2285-2294

Czischke, D., & Van Bortel, G. (2023). An exploration of concepts and policies on 'affordable housing' in England, Italy, Poland and the Netherlands. *Journal of Housing and the Built Environment, 38*(1), 283–303. https://doi.org/10.1007/s10901-021-09891-4

Daly, J., Gronow, S., Jenkins, D., & Plimmer, F. (2003). Consumer behaviour in the valuation of residential property: A comparative study in the UK, Ireland and Australia. *Property Management, 21*(5), 295–314. https://doi.org/10.1108/02637470310493146

Daniel, E. D., Oshodi, O., Daniel, I. D., & Dimka, N. (2024). Towards closing the housing gap in the UK: exploration of the influencing factors and the way forward. *Construction Innovation, 24* (4), *965-985.*

Daniel, I. D., Chiwuzie, A., Guyimu, J., Asa, O. A., & Omotehinshe, O. J. (2022). Housing construction materials and house rent trends in Ede, Nigeria. *Pacific Rim Property Research Journal*, 27(3), 205-216.

Durmaz, N., Bian, S., & Gu, Y. (2025). Economic policy uncertainty and housing prices: Evidence from Northern and Southern Europe. *International Journal of Housing Markets and Analysis*. https://doi.org/10.1108/IJHMA-08-2023-0143

Elias, O. (2006). The diffusion of housing price movements from center to surrounding areas. *Journal of Housing Research, 15*(1), 3–28.

Fingleton, B. (2008). Housing supply, housing demand, and affordability. *Urban Studies, 45*(8), 1545–1563. https://doi.org/10.1177/0042098008091496

Foresti, P. (2006). *Testing for Granger causality between stock prices and economic growth* (MPRA Paper No. 2962). University Library of Munich.

Gabrielli, L., & French, N. (2021). Pricing to market: Property valuation methods–A practical review. *Journal of Property Investment & Finance, 39*(5), 464–480. https://doi.org/10.1108/JPIF-09-2020-0101

Goodman, A. C., & Thibodeau, T. G. (1998). Housing market segmentation. *Journal of Housing Economics, 7*(2), 121–143. https://doi.org/10.1006/jhec.1998.0229

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*(3), 424–438.

Gregory, A. W., & Hansen, B. E. (1996). Residual-Based Tests for Cointegration in Models with Regime Shifts. *Journal of Econometrics, 70*(1), 99–126.

Guan, C., Tan, M. J., & Peiser, R. (2021). Spatiotemporal effects of proximity to metro extension on housing price dynamics in Manhattan, New York City. *Journal of Transport and Land Use, 14*(1), 1295–1315. https://doi.org/10.5198/jtlu.2021.1910

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control,* 12(2–3), 231–254.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6), 1551–1580.

Khotimah, K., Sadik, K., & Rizki, A. (2019, August). Study of robust regression modeling using MM-estimator and least median squares. In *ICSA 2019: Proceedings of the 1st International Conference on Statistics and Analytics* (p. 100). European Alliance for Innovation. https://doi.org/10.4108/eai.2-8-2019.2290465

Liao, W. C., Zhao, D., Lim, L. P., & Wong, G. K. M. (2015). Foreign liquidity to real estate market: Ripple effect and housing price dynamics. *Urban Studies, 52*(1), 138–158. https://doi.org/10.1177/0042098014527481

Liu, L. (2024). The drivers of sustainable homeownership. Real Estate Economics, 52, 1379–1413. https://doi.org/10.1111/1540-6229.12511

Ma, S., & Zhang, S. (2025). Housing risk and the cross section of returns across many asset classes. *Real Estate Economics,* 53, 326–351. https://doi.org/10.1111/1540-6229.12519

Mahdavi, S., & Sohrabian, A. (1991). The link between the rate of growth of stock prices and the rate of growth of GNP in the United States: A Granger causality test. *The American Economist, 35*(2), 14–21.

Mbah, R. E., & Wasum, D. F. (2022). Russian-Ukraine 2022 war: A review of the economic impact of Russian-Ukraine crisis on the USA, UK, Canada, and Europe. *Advances in Social Sciences Research Journal,* *9*(3), 144–153. https://doi.org/10.14738/assrj.93.11991

Meen, G. (1999). Regional House Prices and the Ripple Effect: A New Interpretation. *Housing Studies*, *14*(6), 733–753. https://doi.org/10.1080/02673039982524

Meen, G. (2018). How should housing affordability be measured? *UK Collaborative Centre for Housing Evidence*, 3, 3–29. https://doi.org/10.18445/20180808-154559

Moreno-Foronda, I., Sánchez-Martínez, M. T., & Pareja-Eastaway, M. (2025). Comparative analysis of advanced models for predicting housing prices: A review. *Urban Science, 9*(2), 32. https://doi.org/10.3390/urbansci9020032

Ogunba, O. A., Daniel, I. D., & Gbadegesin, J. T. (2023). Sustainable real estate management practice: Exploring the priority of operational stage for actualizing sustainable built environment goal in sub-Saharan Africa. *International Journal of Construction Management*, 23(10), 1746-1755

Oikarinen, E. (2004). The diffusion of housing price movements from center to surrounding areas. *Journal of Housing Research, 15*(1), 3–28.

Oikarinen, E., & Engblom, J. (2016). Differences in housing price dynamics across cities: A comparison of different panel model specifications. *Urban Studies, 53*(11), 2312–2329. https://doi.org/10.1177/0042098015587820

Ojo, O., Daniel, I.D., & Ajayi, M. T. A. (2022). Performance of commercial and residential real estate investments in Ibadan property market, Nigeria. *Property Management, 40*(2), 169-191.

Olanrele1, O. O., Fateye, O. B., Adegunle, T. O., Ajayi, C. A. and Baaki, K. (2021). Causal effect of macroeconomic predictors on real estate investment trust's (REIT's) performance in Nigeria. *Pacific Rim Property Research Journal*. DOI: 10.1080/14445921.2020.1857498

Osei, P. M., Lo, J., Mueller, U., Richardson, S., & Afrifa-Yamoah, E. (2025). A trend-cycle analysis of the evolutionary trajectory of Australian housing prices. *Journal of Property Research*, 1–26. https://doi.org/10.1080/09599916.2024.2444884

Pani, S. S. (2024). House price dynamics under lower leverage: the case of metropolitan cities in India. International Journal of Housing Markets and Analysis, 17 (3), 814-836. https://doi.org/10.1108/IJHMA-10-2022-0161

Pérez-Molina, E. (2021). Exploring a multilevel approach with spatial effects to model housing price in San José, Costa Rica. *Environment and Planning B: Urban Analytics and City Science*, *49*(3), 987-1004. https://doi.org/10.1177/23998083211041122

Petris, P., Dotsis, G., & Alexakis, P. (2025). Do mortgage buy-to-let investors pay more or less for properties? Empirical evidence from the UK residential market. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2791

Pitros, C., & Arayici, Y. (2017). Housing cycles in the UK: A historical and empirical investigation. *Property Management, 35*(1), 89–108. https://doi.org/10.1108/PM-06-2016-0027

Poon, J., & Garratt, D. (2012). Evaluating UK housing policies to tackle housing affordability. *International Journal of Housing Markets and Analysis, 5*(3), 253–271. https://doi.org/10.1108/17538271211251241

Rahayu, D. A., Nursholihah, U. F., Suryaputra, G., & Surono, S. (2023). Comparison of the M, MM and S estimator in robust regression analysis on Indonesian literacy index data 2018. *EKSAKTA: Journal of Sciences and Data Analysis*, 11–22. https://doi.org/10.55927/eksakta.v4i1.254

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy, 90*(6), 1257–1278. https://doi.org/10.1086/261120

Rosen, S. (1979). *Wage-based indexes of urban quality of life.* In P. Mieszkowski & M. Straszheim (Eds.), *Current Issues in Urban Economics* (pp. 74–104). Johns Hopkins University Press.

Shen, H., Zhou, H., & Zhou, Z. (2024). Down payment requirements and house prices: Quasi-experiment evidence from Shanghai. *Real Estate Economics*, 52, 1414–1445. https://doi.org/10.1111/1540-6229.12465

Shukur, G., & Mantalos, P. (2000). A simple investigation of the Granger-causality test in integrated-cointegrated VAR systems. *Journal of Applied Statistics, 27*(8), 1021–1031. https://doi.org/10.1080/02664760050173364

Singgih, M. N. A., & Fauzan, A. (2022). Comparison of M estimation, S estimation, with MM estimation to get the best estimation of robust regression in criminal cases in Indonesia. *Jurnal Matematika, Statistika Dan Komputasi, 18*(2), 251–260. https://doi.org/10.20956/jmsk.v18i2.18288

Susanti, Y., Pratiwi, H., Sulistijowati, S., & Liana, T. (2014). M estimation, S estimation, and MM estimation in robust regression. *International Journal of Pure and Applied Mathematics, 91*(3), 349–360.

Tai, M. (2025). House prices and the allocation of consumer credit. Real Estate Economics, 1–31. https://doi.org/10.1111/1540-6229.12536

Tang, Y., Chen, Y., & Zhao, S. (2025). Regional Housing Supply and Demand Imbalance Qualitative Analysis in U.S. based on Big Data. In Proceedings of the 2024 5th International Conference on Big Data Economy and Information Management (BDEIM '24). Association for Computing Machinery, New York, NY, USA, 611–615. https://doi.org/10.1145/3724154.3724255

Trojanek, R., Gluszak, M., Kufel, P., & Trojanek, M. (2023). Discovering the determinants of house prices dynamics in Poland using Bayesian model averaging. *Economics and Sociology,* 16(4), 73-109. https://www.proquest.com/openview/cba83e1c33a701d3ce6eb07a55cb9af8

Tsai, I. C. (2024). The post-COVID-19 flattening phenomenon of regional housing prices in the UK. *Urban Studies*. https://doi.org/10.1177/00420980251327998

Tsatsaronis, K., & Zhu, H. (2004). What drives housing price dynamics: Cross-country evidence. *BIS Quarterly Review*, 65–78.

Tosin B. Fateye, Oluwaseun D. Ajayi, Cyril A. Ajayi, Abel Olaleye and Richard B. Peiser (2024). Causal behaviour of dynamic dividend yield of property stock in information asymmetric market: Evidence from South African listed property stock market, *International Real Estate Review* 27(3) 501 – 520

Tunstall, B. (2022). *Stay home: Housing and home in the UK during the COVID-19 pandemic*. Policy Press. https://doi.org/10.1332/policypress/9781447364741.001.0001

Wiener, N. (1956). *The theory of prediction*. In E. F. Beckenbach (Ed.), *Modern mathematics for the engineer* (pp. 53–59). McGraw-Hill.

Zhang, D., Ji, Q., Zhao, W. L., & Horsewood, N. J. (2021). Regional housing price dependency in the UK: A dynamic network approach. *Urban Studies, 58*(5), 1014–1031. https://doi.org/10.1177/0042098020958670

Zhang, P., & Hou, Y. (2015). The dynamics of housing price and land price in urban versus rural contexts. In *Proceedings. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association* (Vol. 108, pp. 1–40).

Regional-Level Analysis of Housing Price Dynamics in the United Kingdom: A Multivariate Causality Approach

Abstract

This paper investigates the dynamic causal relationships between regional housing markets and the national house price index in the United Kingdom from 2005 to 2024, capturing periods of economic expansion, financial crisis, post-Brexit uncertainty, COVID-19 disruption, and inflationary volatility. Drawing on a dual spatial framework, disaggregating the devolved nations and England's NUTS1 regions, this study employs Granger causality testing alongside a triad of robust regression estimators (M-estimator, S-estimator, and MM-estimator) to detect persistent and directional price leadership patterns. Empirical results identify three English sub-regions (the North East, North West, and South West) as consistent 'signal transmitters' whose house price innovations significantly Granger-cause movements in the national index. In contrast, London and the South East exhibit diminishing bidirectional influence, suggesting post-pandemic price decoupling and weakening spatial arbitrage. These findings contradict classical ripple-effect assumptions and indicate increasing segmentation within the UK housing system. The analysis is further strengthened by a series of robustness checks that accounts for structural breaks, heteroskedasticity, and outlier bias, thereby increasing confidence in the model's validity across the complex macro-financial cycles under investigation. The results carry material implications for policymakers, particularly the Bank of England, HM Treasury, and the Office for Budget Responsibility, as early-warning signals from peripheral regions could enhance macroprudential risk forecasting and affordability targeting. This paper contributes to the theoretical discourse on regional integration and market segmentation, offering a multi-scalar, statistically robust framework for assessing housing market dynamics in advanced economies. It also opens new directions for incorporating time-varying causality and spatial dependency into national housing policy design.

Keywords: Housing Market Segmentation, Housing Price Dynamics, Regional Market Integration, Spatial Spillovers, Signal Transmission

1. Introduction

The spatial dynamics of housing markets have emerged as a critical axis of scholarly enquiry and policy concern worldwide, especially in advanced economies where housing systems operate as both investment platforms and social infrastructure. In the United Kingdom (UK) in particular (which is also a reflection of many countries across the globe), the housing market is characterised by acute spatial heterogeneity, manifesting in divergent regional cycles, uneven affordability, and locally contingent demand-supply conditions. This divergence is further complicated by the centralised orientation of UK macroeconomic and regulatory policy, which often operates on national aggregates, despite increasing recognition that housing markets do not move in lockstep. The aftermath of the Global Financial Crisis (GFC), the economic ambiguities surrounding Brexit, the systemic shock of the COVID-19 pandemic, and the inflationary volatility of the post-2021 period have collectively intensified spatial disparities in housing outcomes (Blakeley, 2021; Ojo, et al., 2022; Bailey et al., 2025; Tsai, 2024). In this context, conventional tools and assumptions underpinning housing market analysis, particularly those reliant on national indices, appear increasingly inadequate for guiding policy or understanding inter-regional market behaviour.

Indeed, while the UK House Price Index (HPI) remains a widely consulted indicator of national housing market conditions, its explanatory power has come under scrutiny. National-level aggregates risk concealing the complex interdependencies and temporal asymmetries that characterise regional housing markets. Empirical evidence increasingly suggests that distinct regions experience unique cyclical patterns and may exercise leadership or laggard roles at different times, depending on macroeconomic regime shifts, local policy interventions, or demographic realignments (Zhang et al., 2021; Oikarinen & Engblom, 2016). Traditional ripple-effect models, long predicated on the assumption of spatial price diffusion from London outward (Elias, 2006; Liao et al., 2015), may no longer offer a complete or accurate framework for explaining the evolving structure of UK housing dynamics. As London exhibits signs of decoupling from national trends (Tsai, 2024; Zhang & Hou, 2015), the analytical imperative shifts towards models that can accommodate decentralised sources of market leadership and capture time-varying spatial dependencies.

Despite a robust international literature on housing price interdependencies (Daly et al., 2003; Poon & Garratt, 2012; Carlos et al., 2015; Chiwuzie & Daniel, 2021; Tunstall, 2022; Mbah & Wasum, 2022; Cohen et al., 2023; Ogunba, et al., 2023; Osei et al., 2025; Ma & Zhang, 2025; Moreno-Foronda et al., 2025), the UK-specific evidence base remains partial and fragmented. Existing studies rarely adopt a multilevel spatial framework that includes both the devolved nations (Scotland, Wales, and Northern Ireland) and the nine English regions at the Nomenclature of Territorial Units for Statistics 1 (NUTS1) level. Moreover, relatively few empirical investigations integrate methodological tools capable of accounting for structural breaks and outlier distortions, which are increasingly common in the wake of major economic shocks such as the GFC, Brexit, and the COVID-19 crisis (Contat & Larson, 2024; Caporale & Gil-Alana, 2025). This methodological narrowness limits both the reliability of causal inference and the policy utility of empirical findings. This lacuna is particularly consequential for institutions such as the Bank of England (BoE), HM Treasury, and the Department for Levelling Up, Housing and Communities (DLUHC), which depend on stable and regionally attuned indicators for macroprudential regulation and housing strategy development.

In response to these theoretical, empirical, and policy gaps, this study offers a comprehensive regional-level analysis of housing price dynamics in the United Kingdom over the period 2005 to 2024. The analysis employs a multivariate approach combining Granger causality testing (Granger, 1969; Foresti, 2006; Mahdavi & Sohrabian, 1991), robust regression estimation techniques (M, S, and MM estimators), and structural break diagnostics to assess the nature and stability of interregional housing market linkages in an eclectic analysis. These techniques are particularly well-suited to the challenges posed by housing time series data, which are often characterised by non-normal distributions, heteroskedasticity, and episodic volatility (Susanti et al., 2014; Khotimah et al., 2019; Singgih & Fauzan, 2022; Trojanek et al., 2023; Tai, 2025). The selected timeframe covers multiple macroeconomic regimes including the pre-GFC expansion, the crisis and post-crisis adjustment, Brexit-related uncertainty, the COVID-19 pandemic, and the post-COVID inflationary landscape, thus allowing for a segmented understanding of spatial housing dynamics.

To capture the full breadth of the UK housing geography, the study disaggregates the market into twelve analytical units: nine English NUTS1 regions and the three devolved nations. This spatial granularity facilitates a more nuanced appreciation of political-economic heterogeneity and regional policy divergence. The study introduces the concept of "signal regions" defined as those regional markets whose price innovations Granger-cause movements in the national index over multiple sub-periods. Unlike the traditional ripple-effect theory, which assumes a singular spatial trajectory of influence, the signal region framework allows for multiple, possibly shifting, centres of market transmission. This conceptual innovation draws on and extends recent theoretical debates concerning spatial equilibrium, market segmentation, and regionally contingent housing regimes (Fingleton, 2008; Bressler & Seth, 2011; Gabrielli & French, 2021; Rahayu et al., 2023; Liu, 2024).

While this study is situated within the context of the United Kingdom, its analytical framework and empirical insights hold broader relevance for housing systems across advanced and emerging economies. Spatial asymmetries in housing price dynamics, manifesting through regional divergences, market segmentation, and shifting price leadership are increasingly global phenomena, particularly in nations experiencing rapid urbanisation, decentralisation of labour markets, or regionally uneven policy regimes. The conceptual innovation of identifying "signal regions" as systemic transmitters of price movements, combined with a robust, crisis-resilient empirical methodology, provides a transferable template for cross-national research. As policy institutions worldwide confront the challenge of balancing national financial stability with subnational market volatility, the study's findings offer a replicable and policy-relevant model for detecting early signals of systemic housing risk, designing spatially responsive macroprudential tools, and enriching global debates on housing market integration, resilience, and governance.

The study pursues four key research objectives. First, it assesses the degree of regional price integration by applying bivariate and multivariate Granger causality analysis, thereby determining the extent to which housing market shocks in one region anticipate movements in others or in the national index. Second, it identifies and examines persistent signal regions, those whose price movements serve as leading indicators for national market trends, thus contributing to the development of early-warning systems for macroprudential oversight. Third, it interrogates the robustness of empirical findings by employing a triangulated estimation strategy that includes M-estimation, S-estimation, and MM-estimation approaches. These estimators improve statistical reliability by mitigating the influence of outliers and structural irregularities common in long-run housing data. Fourth, the analysis conducts structural break testing across the five macroeconomic regimes noted earlier, to evaluate whether the causal roles of regions remain stable or shift over time in response to major exogenous shocks.

In synthesising these objectives, the study aims to make three interlocking contributions. Theoretically, it advances the debate on spatial housing market interdependence by introducing a flexible framework that accommodates both price leadership and temporal instability. Empirically, it provides a robust, granular, and temporally segmented analysis of UK housing market dynamics, addressing methodological weaknesses in prior literature. From a policy perspective, it generates actionable insights for spatially targeted housing and financial regulation, especially in the design of regionally differentiated mortgage instruments, credit allocation frameworks, and affordability metrics.

The remainder of this paper is structured as follows. Section 2 reviews theoretical and empirical literatures on spatial housing price dynamics, focusing on inter-regional causality, ripple effects, and market segmentation. Section 3 outlines the data sources and methodological framework, including unit root tests, Granger causality modelling, robust regression techniques, and structural break analysis. Section 4 presents the empirical results, identifying regional hierarchies, evolving price leadership roles, and the stability of causal patterns across macroeconomic regimes. Section 5 concludes with a summary of contributions, implications, and avenues for future research.

2. Theoretical Underpinnings and Literature Review

The theoretical foundation of this study is anchored in several interrelated frameworks that explain regional housing price dynamics, spatial interdependencies, and price leadership hierarchies. These frameworks include the spatial equilibrium theory, ripple effect hypothesis, market segmentation and integration theory, and housing market signalling mechanisms.

2.1 Theoretical Underpinnings

This study adopts a multidimensional theoretical framework that synthesises four interrelated paradigms: spatial equilibrium theory, the ripple effect hypothesis, the segmentation–integration dichotomy, and signal-based price leadership. These frameworks collectively underpin the investigation of how regional housing markets in the United Kingdom transmit, absorb, or resist price shocks across time and space.

At its core, this research draws upon spatial equilibrium theory as originally posited by Rosen (1979) and extended by Roback (1982), which asserts that households choose locations based on a trade-off among wages, housing costs, and local amenities. In long-run equilibrium, these trade-offs lead to utility equalisation across regions. However, persistent regional price differentials signal the presence of spatial frictions—including land use regulation, transaction costs, information asymmetries, and labour immobility—that inhibit arbitrage and delay convergence. These frictions are particularly acute in the UK, where centralised macroeconomic policies are layered upon regionally uneven planning regimes and divergent housing supply elasticities (Meen, 1999; Fingleton, 2008).

Superimposed on this spatial framework is the ripple effect hypothesis, which traditionally posits a unidirectional diffusion of housing market shocks from core urban centres—most notably London—towards peripheral regions (Meen, 1999; Oikarinen, 2004). This perspective has historically informed much of UK housing research and policy. However, emerging empirical evidence suggests that this mechanism has become increasingly episodic, nonlinear, and asymmetric, particularly following macroeconomic dislocations such as the Global Financial Crisis, Brexit, and the COVID-19 pandemic (Cook, 2003; Zhang et al., 2021). These systemic shocks have contributed to a decline in London's price leadership, driven by structural behavioural shifts—including the rise of remote working, increased demand for space, and the suburbanisation of affordability-seeking households—which have reshaped spatial preferences and investment patterns. The result is a weakening of the classic concentric diffusion paradigm and the emergence of multiple, context-specific sources of price volatility.

In tandem, the literature on housing market segmentation and integration offers a critical lens to interpret these spatial asymmetries. In an integrated market, housing prices co-move in response to shared macroeconomic fundamentals, such as monetary policy, credit conditions, and national income trends. In contrast, segmented markets exhibit independent trajectories due to localised demand drivers, policy divergence, or institutional barriers (Goodman & Thibodeau, 1998; Case & Shiller, 1989). The UK's post-2016 housing dynamics increasingly reflect such structural segmentation, as regional affordability pressures, credit availability, and household formation diverge. Recent studies demonstrate similar tendencies in other advanced housing systems—including the United States, Germany, and Canada—where national indices obscure pronounced regional disparities and local frictions decouple regional prices from aggregate trends (Zhang et al., 2021; Gabrielli & French, 2021). These global parallels highlight the limits of treating national housing markets as homogenous entities, reinforcing the need for multi-scalar analysis.

Finally, this framework integrates the concept of price leadership and signal transmission, which challenges the traditional ripple effect by identifying “signal regions”—local housing markets whose price innovations Granger-cause movements in the national index (Zhang et al., 2021; Cohen et al., 2023). Unlike ripple-based diffusion, signal transmission recognises that leadership in housing markets can be discontinuous, multi-nodal, and time-varying, with certain regions emerging as bellwethers under specific macroeconomic regimes. These regions often reflect underlying investor sentiment, institutional adjustments, or policy inflections that anticipate broader systemic changes. By focusing on dynamic causality and leadership asymmetries, this approach aligns more closely with how housing markets behave under uncertainty and decentralised demand structures.

In summary, the theoretical architecture of this research weaves together spatial equilibrium logic, ripple diffusion critique, segmentation–integration analysis, and dynamic signal theory to reflect the complex, uneven, and evolving structure of UK housing markets. It conceptualises regional housing systems not as passive recipients of national trends but as active participants in a fragmented housing network, with the capacity to influence national aggregates under specific structural and behavioural conditions. This composite framework informs the study’s empirical design, which seeks to detect not only directionality of price influence but also the temporal stability and robustness of interregional linkages.

2.2. Literature Review

Understanding housing price dynamics within a multiregional context has long occupied scholars of urban economics, real estate finance, and regional planning. The literature spans conceptual, empirical, and policy-oriented dimensions, yet key gaps remain concerning the causal linkages between regions, temporal stability of interdependencies, and robustness of methods in the presence of structural shocks. This review addresses four major themes: (i) regional price interdependence and the ripple effect; (ii) market segmentation and integration in the UK housing market; (iii) methodological approaches to causality and robustness; and (iv) structural shocks and recent empirical advances.

2.2.1 Regional Price Interdependence and the Ripple Effect

Much of the early and mid-2000s literature on regional house price dynamics builds on the ripple effect hypothesis, which posits that price changes in dominant urban centres propagate outward over time (Oikarinen, 2004; Elias, 2006; Chuang, et al., 2018; Daniel et al., 2022; Osei et al., 2025). In the UK, London has traditionally been viewed as the epicentre of such ripples. However, the strength and direction of diffusion vary across cycles and subregions. Oikarinen and Engblom (2016) demonstrate that spatial diffusion is not uniform and may be conditioned by demographic, institutional, and policy differences across regions. Liao et al. (2015) further showed that capital inflows and foreign liquidity can amplify ripple effects in high-end markets but do not necessarily transmit to secondary cities.

More recent work challenges the linearity and stability of this effect. Zhang et al. (2021), using a dynamic network approach, identify evolving price leadership patterns, with northern and western regions occasionally leading, especially during the COVID-19 era. Similarly, Tsai (2024) documents a "flattening" of the traditional ripple pattern in post-pandemic UK, as hybrid work and affordability constraints shifted demand away from London to peripheral regions. These studies suggest a need to reconceptualise spatial interdependence beyond simple concentric diffusion models.

2.2.2 Market Segmentation and Integration in the UK

Closely related is the debate on housing market segmentation versus integration. In an integrated market, regional price movements co-move strongly due to arbitrage mechanisms, investor mobility, and common macroeconomic exposures. Conversely, segmented markets exhibit idiosyncratic trends, often reflecting local demand-supply imbalances, policy divergence, or structural barriers (Gabrielli & French, 2021; Czischke & Van Bortel, 2023; Pani, 2024; Daniel et al., 2024; Petris et al., 2025).

Evidence from UK studies remains mixed. Zhang et al. (2021) find increasing market segmentation post-2016, coinciding with Brexit and a weakening of London's price influence. Meen (2018) suggests affordability disparities across regions reflect structural segmentation, while Fingleton (2008) argues that housing supply rigidities reinforce localised market dynamics. Liu (2024) extends this argument by highlighting behavioural and credit-market frictions that limit arbitrage across regions.

The literature remains underdeveloped in identifying which regions act as consistent leaders or laggards, and few studies explicitly consider how price signals from some markets predict national trends. This paper addresses that gap by introducing the concept of "signal regions" and testing it empirically over a long temporal horizon.

2.2.3 Methodological Approaches to Causality and Robustness

Methodologically, many existing studies use bivariate or multivariate vector autoregressive (VAR) models to test for Granger causality or cointegration among regional housing markets (Shukur & Mantalos, 2000; Perez-Molina, 2021; Cohen et al., 2023;). While useful, these methods are often sensitive to violations of normality, structural breaks, and outliers common features in housing data due to policy shocks, market cycles, and transaction lags.

Recent contributions have advanced methodological approaches for analysing housing market dynamics. Caporale and Gil-Alana (2025) apply long-memory models to U.S. housing cycles, while Cohen et al. (2023) use Markov-switching frameworks to capture regime-dependent comovements. In the UK, Contat and Larson (2024) propose repeat-sales aggregation techniques to address transaction heterogeneity, and Zhang et al. (2021) employ dynamic network modelling to examine time-varying causality. Together, these studies reflect a shift toward frameworks that explicitly recognise persistence, heterogeneity, and regime changes in housing markets.

Beyond classical Johansen (1988, 1991) cointegration, which provides a likelihood-based framework for identifying and testing multiple cointegrating relationships in vector autoregressive models, this study extends the analysis to account for structural breaks and regime-dependent volatility. Johansen's methodology is particularly relevant here because it allows us to assess whether regional housing markets and the national index share long-run equilibria, a crucial step in determining whether "signal regions" persist beyond short-term causal dynamics. Subsequent advances beyond Johansen's methodology emphasise the importance of endogenously determined structural breaks. Gregory and Hansen (1996) introduced cointegration models with regime shifts, while Bai and Perron (2003) developed multiple-breakpoint tests for long time series. More recent applications by Caporale & Gil-Alana (2025) show that ignoring structural breaks can bias inference, particularly during disruptive events such as the Global Financial Crisis, Brexit, and COVID-19. To align with these developments, this study integrates Johansen cointegration analysis with structural break diagnostics, ensuring a robust assessment of both short-run adjustments and long-run equilibrium dynamics in UK housing markets.

At the same time, robust regression estimators remain underutilised in this domain, despite their advantages in addressing non-normality and volatility. MM-estimators, for instance, resist the influence of leverage points and heavy-tailed distributions (Khotimah et al., 2019; Rahayu et al., 2023). Similarly, Susanti et al. (2014) and Singgih and Fauzan (2022) demonstrate that M-, S-, and MM-estimators yield more reliable coefficients in crisis-prone datasets. This study therefore adopts a robust estimation framework to enhance the validity of causal inferences and ensure resilience against structural irregularities.

2.2.4 Structural Shocks and Empirical Advances

A final body of literature examines how macroeconomic shocks including financial crises, pandemics, geopolitical tensions—reshape regional housing markets. Pitros and Arayici (2017) show that housing cycles in the UK are punctuated by regime changes, suggesting a need for structural break modelling. Blakeley (2021) and Tunstall (2022) trace the COVID-19 pandemic's disruptions to housing consumption patterns, while Bailey et al. (2025) document the suburbanisation of poverty and uneven affordability shocks across UK cities.

More recent contributions incorporate uncertainty and volatility indices. Durmaz et al. (2025) demonstrate that economic policy uncertainty significantly alters housing price volatility in Southern Europe. Zhang et al. (2021) find that London's price influence diminished during periods of systemic uncertainty, reinforcing the need for time-varying analytical techniques.

These studies suggest that regional price causality is unlikely to be stable over time and must be empirically re-evaluated in light of recent shocks. This paper responds by conducting structural break tests and dividing the sample into key macroeconomic phases to assess the stability of interregional dynamics.

Despite the extensive body of literature on regional housing dynamics, much of the existing work remains fragmented, either constrained by pre-2020 data horizons, focused narrowly on London-centric ripple effects, or methodologically reliant on estimators sensitive to structural shocks and outliers. While spatial equilibrium theory, ripple diffusion models, and segmentation-integration paradigms have individually advanced our understanding of regional price behaviour, they have not been fully integrated into a unified empirical strategy that captures both the directionality and robustness of interregional price relationships. Recent macroeconomic disruptions including Brexit, the COVID-19 pandemic, and subsequent inflationary pressures have further destabilised traditional spatial hierarchies, raising fundamental questions about which regions now serve as price leaders or systemic signal transmitters. This study is motivated by the need to close this empirical and conceptual gap by applying a multivariate, robustness-enhanced framework to assess UK regional housing price dynamics across devolved nations and English NUTS1 regions from 2005 to 2024. In doing so, it leverages spatial equilibrium logic to assess convergence, ripple-effect logic to evaluate price diffusion, segmentation theory to interpret causal asymmetries, and leadership theory to identify signal regions. By unifying these strands and deploying Granger causality testing with M/S/MM robust estimation and structural break analysis, this research delivers a temporally sensitive and theoretically grounded assessment of UK housing market interdependencies. The findings not only refine the theoretical map of spatial housing dynamics but also respond directly to policy demands for more accurate, regionally disaggregated market signals to support macroprudential surveillance and spatially targeted housing interventions.

3. Methods

Variable Description and Study Area

This study employs monthly time-series data on housing price indices to examine housing price dynamics in the UK housing market over the past two decades, from January 2005 to December 2024. During this period, the global economy experienced several major disruptions, including the Global Financial Crisis (2007/2008), the COVID-19 pandemic (2019/2020), and the ongoing Russia-Ukraine war, each exacerbating tensions in housing price trends in the region.

All housing price indices were sourced from the UK House Price Index (HPI), published by HM Land Registry and available on GOV.UK (https://www.gov.uk). The HPI database categorizes UK housing prices into two main groups. The first category covers the four constituent nations of the UK (England, Northern Ireland, Scotland, and Wales) referred to in this study as the UK sub-regions. The second category breaks down England into nine regions: East, East Midlands, London, North East, North West, South East, South West, West Midlands, and Yorkshire and The Humber, collectively referred to as the England sub-regions in this study (*Figure 1*). A detailed description of the variables used, their sources, and data manipulation is provided in Table 1.

Table 1: Variable Description

Category	**Acronyms**	**Descriptions**
UK sub-Regions (Model 1)		
England	ENGL	Housing price index for the respective continent nations generated from HM Land Registry at GOV.UK, monthly data, unit £, 2005 Jan.-2024 Dec., 277 observations, not seasoned, log transformed, independent variable.
Northern Ireland	NORI	
Scotland	SCOT	
Wales	WALS	
England sub-Regions (Model 2)		
East	EAST	Housing price index for the respective region in England generated from HM Land Registry at GOV.UK, unit £, monthly data, 2005 Jan.-2024 Dec., 277 observations, not seasoned, log transformed, independent variable.
East Midlands	EASM	
London	LOND	
North East	NORE	
North West	NORW	
South East	SOUE	
South West	SOUW	
West Midlands	WESM	
Yorkshire and The Humber	YORH	
UK Average House Price	AVHP	UK housing price index generated from HM Land Registry at GOV.UK, monthly data, unit £, 2005 Jan.-2024 Dec., 277 observations, not seasoned, log transformed, Dependent variable.

The terms 'UK sub-Regions' and 'England sub-Regions' are acronyms used in this study to group the housing price data for analytical purposes. 'UK sub-Regions' refers to the four constituent nations of the United Kingdom (England, Scotland, Wales, and Northern Ireland) while 'England sub-Regions' denotes the nine official regions within England.

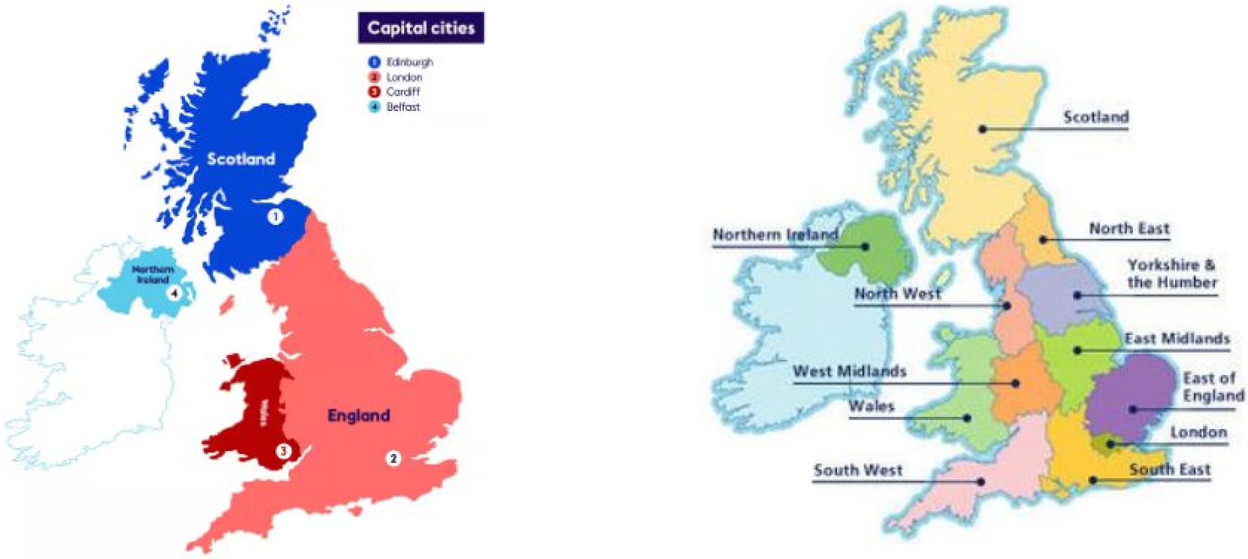


Figure 1 showing the UK sub-Regions and the England sub-Regions

Normal Distribution and Unit Root Tests

Preliminary tests, including normality and unit root assessments, were conducted to evaluate the model's fitness and the precision of the time-series data. To assess the data distribution pattern, the Quantile-Quantile (Q-Q) plot technique was employed. Unit root testing, a crucial step for analysing time-series data, was conducted to determine the stationarity of the dataset. The study applied both the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to enhance robustness. Evidence of stationarity is confirmed when the null hypothesis of a unit root is rejected at a significance level of 5% ($p < 0.05$). These tests were performed at level I(0) and first difference I(1), using a model specification that includes an intercept and the Schwarz Information Criterion. Ensuring stationarity and structural stability is essential for reliable econometric modelling and confidence in the resulting estimates.

Main Analysis: Bivariate Analysis

The bivariate analysis employed in this study utilizes the pairwise Granger causality test, originally conceptualized by Norbert Wiener (Wiener, 1956) and later formalized by Clive Granger (Granger, 1968). This test is a feedback-based stochastic technique used to measure causal relationships between two time-varying series over a specified review period. As explained by Bressler and Seth (2011), consider two variables, A and B. If we attempt to predict A_{t+1} using only the historical values of A, and then compare this with a prediction of A_{t+1} using both the past values of A and B, a significant improvement in prediction in the latter case implies that B contains useful information for predicting A_{t+1} that is not in the past of A for forecasting A. Causality is established by *rejecting* the null hypothesis, which states that *"B does not Granger-cause A,"* at a probability value less than the 5% significance level ($p < 0.05$). In such a case, B is said to *Granger-cause* A. Following Foresti (2006), the causal relationship between A and B may be *unidirectional* or *reciprocal.*

In the context of this study, for instance, we explore the directional causal relationship between the UK average house price index ($(AVHP_i$) and the London house price index ($LOND_i$) in a VAR environment. As discussed by Mahdavi and Sohrabian (1989), this interaction can be expressed using two equations, with the first equation presented in Eqn 1

$$AVHP_t = \alpha + \sum_{i=1}^{p} \beta_i (AVHP)_{t-1} + \sum_{j-1}^{q} \tau_t (LOND)_{t-j} + \varepsilon_t ----- Eqn.1$$

Where α is a constant and ε_t represents the residual error term. In this model, $AVHP_t$ is the dependent variable, explained by its own lagged values $AVHP_{t-1}$ through the coefficients (β_i) and by the lagged values of the London house price index ($LOND_{i-j}$). If the inclusion of past values of ($LOND_{i-j}$) leads to a statistically significant improvement in the prediction of $AVHP_{t-1}$, then it can be concluded that ($LOND_{i-j}$) *Granger-causes*$AVHP_{t-1}$.

In the second equation presented in Eqn 2, the dependent variable is London house price index ($LOND$) while the UK average house price index ($AVHP$). Thus $AVHP_{t-1}$ granger cause $LOND_t$, If the knowledge of past information contains $AVHP_{t-1}$ leads to significant improvement in the prediction of $LOND_t$

$$LOND_t = \alpha + \sum_{i=1}^{p} \tau_i (LOND)_{t-1} + \sum_{j-1}^{q} \beta_t (AVHP)_{t-j} + \varepsilon_t ----- Eqn.2$$

From the g-causality analysis in $Eqn.1$ and $Eqn.2$, hypotheses of four cases can be identified and tested (Foresti, 2006). They are:

a) UK average house price index ($AVHP_{t-i}$) can *granger-cause* London house price index ($LOND_{t-j}$) but not vice versa (Unidirectional) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} = 0 \; and \sum_{t=j}^{q} \tau_t (LOND)_{t-j} \neq 0 ----- Eqn\ 3$$

b) London house price index ($LOND_{t-j}$) can *granger-cause* UK average house price index ($AVHP_{t-i}$) but not vice versa (Unidirectional) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} \neq 0 \; and \sum_{t=j}^{q} \tau_t (LOND)_{t-j} = 0 ----- Eqn\ 4$$

c) UK average house price index ($AVHP_{t-i}$) can *granger-cause* London house price index ($LOND_{t-j}$) and vice versa (Bidirectional) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} = 0 \; and \sum_{t=j}^{q} \tau_t (LOND)_{t-j} = 0 ----- Eqn\ 5$$

d) UK average house price index $(AVHP_{t-i})$ cannot *granger-cause* London house price index $(LOND_{t-j})$ and vice versa (Independent) i.e.

$$\sum_{t=i}^{p} \beta_i (AVHP)_{t-1} \neq 0 \; and \; \sum_{t=j}^{q} \tau_t (LOND)_{t-j} \neq 0 \; ------ Eqn\ 6$$

The lag length was varied from order 1 to 5 to account for the model's sensitivity to lag structure. The bivariate Granger causality test was conducted between the UK average housing price index and the housing prices of both UK national regions and England counties.

Optimal lag lengths for the VAR and VECM specifications were determined using the Akaike Information Criterion (AIC), ensuring both statistical adequacy and model parsimony. The analysis is conducted at the NUTS1 regional level, encompassing the devolved nations (Scotland, Wales, Northern Ireland) and the nine English regions, as published in the UK House Price Index by HM Land Registry. County-level data were not employed, as they are not consistently available in monthly frequency over the study period, and the regional scale aligns with macroprudential policy frameworks. Structural break tests were implemented which identifies regime shifts endogenously. The detected breakpoints coincide closely with major macroeconomic disruptions namely the Global Financial Crisis (2008), Brexit referendum (2016), the onset of the COVID-19 pandemic (2020), and post-pandemic inflationary pressures (2021), thereby enhancing the robustness of the causality and cointegration results.

For the multivariate model estimation, a Granger Causality Wald Test statistic (see *Eqn. 7*) was employed. The test uses a chi-square distribution to evaluate joint hypotheses about the coefficients of time-varying series within a VAR framework. To clarify the econometric framework, Granger causality is employed to test whether lagged values of one regional housing price series contain predictive information about another series beyond its own history. In this context, the null hypothesis states that regional prices do not Granger-cause movements in the national index, while rejection of the null indicates predictive or directional influence. This approach is operationalised within a vector autoregressive (VAR) setting, with optimal lag lengths determined by information criteria. By summarising these hypotheses and their application, we ensure transparency in how Granger causality is used to identify "signal regions" within the UK housing market.

$$W = \left(R\acute{\beta} - r\right)' \left[R(\widehat{Var}(\hat{\beta}))\acute{R}\right]^{-1} (R\hat{\beta} - \acute{r}) ------ Eqn\ 7$$

$\hat{\beta}$ represents the estimated coefficients from the unrestricted regression. RRR is the matrix that selects the relevant coefficients for testing, while R is the vector of hypothesized values under the null hypothesis. The null hypothesis that *"X does not Granger-cause Y"* is rejected if the probability value is less than the 5% significance level ($p < 0.05$), indicating that past values of X significantly improve the prediction of Y.

Cointegration Equation (CE)

The cointegration equation is employed to determine whether a long-run relationship exists between the exogenous variable (UK national housing prices) and the explanatory variables: UK sub-national housing prices (Model 1) and England sub-national housing prices (Model 2). Given the multivariate nature of the analysis, this study adopts the Johansen cointegration technique. The Johansen approach produces two key test statistics: the Trace Statistic and the Maximum Eigenvalue Statistic. The conventional equations for the Trace and Max-Eigen statistics are presented in $Eqn.$ 8 and $Eqn.$ 9, respectively.

i) Trace Statistic (r)

$$r = -T \sum_{i=r+1}^{n} ln(1-\pi_i) - - - - - - - - - - - - - - Eqn.\, 8$$

ii) Maximum Eigenvalue Statistic *(r, r+1)*

$$r = -T\, ln(1-\pi_{r+1}) - - - - - - - - - - - - - - Eqn.\, 9$$

Based on the Johansen cointegration test, the null hypothesis of no cointegrating vector is rejected at the 5% significance level

Vector Error Correction Model (VECM)

The presence of cointegration implies that both immediate (short-run) and long-term relationships exist among the time-varying series. In such cases, the Vector Error Correction Model (VECM) is an appropriate modelling approach within the Vector Autoregression (VAR) framework. The VECM not only captures the short-run dynamics and long-run equilibrium relationships but also accounts for deviations from the long-run path, indicating the speed at which the system adjusts back to equilibrium following a shock. The conventional specification of the Vector Error Correction Model (VECM) is provided in $Eqn.$ 10.

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + \epsilon_t - - - - - - - - - - - - - - Eqn.\, 10$$

Where Δ denotes the first-difference operator applied to an (n x 1) vector of variables; Π and Γ_i capture information about the long-run relationships and short-run dynamics, respectively. The parameter k represents the lag length corresponding to the integration order of the VAR model. μ denotes the constant or deterministic component, ϵ_t is the vector of error terms. A 5% significance level is adopted as the threshold for determining statistical significance in the model.

Robustness Checks.

For the robustness check, we employed robust least squares techniques namely M-estimation, S-estimation, and MM-estimation. These methods are particularly effective in addressing key econometric challenges such as the influence of outliers, variability in estimates, heteroscedasticity, and the non-normal distribution of time series data. Their application enhances the reliability and precision of model estimates, especially when standard ordinary least squares (OLS) assumptions are violated.

These techniques have been widely endorsed in the literature where applied robust least squares methods in real estate valuation analysis have demonstrated their effectiveness in managing outlier-influenced datasets (Rahayu et al., 2023; Singgih & Fauzan, 2022; Khotimah et al., 2019; Susanti et al., 2014). The study found that these estimators provided more stable and reliable parameter estimates compared to conventional OLS, thereby improving the overall robustness of empirical findings.

The conventional equation function of for the M-estimation, S-estimation, and MM-estimation is expressed in *Eqn. 11*, *Eqn. 12* and *Eqn. 13*.

i) M-estimator minimize influence of outlier

$$\widehat{\beta_s} = \arg_\beta \min \sum_{i=1}^{n} \rho \left(\frac{y_i - {x_i}^T \beta}{\hat{\sigma}} \right) ------ Eqn\ 11$$

ii) S-estimators minimize residual error

$$\widehat{\beta_s} = \arg_\beta min \ \ s(r_1(\beta), r_2(\beta), \ldots, r_n(\beta)) ------ Eqn\ 12$$

iii) MM-estimators refine M-estimators to provide high statistical efficiency

$$\widehat{\beta_{MM}} = \arg_\beta \min \sum_{i=1}^{n} \rho \left(\frac{y_i - {x_i}^T \beta}{\hat{\sigma}} \right) ------ Eqn\ 13$$

While Granger causality techniques were employed to test predictive precedence between variables within a VAR framework, robust least squares methods (specifically M-estimators, S-estimators, and MM-estimators) were used to enhance the accuracy and reliability of parameter estimates in the presence of data irregularities such as outliers and high-leverage points. Unlike traditional Ordinary Least Squares (OLS), which is highly sensitive to such anomalies, these robust techniques are designed to minimize the influence of outliers and maintain model stability even when classical regression assumptions (e.g., homoscedasticity and normality) are violated, thereby improving the overall precision and validity of the model.

4. Findings

Preliminary Result

The summary descriptive statistics of the average housing price index for the UK, both at the UK sub-regions and England sub-regions are presented in Table 2 and Table 3. Empirical evidence indicates that among the UK's sub-regions, only England exhibits mean and median housing price index values that exceed the national average. In contrast, other sub-regions namely Northern Ireland, Scotland, and Wales, have housing price indices below the national average. This finding underscores the significantly higher housing prices in England, which are strongly linked to an intensifying affordability crisis, particularly affecting vulnerable and urban-poor populations.

The elevated housing prices in England are largely attributed to the competitiveness of its housing market and the cosmopolitan nature of its urban centres. These factors have drawn substantial internal and external migration, contributing to rapid population growth and increasing demand, thereby putting upward pressure on housing prices. On the other hand, the lower housing price indices recorded in regions such as Northern Ireland reflect relatively more affordable housing markets. However, these regions are characterized by less competitive markets and lower population pressures.

Table 2: Summary Descriptive Statistics for Average UK housing Price index and UK sub-Nationals

	AVHP	ENGL	NORI	SCOT	WALE
Mean	203812.5	215491.7	139377.0	141989.1	151066.2
Median	190032.0	200825.0	134619.0	136891.0	141503.0
Max.	291716.0	311059.0	224670.0	193673.0	220878.0
Min.	150488.0	158609.0	97428.00	93554.00	121070.0
Std. Dev.	40035.22	44518.62	29529.32	21255.62	27079.12
Skew	0.726806	0.657041	0.889624	0.804637	1.270024
Kurt	2.371791	2.214117	3.342634	3.242591	3.479008
Jarque-Bera	23.71805	22.17436	31.05287	25.05147	63.19392
Prob	0.000007	0.000015	0.000000	0.000004	0.000000
Obs.	227	227	227	227	227

Note: Average UK Housing price (AVHP), England (ENGL), North Ireland (MORI), Scotland (SCOT), and Wales (WALS), Maximum (Max.), Minimum (Min.), Standard Deviation (Std. Dev.), Probability (Prob), No of observations (Obs.)

Significantly higher variability in England's housing price index is observed, with price index extremes ranging from 158609.00 to 311059.00 and a standard deviation of 44518.62. This variability is expected due to sub-regional disparities, where housing prices in central urban areas are markedly higher than in peripheral zones. These urban centers tend to attract private investment due to their profitability and strategic location. Similarly, the average UK housing price index demonstrates fluctuations between 150488.00 (minimum) and 291716.00 (maximum), with a standard deviation of 40035.22.

In contrast, the housing price indices for other UK sub-regions show lower levels of variability, indicating more stable housing markets with less volatility and uncertainty. Nevertheless, the price indices for all UK regions, including the national average, follow a relatively none-normal distribution (see Figure 2). Notably, Scotland and Wales exhibit leptokurtic distributions, as evidenced by skewness and kurtosis statistics. The statistically significant Jarque-Bera test further confirms the dispersion and non-linear distribution patterns of the housing price index time-series data.

Table 3: Summary Descriptive Statistics for England sub-Regions

	EAST	EASM	LOND	NORE	NORW	SOUE	SOUW	WESM	YORH
Mean	242990.4	170315.3	383049.9	128648.1	152168.4	274479.3	227925.4	176050.4	151537.9
Median	221817.0	155033.0	398737.0	124799.0	143009.0	257701.0	211576.0	161813.0	144594.0
Max.	358418.0	251161.0	543572.0	163100.0	218353.0	397696.0	333922.0	253854.0	211911.0
Min.	168263.0	129876.0	231263.0	110454.0	117630.0	191156.0	171356.0	136966.0	120419.0
Std. Dev.	57902.22	35056.31	103265.4	12307.21	26301.13	61953.20	45203.04	33419.64	24307.82
Skew	0.489006	0.940111	0.000207	1.185688	1.159698	0.441651	0.859407	0.959391	1.095189
Kurt	1.830649	2.720011	1.339929	3.669093	3.288690	1.852596	2.638989	2.756208	3.172200
Jarque-Bera	21.98012	34.17890	26.06560	57.42256	51.67031	19.83182	29.17564	35.38512	45.65928
Prob	0.000017	0.000000	0.000002	0.000000	0.000000	0.000049	0.000000	0.000000	0.000000
Obs.	227	227	227	227	227	227	227	227	227

Note: East (EAST), East Midlands (EASM), London (LOND), North-east (NORE) North-west (NORW), South-east (SOUE), South-west (SOUW), West Midlands (WESM), Yorkshire and The Humber (YORH)

An analysis of the housing price index across regions in England reveals that London has the highest mean price index (383,049.9) and median value (398,737.0), significantly surpassing the national average. London also exhibits the greatest variability, with a standard deviation of 543572.0 and a wide range between the highest (543572.0) and lowest (231263.0) values. This suggests that housing prices in London do not reflect the overall UK housing market. Beyond London, higher-than-average price indices are observed in the East (242990.0), South East (274479.3), and South West (227925.4), all showing relatively greater price fluctuations over the review period. In contrast, other regions in England recorded housing price indices below the national average, with the lowest observed in Yorkshire and the Humber (YORH). The distribution of the housing price index data follows a non-linear pattern, as evidenced by skewness and kurtosis statistics and a statistically significant Jarque-Bera test ($p < 0.05$).

In addition, *Figure 2* illustrates the non-linear distribution patterns of housing price indices across the UK and its sub-regions, including those within England using Quantile-Quantile plot (Q-Q) techniques. Notably, *Figure 3* highlights the overall trajectory of housing price indices, reflecting long-term trends and regional disparities within the broader UK housing market.

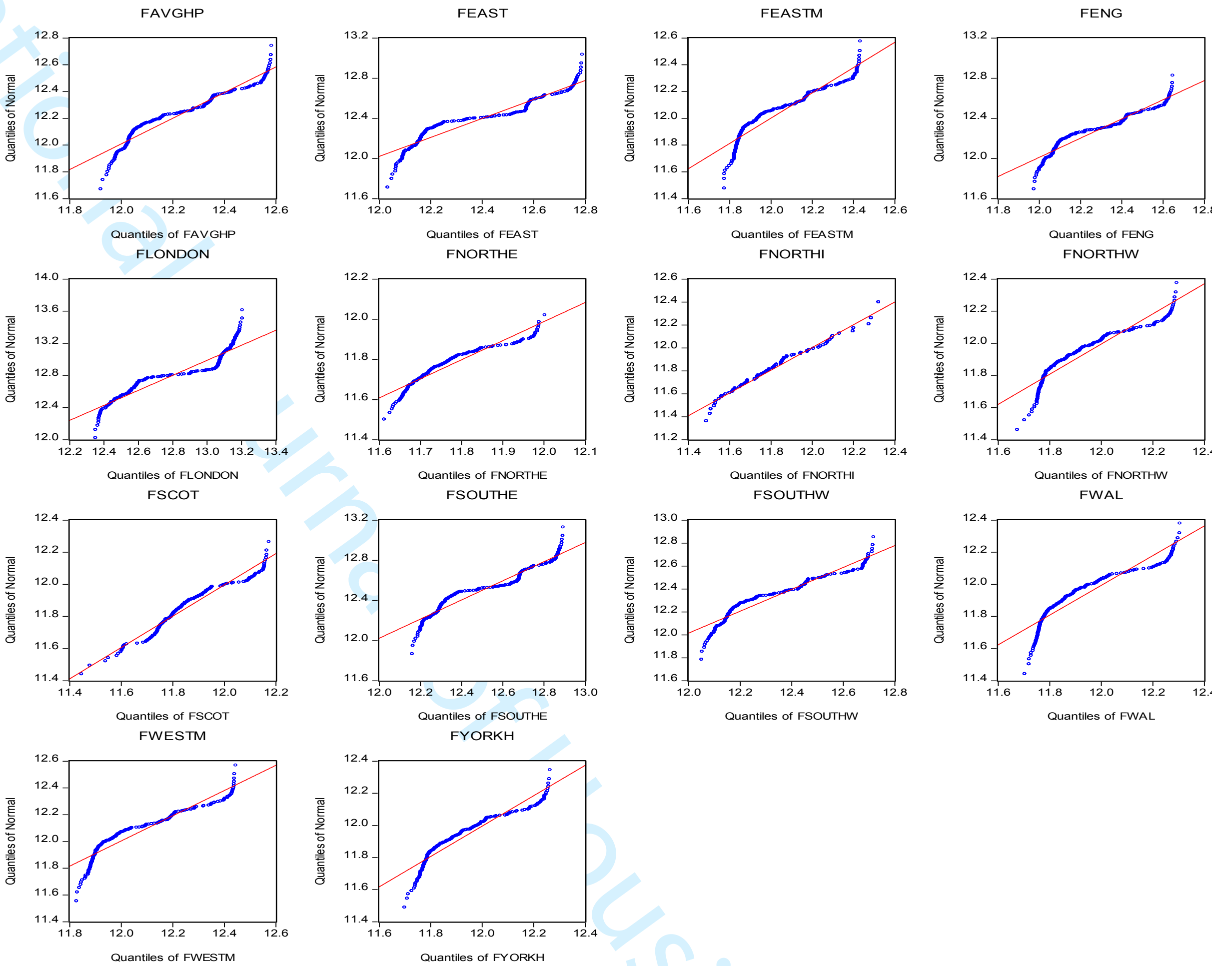


Figure 2 illustrates the normal distribution pattern of the variables using a Q-Q (quantile-quantile) plot.

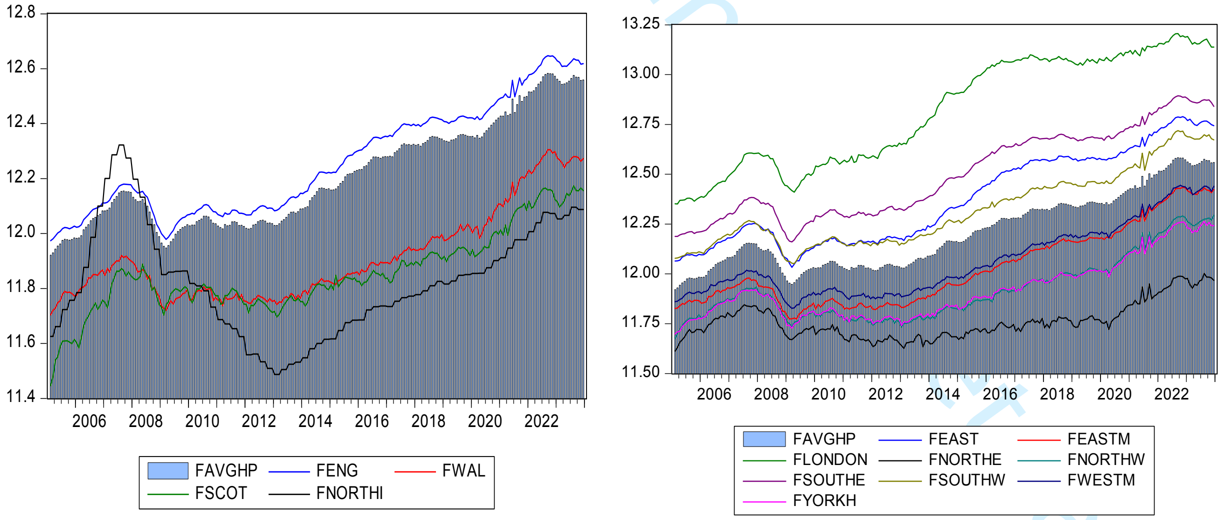


Figure 3 displays the trends in the Housing Price Index (HPI) for the UK average national housing prices, the devolved UK regions (England, Scotland, Wales, and Northern Ireland), as well as the regions within England.

In addition to the descriptive statistics (Table 3), which indicate deviations from normality through skewness, excess kurtosis, and the Jarque–Bera test, the unit root tests (Table 4) further confirm that the regional housing price series are non-stationary in levels. Taken together, the evidence of non-normality and non-stationarity justifies the modelling approach adopted in this study. Specifically, differencing the series ensures valid inference in the time-series framework, while the application of robust estimation techniques mitigates the influence of heavy-tailed distributions and volatility clustering that are characteristic of housing price dynamics, particularly during crisis periods.

The stationarity tests for the variables were conducted using the Augmented Dickey-Fuller (ADF). Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) techniques for the UK average housing price index, UK sub-regions, and England sub-regions. The results presented in Table 4 indicate that all data series become stationary at their first differences, i.e., they are integrated of order one [I(1)]. This finding is consistent with previous studies, which frequently report that economic indicators typically achieve stationarity at the I(1) level (Fateye et al., 2024; Olanrele et al., 2021). To ensure the robustness of the unit root testing, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test was employed as a complementary approach. The KPSS test results were consistent with those of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, confirming the stationarity of the variables at first difference lag length order (I(1)). The stationarity characteristics of the time series data confirm the appropriateness of the dataset for econometric analysis, ensuring the reliability, validity, and accuracy of subsequent estimations.

Table 4: Unit Root tests

Variable	**ADF**			**PP**			**KPSS LM-Stat (critical value @5%)**		
	@ Level	**@1st Diff.**	**Stat.**	**@ Level**	**@1st Diff.**	**Stat.**	**@ Level**	**@1st Diff.**	**Stat.**
Model 1: UK sub-Regions									
AVHP	0.2051	-4.6061	*I[1]*	-0.1274	-13.129	*I[1]*	1.7855	0.1193	I[1]
	(0.9724)	*(0.0002)**		(0.9438)	*(0.0000)**		(0.463)	(0.463)	
ENGL	0.1042	-6.0931	*I[1]*	-0.0650	-14.601	*I[1]*	1.8277	0.1165	I[1]
	(0.9654)	*(0.0000)**		(0.9505)	*(0.0000)**		(0.463)	(0.463)	
NORI	-2.3625	-3.0994	*I[1]*	-1.3612	-17.031	*I[1]*	0.3439	0.1574	I[1]
	(0.1537)	*(0.0280)**		(0.6008)	*(0.0000)**		(0.463)	(0.463)	
SCOT	-0.8671	-2.5282	-	-1.9090	-14.464	*I[1]*	1.5702	0.1641	I[1]
	(0.7971)	*(0.1102)*		(0.3278)	*(0.0000)**		(0.463)	(0.463)	
WALS	1.00152	-18.341	*I[1]*	(0.5089)	-17.971	*I[1]*	1.4781	0.3034	I[1]
	(0.9966)	*(0.0000)**		(0.9867)	*(0.0000)**		(0.463)	(0.463)	
Model 2: England sub-Regions									
EAST	-0.5387	-4.6056	*I[1]*	-0.1965	-14.744	*I[1]*	1.8539	0.1124	I[1]
	(0.8798)	*(0.0002)**		*(0.9356)*	*(0.0000)**		(0.463)	(0.463)	
EASM	0.4855	-5.6126	*I[1]*	0.8582	-16.453	*I[1]*	1.6807	0.3575	I[1]
	(0.9859)	*(0.0000)**		*(0.9948)*	*(0.0000)**		(0.463)	(0.463)	
LOND	-1.2477	-5.4448	*I[1]*	-1.2364	-13.787	*I[1]*	1.9044	0.1648	I[1]
	(0.6538)	*(0.0000)**		*(0.6589)*	*(0.0000)**		(0.463)	(0.463)	
NORE	-0.5639	-19.181	*I[1]*	-0.9647	-18.912	*I[1]*	0.9093	0.1457	I[1]
	(0.8746)	*(0.0000)**		*(0.7658)*	*(0.0000)**		(0.463)	(0.463)	
NORW	0.5448	-6.4416	*I[1]*	0.3478	-18.376	*I[1]*	1.4917	0.2665	I[1]
	(0.9879)	*(0.0000*)*		*(0.9803)*	*(0.0000)**		(0.463)	(0.463)	
SOUE	-0.8886	-4.4885	*I[1]*	-0.4060	-12.788	*I[1]*	1.8761	0.0776	I[1]
	(0.7906)	*(0.0003)**		*(0.9046)*	*(0.0000)**		(0.463)	(0.463)	

SOUW	-0.3747 *(0.9099)*	-5.1886 *(0.0000)**	*I[1]*	0.1389 *(0.9680)*	-16.910 *(0.0000)**	*I[1]*	1.7641 (0.463)	0.1564 (0.463)	I[1]
WESM	0.4507 *(0.9847)*	-5.8935 *(0.0000)**	*I[1]*	0.8179 *(0.9942)*	-17.693 *(0.0000)**	*I[1]*	1.6732 (0.463)	0.3274 (0.463)	I[1]
YORH	-0.0133 *(0.9555)*	-6.3794 *(0.0000)**	*I[1]*	0.0936 *(0.9647)*	-18.176 *(0.0000)**	*I[1]*	1.5405 (0.463)	0.2022 (0.463)	I[1]

This table presents the stationarity characteristics of the time-varying data series used in the analysis, based on unit root test statistics: the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The tests are conducted at both the level form (I(0)) and the first-differenced form (I(1)). For the ADF and PP tests, the null hypothesis of a unit root (i.e., non-stationarity) is rejected at the 5% significance level when the p-value is less than 0.05. In contrast, for the KPSS test, the null hypothesis assumes stationarity, and it is not rejected if the test statistic is below the 5% critical value. This study adopts the 5% threshold to evaluate statistical significance and determine the integration order of each series.

The strength of stationarity at first difference also varies across regions, and this variation has an important economic context. Regions such as Wales (WALS) and Northern Ireland (NORI) record larger negative ADF statistics at the first-difference level, indicating sharper price adjustments and stronger mean-reverting behaviour. This can be explained by their relatively smaller and less diversified economies, which render housing markets more sensitive to national credit cycles and policy shocks. By contrast, regions with more diversified and internationally exposed housing demand, such as London, display slower adjustment dynamics and correspondingly weaker test statistics. These differences highlight how structural and economic characteristics condition the speed and strength of adjustment in regional housing markets, adding depth to the interpretation of the unit root results.

Main Result

The volatility of housing price indexes across UK sub-regions and England sub-regions is further highlighted by the Cholesky factor analysis presented in Figure 4. The national housing price index exhibited relatively mild fluctuations in its structural response to external shocks, with a notable structural break occurring around 2021 coinciding with the period of economic recovery following the COVID-19 disruptions.

In contrast, Northern Ireland experienced higher volatility in housing prices during the early part of the review period (2006–2008), while regions such as England showed greater turbulence in the later years (2020–2022). These differences in structural adjustment to external forces across UK regions suggest that housing price dynamics are more locally driven rather than being determined by national trends. Similar volatility patterns were also observed in housing price indexes within England, with certain areas such as Yorkshire experiencing marked fluctuations during specific periods. These results are consistent with Meen's (1999) argument that housing markets exhibit sluggish adjustment to shocks, and with Oikarinen's (2004) findings of persistence in regional price dynamics. The weaker evidence for Scotland reflects institutional and policy differences in devolved housing systems, which often lead to distinctive adjustment speeds.


VAR Structural Residuals using Cholesky (d.f. adjusted) Factors
FAVGHP Structural Residuals
FENG Structural Residuals
FNORTHI Structural Residuals
FSCOT Structural Residuals
FWAL Structural Residuals

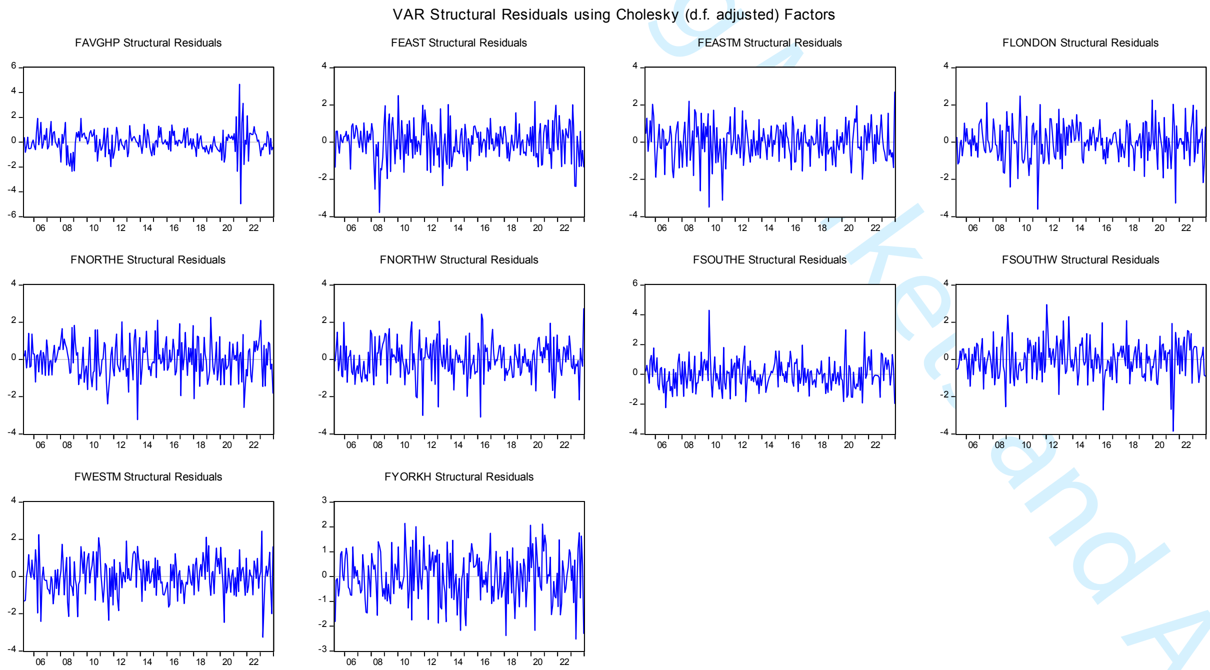

VAR Structural Residuals using Cholesky (d.f. adjusted) Factors
FAVGHP Structural Residuals
FEAST Structural Residuals
FEASTM Structural Residuals
FLONDON Structural Residuals
FNORTHE Structural Residuals
FNORTHW Structural Residuals
FSOUTHE Structural Residuals
FSOUTHW Structural Residuals
FWESTM Structural Residuals
FYORKH Structural Residuals

Figure 4 present the structural response of the UK sub-regions and England sub-regions to national housing index over the review period (2005-2024) in the VAR framework. The housing price index experienced fluctuations across the study areas at varying levels, with highest volatility regime in England at National level and Yorkshire at England counties. The depict the spatial differences in the housing prices across UK indicating more segregated housing market

The correlation matrices presented in Table 5a and Table 5b summarize the strength of association among the variables included in Model 1 and Model 2, respectively. In Model 1, which examines the relationship between the average UK housing price index and regional housing markets, all sub-regions exhibit strong positive correlations with the national average, with the exception of Northern Ireland (r = 0.4067), which shows a relatively weaker degree of association. In Model 2, the England sub-regions exhibit stronger correlations with the national housing price trends. Notably, the South West (r = 0.7978), East Midlands (r = 0.7897), and East of England (r = 0.7896) demonstrate the highest degrees of association, indicating a more pronounced alignment with the overall UK housing market dynamics. Nevertheless, the overall positive correlations suggest a degree of co-movement between regional housing prices and national housing trends, albeit with varying strengths across regions.

Table 5a: Correlation Matrix for Model 1: UK sub-Regions

	X_1	X_2	X_3	X_4	X_5
X_1	1				
X_2	0.7984	1			
X_3	0.4067	0.3608	1		
X_4	0.7393	0.7254	0.5103	1	
X_5	0.7567	0.7422	0.5653	0.7361	1

X_1-AVGHP, X_2-ENG, X_3-NORTHI, X_4-SCOT, X_5-WAL

Table 5b: Correlation Matrix for Model 2: England sub-Regions

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	1									
X_2	0.7896	1								
X_3	0.7897	0.7704	1							
X_4	0.7252	0.7611	0.6729	1						
X_5	0.6111	0.5283	0.6501	0.5483	1					
X_6	0.7632	0.7193	0.7815	0.7914	0.8262	1				
X_7	0.7865	0.7981	0.7611	0.7116	0.7126	0.8075	1			
X_8	0.7978	0.7848	0.7932	0.7109	0.8209	0.7685	0.7809	1		
X_9	0.7890	0.7669	0.7989	0.6665	0.8595	0.7855	0.7574	0.6926	1	
X_{10}	0.7729	0.7331	0.7858	0.6153	0.7158	0.7981	0.7233	0.67701	0.7893	1

X_1-AVGHP, X_2-EAST, X_3-EASTM, X_4-LONDON, X_5-NORTHE, X_6-NORTHW, X_7-SOUTHE, X_8-SOUTHW, X_9-WESTM, X_{10}-YORKH

The study conducted a bivariate causality test to determine the direction of causal relationships between the average UK housing price and the housing prices in UK sub-regions and England sub-regions. The test was performed across lags 1 to 5 to account for the sensitivity of the method to changes in lag order. As presented in Table 6, the p-values indicate statistically significant causal relationships ($p < 0.05$) between the average housing price index and all the UK sub-regions namely, England, Northern Ireland, and Scotland, suggesting a bidirectional causal effect across all lags. For example, changes in the national average housing price strongly influence housing price dynamics in England, and conversely, fluctuations in England's housing prices significantly affect the national index. Similar bidirectional causality is observed in the relationships with Northern Ireland and Scotland.

At the regions level within England, bidirectional causality is evident between the UK national average housing price and England sub-regions such as the North-East, North-West, and South-East, implying mutual influence. However, other counties including the East, East Midlands, London, South West, and West Midlands. exhibit a unidirectional causal relationship. In these cases, changes in the UK national average housing price significantly influence regional housing prices, but the reverse effect is not statistically supported across the tested lags.

Table 6: Bivariate Granger Causality Test

Null Hypothesis	X_{-1}	X_{-2}	X_{-3}	X_{-4}	X_{-5}	Decision
Model 1: UK sub-Regions						
ENGL ≠ AVHP	2.6757	19.453	11.780	8.7763	7.8906	
	(0.1033)	*(2.E-08)**	*(4.E-07)**	*(1.E-06)**	*(8.E-07)**	*Bidirectional*
AVHP ≠ ENGL	1.9454	24.666	15.695	10.988	10.751	
	(0.1645)	*(2.E-10)**	*(3.E-09)**	*(4.E-08)**	*(3.E-09)**	
NOR1 ≠ AVHP	2.7148	8.0396	8.78054	5.23214	4.5702	
	(0.1008)	*(0.001)**	*(2.E-05)**	*(0.0005)**	*(0.0006)**	*Bidirectional*
AVHP ≠ NORI	1.6165	10.810	12.169	2.0739	2.7170	
	(0.2049)	*(3.E-05)**	*(2.E-07)**	*(0.0853)**	*(0.0211)**	
SCOT ≠ AVHP	6.0588	15.005	8.5276	7.4272	6.4574	
	*(0.0146)***	*(8.E-07)**	*(2.E-05)**	*(1.E-05)**	*(1.E-05)**	*Bidirectional*
AVHP ≠ SCOT	18.335	11.530	5.1133	3.9467	4.0085	
	*(3.E-05)**	*(2.E-05)**	*(0.0019)**	*(0.0041)**	*(0.0017)**	
WALS ≠ AVHP	0.4334	0.1972	0.3955	0.5097	0.5686	
	(0.5110)	*(0.8211)**	*(0.7563)**	*(0.7287)**	*(0.7240)**	*Bidirectional*
AVHP ≠ WALS	3.5883	15.89	18.995	13.999	10.469	
	*(0.0595)***	*(4.E-07)**	*(6.E-11)**	*(4.E-10)**	*(5.E-09)**	
Model 2: England sub-Regions						
EAST ≠ AVHP	3.0375	1.4943	1.0454	1.3639	0.8126	
	(0.0827)	*(0.2267)*	*(0.3733)*	*(0.2475)*	*(0.5418)*	*Unidirectional*
AVHP ≠ EAST	1.2931	9.5422	0.3733	8.7193	8.9124	
	(0.2567)	*(0.0001)**	*(3.E-05)**	*(2.E-06)**	*(1.E-07)**	
ESTM ≠ AVHP	0.7815	1.6014	0.8609	1.2486	1.0664	
	(0.3776)	*(0.2040)*	*(0.4622)*	*(0.2914)*	*(0.3800)*	*Unidirectional*
AVHP ≠ ESTM	1.1582	19.1784	12.9295	12.4266	9.8559	
	(0.2830)	*(2.E-08)**	*(8.E-08)**	*(4.E-09)**	*(2.E-08)**	
LOND ≠ AVHP	1.7168	1.6759	0.8106	1.0730	1.0601	
	(0.1915)	*(0.1895)*	*(0.4892)*	*(0.3708)*	*(0.3835)*	*Unidirectional*
AVHP ≠ LOND	4.3566	7.1545	10.1521	6.5625	6.2651	
	*(0.0380)**	*(0.0010)**	*(3.E-06)**	*(5.E-05)**	(2.E-05)*	
NORE ≠ AVHP	5.4826	4.9733	3.1069	2.3975	2.1616	
	*(0.0201)**	*(0.0077)**	*(0.0274)***	*(0.0513)**	*(0.0596)**	*Bidirectional*
AVHP ≠ NORE	4.3063	11.9176	9.4531	8.0354	7.1453	
	*(0.0391)**	*(1.E-05)**	*(7.E-06)**	(5.E-06)*	*(3.E-06)**	
NORW ≠ AVHP	3.9149	9.5262	7.5119	3.9430	3.8537	
	*(0.0491)***	*(0.0001)**	*(8.E-05)**	*(0.0041)**	*(0.0023)**	*Bidirectional*
AVHP ≠ NORW	3.7804	24.007	21.088	14.016	13.748	
	*(0.0531)**	*(4.E-10)**	*(5.E-12)**	*(4.E-10)**	*(1.E-11)**	
SOUE ≠ AVHP	2.6727	1.68825	1.44187	0.72922	0.93611	
	(0.1035)	*(0.1872)*	*(0.2315)*	*(0.5729)*	*(0.4585)*	*Unidirectional*
AVHP ≠ SOUE	2.0313	5.56034	4.13871	4.41998	5.34347	
	(0.1555)	*(0.0044)**	*(0.0070)**	*(0.0019)**	*(0.0001)**	
SOUW ≠AVHP	0.0111	4.1088	3.2347	2.3295	1.4026	

	(0.9161)	*(0.0177)**	*(0.0232)***	*(0.0571)**	*(0.2246)*	*Bidirectional*
AVHP ≠ SOUW	8.9969	15.864	17.172	11.611	9.5829	
	*(0.0030)**	*(4.E-07)**	*(5.E-10)**	*(1.E-08)**	*(3.E-08)**	
WESM ≠ AVHP	0.0505	1.9574	1.1841	1.6399	1.4091	
	(0.8223)	*(0.1437)*	*(0.3167)*	*(0.1653)*	*(0.2222)*	*Unidirectional*
AVHP ≠ WESM	3.3907	18.059	17.647	17.253	13.454	
	(0.0669)	*(5.E-08)**	*(3.E-10)**	*(3.E-12)**	*(2.E-11)**	
YORH ≠ AVHP	3.9025	6.2867	3.3520	2.2724	2.5818	
	*(0.0494)**	*(0.0022)**	*(0.0199)**	*(0.0625)*	*(0.0272)**	*Bidirectional*
AVHP ≠ YORH	5.2355	15.768	14.317	9.0417	8.9751	
	*(0.0231)***	*(4.E-07)**	*(2.E-08)**	*(9.E-07)**	*(1.E-07)**	

The table presents the results of the bivariate analysis examining the causal relationship between the average UK housing price index (AVHP) and housing prices (HP) across UK sub-regions and England sub-regions. The Granger causality test was conducted across lags 1 to 5. The direction of causality may be: (i) unidirectional, where AVHP Granger-causes HP but not vice versa (AVHP → HP, HP ≠ AVHP); (ii) bidirectional, where both variables Granger-cause each other (AVHP ↔ HP); or (iii) no causal effect, where neither variable Granger-causes the other (AVHP ≠ HP, HP ≠ AVHP). The reported values are F-statistics, with corresponding probabilities in parentheses. The null hypothesis of no causal relationship is rejected at the 5% significance level ($p < 0.05$).

The study presents mixed results regarding the diffusion of national housing prices to regional housing markets. On one hand, the observed bidirectional influences between UK national housing prices and the national housing market contradict the ripple effect and spatial equilibrium theories, which emphasize price divergence across regions (Zhang et al., 2021; Fingleton, 2008). This mutual influence suggests a price synergy between national housing prices and overall market dynamics, indicating a degree of market integration. On the other hand, at the sub-national level within England, the majority of regions exhibit a unidirectional influence, where local housing prices contribute to national housing price movements. Notably, the North East, North West, and South East regions display bidirectional causal relationships with national housing price trends. These disparities in causal effects imply that national housing prices do not fully reflect regional price dynamics, supporting the ripple effect hypothesis, which is based on the assumption of segmented market behaviour, particularly at regional levels (Zhang et al., 2021; Cohen et al., 2023). The presence of bidirectional causality in this study reflects the interdependence of regional housing and labour markets, consistent with Rosen's (1979) and Roback's (1982) spatial equilibrium models, and with Goodman and Thibodeau's (1998) evidence of feedback effects between regional price shocks

In Table 7, the Granger Causality Wald Test was conducted, and two models were developed. Model 1 comprises the UK sub-regions (England, Northern Ireland, Scotland, and Wales) while Model 2 includes the England sub-regions: East, East Midlands, London, North East, North West, South West, West Midlands, and Yorkshire and the Humber (YORH). The test was conducted across multiple lag structures (lag 1 to lag 5).

In Model 1, the average UK national housing price is statistically significantly influenced ($p < 0.05$) by all the UK sub-regions at lag 1, including by the historical values of their housing prices at lags 4 and 5 except for Wales, which shows no statistically significant effect ($p > 0.05$) across all lags showing higher housing market price integration with the national housing trends. For Model 2, which examines the England sub-regions, the explanatory power of regional housing prices on the national housing price index is generally less statistically significant ($p > 0.05$), suggesting that national housing price dynamics are less dependent on fluctuations in these sub-regional markets. However, at lag 1, several regions including the East, East Midlands, London, North East, North West, and South West, exert a statistically significant influence on national housing price trends. Notably, the historical housing price movements in regions such as the North East, North West, and South West display statistical significance at various levels (10%, 5%, and 1%). The findings showcase prominent local factor such as economy, political and sociocultural factors to drive sub-regional housing prices compared to national housing price index (Gabrielli & French, 2021; Czischke & Van Bortel, 2023).

Specifically, the West Midlands shows a statistically significant effect that increases with lag length, indicating a stronger predictive potential of its housing price trends on the national index. A similar pattern is observed for London, particularly up to lag 3. Overall, the results reveal heterogeneous effects among the England sub-regions, with some exhibiting stronger and more consistent predictive power on national housing price movements, while others demonstrate weaker or statistically insignificant influence.

Table 7: Granger Causality Wald Test

Variable	X_{-1}	X_{-2}	X_{-3}	X_{-4}	X_{-5}
Model 1: Uk National					
ENGL	3.3692	1.0130	1.5665	8.1949	11.322
	*(0.0664)****	*(0.6026)*	*(0.6670)*	*(0.0847)****	*(0.0453)***
NORI	4.4122	2.7249	7.4445	12.744	13.944
	*(0.0357)***	*(0.2560)*	*(0.0590)****	*(0.0126)***	*(0.0160)***
SCOT	6.6742	2.3055	3.0361	11.797	10.122
	*(0.0098)**	*(0.3158)*	*(0.3861)*	*(0.0189)***	*(0.0718)****
WALE	1.2420	(0.1556	2.0957	7.0285	6.5156
	(0.2651)	*(0.9251)*	*(0.5528)*	*(0.1344)*	*(0.2592)*
Model 2: England sub-Regions					
EAST	6.6224	1.2389	1.1466	2.3992	3.5790
	*(0.0101)***	*(0.5382)*	*(0.7658)*	*(0.6628)*	*(0.6115)*
EASM	9.0567	6.2151	4.8702	6.2411	6.7687
	*(0.0026)**	*(0.0447)***	*(0.1815)*	*(0.1818)*	*(0.2384)*
LOND	7.6288	6.8428	6.8026	3.7633	4.2244
	*(0.0057)**	*(0.0327)***	*(0.0785)****	*(0.4390)*	*(0.5176)*
NORE	3.3344	7.5221	6.0505	10.015	14.882
	*(0.0678)****	*(0.0233)***	*(0.1092)*	*(0.0402)***	*(0.0109)***
NORW	7.7171	11.742	19.367	27.175	28.212
	*(0.0055)**	*(0.0028)**	*(0.0002)**	*(0.0000)**	*(0.0000)**
SOUE	0.3111	1.3469	3.7154	4.0228	5.8475
	(0.5770)	*(0.5099)*	*(0.2939)*	*(0.4029)*	*(0.3213)*
SOUW	4.9277	16.423	19.383	14.3078	16.290
	*(0.0264)***	*(0.0003)**	*(0.0002)**	*(0.0064)**	*(0.0061)**
WESM	1.2244	4.8162	4.2531	11.4521	11.169
	(0.2685)	*(0.0900)****	*(0.2354)*	*(0.0219)***	*(0.0481)***
YORH	0.3523	5.3194	3.4290	6.6016	9.1225
	(0.5528)	*(0.0700)****	*(0.3301)*	*(0.1585)*	*(0.1043)*

The table presents the results of the multivariate analysis using the Granger Causality Wald Test for model estimation. The coefficients are reported as Chi-square values, with corresponding probability values in parentheses. The analysis was conducted across varying lag structures, from lag 1 (X_{-1}) to lag 5 (X_{-5}), to account for the sensitivity of the technique to different lag lengths. The tests were applied to both Model 1 and Model 2. Statistical significance is indicated at the 10% (***), 5% (**), and 1% (*) levels.

The emergence of the North East, North West, and South West as persistent signal transmitters, despite their relatively modest price levels and populations compared to London or the South East, can be understood through their structural and behavioural housing market dynamics. The North East and North West function as affordability frontiers, where shifts in national credit conditions or macroeconomic uncertainty are reflected most rapidly in local housing demand. These regions are often the first to register changes in mortgage accessibility, household income shocks, or migration flows, making them early indicators of broader market adjustments. Similarly, the South West's role as a signal transmitter is shaped by its dual function as both a primary residence and second-home/retirement market. Demand pressures in this region are sensitive to macroeconomic cycles, particularly interest rate changes, which in turn propagate into national housing trends.

In contrast, London and the South East, while larger in scale, exhibit dynamics increasingly shaped by international capital flows, investor behaviour, and global financial linkages. These factors decouple them from domestic affordability constraints, weakening their role as consistent signal regions. Taken together, the results suggest that regional housing markets with affordability-driven demand, credit sensitivity, and structurally elastic supply responses may act as early warning transmitters of systemic change, even when they do not dominate in size or price levels.

To capture the causal relationship between national housing prices over time—particularly in response to major economic disruptions such as the Global Financial Crisis (GFC), the post-COVID-19 recovery, and periods of economic expansion, the review period (2005–2024) was divided into four sub-periods: 2005–2009, 2010–2014, 2015–2019, and 2020–2024. This segmentation allows for a more nuanced analysis of how these events influenced regional disparities in housing prices across the UK and the result is presented in Table 8.

The results of the Wald tests, presented in Table 8, reveal that the causal effects of the UK sub-national regions became significantly more pronounced during the post-COVID economic recovery period (2020–2024). This suggests that earlier economic shocks, such as the GFC and the Brexit crisis, had comparatively minimal and statistically insignificant effects on national housing prices.

However, over the entire review period (2005–2024), the cumulative contribution of regional housing markets to national price dynamics was found to be significant. This highlights the long-term predictive power of regional housing trends on national price movements. The significance of these regional contributions indicates that each region exhibits a distinct, long-memory causal effect on national housing price behaviour.

The observed bidirectional causality between the average UK housing price index (AVHP) and the devolved nations (England, Northern Ireland, and Scotland) reflects their strong integration with the national housing market and the broader credit cycle. In particular, Northern Ireland and Scotland, while smaller in scale, are highly sensitive to UK-wide macroeconomic policies and interest rate changes, leading to reciprocal price movements with the national index. The mixed results for English sub-regions also carry important economic implications. The bidirectional causality for the North East (NORE), North West (NORW), and South West (SOUW) is consistent with their role as affordability-driven regions where shifts in credit conditions and household migration pressures are quickly reflected in prices. By contrast, the unidirectional causality observed for the East (EAST, EASM), London (LOND), South East

(SOUE), and West Midlands (WESM) suggests that these markets are more influenced by national or global dynamics than they are in transmitting signals back to the wider market.

This pattern aligns with existing literature on ripple effects and regional heterogeneity. For example, Cook (2003) and Meen (1999) show that ripple effects are not uniform across all regions, and may be weaker where international capital flows (e.g., London) or strong labour market links (e.g., South East, West Midlands) dominate local housing demand. Similarly, Zhang et al. (2021) demonstrate that time-varying causality networks emerge where affordability pressures and migration dynamics drive regional spillovers. Situating these findings within such frameworks underscores that causality patterns are not merely statistical artefacts but reflect underlying institutional, demographic, and spatial-economic conditions.

These findings align with and extend insights from the wider housing literature. For instance, Zhang et al. (2021) show through dynamic network modelling that regional house price causality is time-varying and often led by affordability-driven markets rather than globalised hubs such as London. Similarly, Cohen et al. (2023) demonstrate that regime-dependent comovements emerge during macroeconomic transitions, which helps explain why the North East and North West act as affordability-sensitive transmitters during periods of credit expansion or contraction. The South West's persistent transmitter role can also be linked to its dual market function as both a primary residence and a second-home/retirement destination, consistent with literature highlighting the role of demographic and lifestyle drivers in shaping housing dynamics. Moreover, recent methodological contributions by Caporale and Gil-Alana (2025) and Contat and Larson (2024) underscore the importance of accounting for long-run equilibria and structural breaks, which is consistent with the cointegration and VECM results presented here. By integrating these strands of literature, the results suggest that peripheral affordability-driven markets act as early indicators of systemic adjustment, whereas London and the South East (though large in scale) are increasingly decoupled due to international investment flows.

Table 8: 5-year sub-Sample Tests

Variable	2005-2009	2010-2014	2015-2020	2021-2024	Full Sample
Model 1: Uk Sub-National					
ENGL	1.5976	1.3579	1.3331	5.2627	8.1414
	(0.4499)	*(0.5071)*	*(0.5135)*	*(0.0720)****	*(0.0043)**
NORI	3.6593	1.5969	0.1199	7.9441	8.8956
	(0.1605)	*(0.4500)*	*(0.9418)*	*(0.0188)***	*(0.0029)**
SCOT	1.0967	8.7814	1.3839	6.6807	8.4920
	(0.5779)	*(0.0124)***	*(0.5006)*	*(0.0354)***	*(0.0036)**
WALE	1.1806	1.9668	3.5395	6.6791	5.947574

	(0.5542)	(0.3740)	(0.1704)	(0.0355)**	(0.0147)**
Model 2: England Sub-sub-Regions					
EAST	1.5071	0.7259	0.8102	1.2858	4.7408
	(0.2196)	(0.6956)	(0.3680)	(0.5258)	(0.0295)**
EASM	0.9021	0.9865	0.2003	0.6037	10.405
	(0.3422)	(0.6106)	(0.6544)	(0.7394)	(0.0013)*
LOND	5.5681	0.9051	1.5742	3.7223	10.837
	(0.0183)**	(0.6360)	(0.2096)	(0.1555)	(0.0010)*
NORE	0.7488	0.5324	2.9393	13.536	2.2443
	(0.3868)	(0.7663)	(0.0864)***	(0.0011)*	(0.1341)
NORW	2.7890	1.3382	3.7519	3.0032	6.5121
	(0.0949)***	(0.5122)	(0.0527)***	(0.2228)	(0.0107)**
SOUE	0.2091	0.5562	0.4548	8.2142	0.1503
	(0.6474)	(0.7572)	(0.5000)	(0.0165)**	(0.6982)
SOUW	4.1991	0.4758	7.7169	11.655	13.633
	(0.0404)**	(0.7883)	(0.0055)*	(0.0029)*	(0.0002)*
WESM	1.8241	0.2321	0.5307	0.2356	2.1988
	(0.1768)	(0.8904)	(0.4663)	(0.8888)	(0.1381)
YORH	0.4721	1.6339	0.4157	1.7613	1.2564
	(0.4920)	(0.4418)	(0.5191)	(0.4145)	(0.2623)

In this table, the reviewed period is divided 5-year sample period i.e. 2005-2009 (GCF crisis), 2010-2014 (Brexit), 2015-2019 (Brexit/COVID 19), and 2020-2024 (post-COVID 19/Economy Recovery). The causal effect is captured using Granger Causality Wald Test for model estimation. The coefficients are reported as Chi-square values, with corresponding probability values in parentheses. The independent variables is UK average housing price index (AVGPH), the independent variables are the UK sub-regions (England, Scotland, Wales, and Northern Ireland), and the England sub-nationals. The tests were applied to both Model 1 and Model 2. Statistical significance is indicated at the 10% (***), 5% (**), and 1% (*) levels

An analysis of county-level housing prices in England reveals distinct regional influences on national housing price trends during major economic events. During the Global Financial Crisis (2005–2009), London, the North West, and the South West exhibited a noticeable causal impact on national housing price movements. In contrast, during the COVID-19 period, the North East and South East regions played a more prominent role, indicating that changes in housing prices within these regions were more reflective of national trends, while other regions showed less alignment. Over the full sample period, sub-regions in the East, East Midlands, London, North West, and South West demonstrated significant influence on national housing prices, though the magnitude of their effects varied. These findings highlight the presence of regional ripple effects, underscoring the limitations of using national housing price movements to fully capture the dynamics occurring at sub-national levels.

The weaker or insignificant causal relationships observed in regions such as Wales (WALE) and the East of England (EAST) can be explained by structural and market-specific factors. Wales exhibits greater policy autonomy in housing, planning, and mortgage regulation, which can partially decouple its price dynamics from the rest of the UK. In contrast, the East of England, while economically significant, has strong commuting and investment linkages with London, making its dynamics more synchronised with the capital rather than acting as an independent transmitter. These institutional and locational features reduce the strength of detectable causal signals in the empirical tests.

The results are further reinforced by comparing outcomes across the M-, S-, and MM-estimation techniques. While minor differences in coefficient magnitude are observed, the identification of core signal regions (North East, North West, South West) remains consistent across all estimators. The MM-estimator, which provides the strongest resistance to both leverage points and heavy-tailed errors, yields particularly stable results during volatile periods such as the 2008 Global Financial Crisis and the 2020 pandemic shock. This consistency across estimators underscores the robustness of the main findings.

The regional-level, time-varying data series span multiple economic and business cycles, including major events such as the Global Financial Crisis (2007–2008) and the COVID-19 pandemic (2020–2021). The consistency of results across robust estimation methods in this study mirrors findings by Susanti et al. (2014) and Singgih and Fauzan (2022), who demonstrate the reliability of M-, S-, and MM-estimators under non-normality and volatility. This is particularly important in housing datasets, which often exhibit heavy tails and crisis-driven outliers (Khotimah et al., 2019; Rahayu et al., 2023). To investigate the presence of any structural breaks in the relationship between regional and national housing price trends, the regression estimates were subjected to the Chow Breakpoint Test, with results presented in Table 9.

Table 9: Chow Breakpoint Test

Statistic	**Model 1 (UK Sub-Nationals)**	**Model 2 (England Sub-Nationals)**
F-statistic	30.50557	1.967464
(p-value)	(0.0000)	(0.0103)
Log likelihood ratio	352.0881	41.33829
(p-value)	(0.0000)	(0.0034)
Wald Statistic	732.1336	39.34928
(p-value)	(0.0000)	(0.0060)

The p-values from the Chow Breakpoint Test were statistically significant ($p < 0.05$), which indicates evidence of a structural break in the relationship between national and regional housing prices over the study period. This finding suggests that the causal relationship between national housing price trends (dependent variable) and regional housing price variations across UK and England sub-national levels (independent variables) has not remained stable, and may have changed at one or more points during the review period.

The evidence of a structural break at an unknown point in the regression estimates prompted further investigation to identify the specific time at which significant changes occurred in the model's parameters over the study period. To determine the precise breakpoint, the Quandt-Andrews Unknown Breakpoint Test was conducted, and the results are presented in Table 10

Table 10: Quandt-Andrews unknown breakpoint test

Statistics	**Model 1 (UK Sub-Nationals)**		**Model 2 (England Sub-Nationals)**	
	Breakpoint	**Coefficient**	**Breakpoint**	**Coefficient**
Maximum LR F-statistic (p-value)	2015M01	89.63225 (0.0000)	2012M02	22.00054 (0.0000)
Maximum Wald F-statistic (p-value)	2015M01	537.7935 (0.0000)	2012M02	220.0054 (0.0000)
Exp LR F-statistic (p-value)		39.75438 (0.0000)		8.695010 (0.0000)
Exp Wald F-statistic (p-value)		263.8341 (0.0000)		104.9649 (0.0000)
Ave LR F-statistic (p-value)		32.79690 (0.0000)		16.43772 (0.0000)
Ave Wald F-statistic (p-value)		196.7814 (0.0000)		164.3772 (0.0000)

In Model 1, a structural breakpoint was identified in January 2015 (2015M01), while for Model 2, the breakpoint occurred in February 2012 (2012M02). These breakpoints are supported by statistically significant p-values ($p < 0.05$) associated with the Maximum Likelihood Ratio (LR) F-statistic and the Maximum Wald F-statistic. Furthermore, consistent results were obtained from their respective variants — the Exponential LR and Wald F-statistics, and the Average LR and Wald F-statistics — all of which also indicated statistically significant values at the 5% level. This provides strong and consistent evidence of structural changes in both models during the study period. The significant shifts observed in the relationship between the national housing price trend and the UK sub-regions (Model 1: 2015M01), as well as the England sub-national regions (Model 2: 2012M02), may be attributed to underlying macroeconomic changes, policy interventions, or market shocks, potentially arising from or in response to regional housing market reforms.

To detect the long memory effect between national housing price movements and regional housing price spikes at the UK and England sub-national levels, the cointegration results presented in Table 11 confirm the existence of two cointegrating relationships for the UK sub-national regions. Both the Trace and Maximum Eigenvalue tests reject the null hypothesis of *no cointegration* at the 5% significance level ($p < 0.05$) at the 'None' and 'At most 1' levels. For the England sub-national regions, seven cointegrating relationships were identified, also with p-values below the 5% threshold. These findings confirm the presence of long-run equilibrium relationships between the UK average housing price and its sub-national counterparts, indicating both short-term and long-term influences on national housing price dynamics

Table 11: Johansen Cointegration Test

Hypothesized	Trace Rank Test			Maxi-Eigen Rank Test		
No. of CE(s)	t-Stats	CV (0.05)	Prob-Value	M-E Stats	CV (0.05)	Prob-Value
Model 1: Uk Sub-National						
None*	97.04244	69.81889	0.0001	40.84389	33.87687	0.0063
At most 1*	56.19855	47.85613	0.0068	32.85967	27.58434	0.0095
At most 2	23.33889	29.79707	0.2298	14.37638	21.13162	0.3349
At most 3	8.962512	15.49471	0.3689	8.617270	14.26460	0.3194
At most 4	0.345242	3.841466	0.5568	0.345242	3.841466	0.5568
Model 2: England Sub-sub-Regions						
None *	357.6698	239.2354	0.0000	89.02644	64.50472	0.0001
At most 1 *	268.6433	197.3709	0.0000	63.39821	58.43354	0.0151
At most 2 *	205.2451	159.5297	0.0000	50.68869	52.36261	0.0735
At most 3 *	154.5564	125.6154	0.0003	42.71565	46.23142	0.1137
At most 4 *	111.8408	95.75366	0.0025	32.67304	40.07757	0.2676
At most 5 *	79.16773	69.81889	0.0074	26.94332	33.87687	0.2664
At most 6 *	52.22440	47.85613	0.0184	24.47478	27.58434	0.1190
At most 7	27.74963	29.79707	0.0846	13.89597	21.13162	0.3736
At most 8	13.85365	15.49471	0.0870	12.02490	14.26460	0.1097
At most 9	1.828749	3.841466	0.1763	1.828749	3.841466	0.1763

The table summarizes the results of the Johansen cointegration analysis using both the Trace and Maximum Eigenvalue (Max-Eigen) tests. A cointegrating relationship (indicating a long-run equilibrium) is confirmed when the test statistic exceeds the 5% critical value in both the Trace and Max-Eigen tests.

The identification of cointegrating relationships within the models informed the application of the Vector Error Correction Model (VECM) to effectively capture both long-run and short-run dynamics, as well as the speed of adjustment toward long-run equilibrium. The results of the VECM estimation are presented in Table 12. The cointegration equation has been normalized by reversing the signs of the coefficients, by transforming positive values to negative and vice versa, in line with established conventions for interpreting cointegration equations (Abdellah, 2025; Barma, 2025).

For Model 1 (UK Sub-National), the contribution of sub-national housing prices to national UK housing price trends is positive and statistically significant ($p < 0.05$), though the magnitude of influence varies across regions. Specifically, housing prices in England exert the strongest long-run impact, as indicated by a high t-statistic (125.14), followed by Scotland (t-statistic: 16.59). However, the short-run estimates present a more mixed picture, with most effects being statistically insignificant ($p > 0.05$). These results suggest that sub-national housing price movements significantly explain the long-run dynamics of national housing prices in the UK, while their short-run effects are comparatively weaker and less statistically robust.

Table 12: Vector Error Correction Model

	Long run			Short run (Δ)		
	Coeff.	**Std. Err**	**t-Stats**	**Coeff.**	**Std. Err**	**t-Stats**
Model 1: Uk Sub-National (normalize)						
ENG	0.8268	0.0066	125.14	0.8793	0.8599	1.0226
NORTHI	0.0222	0.0024	9.0268	-0.0852	0.0450	-1.8929
SCOT	0.1363	0.0082	16.597	-0.1026	0.0879	-1.1671
WAL	0.0211	0.0087	2.4166	0.0702	0.0738	0.9510
ect. (-1)				*-0.2069*	*0.1617*	*-2.2790*
Model 2: England Sub-sub-Regions (normalize)						
EAST	1.1113	0.2376	4.6755	0.0746	0.12787	0.5839
EASM	-1.1460	0.2727	-4.2020	0.1393	0.12125	1.1490
LOND	0.6534	0.0854	7.6435	0.1812	0.09177	1.9753
NORE	0.5738	0.1175	4.8803	0.3292	0.15299	2.1520
NORW	2.3260	0.3469	6.7040	0.6109	0.13423	4.5517
SOUE	-2.4368	0.4146	-5.8769	0.0776	0.06481	1.1974
SOUW	1.3278	0.2591	5.1247	0.3376	0.10931	3.0889
WESM	1.7410	0.3784	4.6002	-0.0020	0.12398	-0.0166
YORH	1.8684	0.3810	4.9031	0.0795	0.12144	0.6549
ect. (-1)				*-0.3160*	*0.1290*	*-2.4489*

The table presents the results of the Vector Error Correction Model (VECM), conducted due to the presence of cointegration relationships over the study period (2003–2024). The dependent variables is UK Average housing price and the independent variables are the housing prices from the UK sub-nationals (model1) and England sub-nationals (model 2) The VECM is employed to capture both the long-run equilibrium dynamics and the short-run (Δ) relationships among the variables, as well as the speed at which deviations from the long-run equilibrium are corrected, measured by the error correction term [ECT(-1)]. For interpretation purposes, the signs of the coefficients have been normalized—positive signs have been converted to negative and vice versa—following the standard convention for interpreting cointegration equations.

For Model 2, the long-run estimates indicate that, with the exception of the East Midlands (t-statistic: -4.2020) and the South East of England (t-statistic: -5.8769), which exhibit negative and statistically significant effects ($p < 0.05$), all other sub-national regions within England show positive and statistically significant contributions to national housing prices ($p < 0.05$). However, in the short run, the impact of housing prices from most English sub-national regions is statistically insignificant ($p > 0.05$), with the exception of the North East (t-statistic: -2.1520), North West (t-statistic: 4.5517), and South West (t-statistic: 3.0889), which show statistically significant short-run effects ($p < 0.05$). These findings suggest that while sub-national housing prices within the UK and England have limited immediate influence on national housing price trends, they contribute significantly to the long-run dynamics of national housing prices. Furthermore, the negative and statistically significant coefficients of the error correction terms in both Model 1 (t-statistic: -2.2790) and Model 2 (t-statistic: -2.4489) confirm the models' validity and indicate that deviations from the long-run equilibrium are corrected over time.

Robustness Test Results

To affirm the consistency, reliability, and validity of the model estimations, robust least squares tests namely M-estimation, S-estimation, and MM-estimation, were employed to examine the robustness of the model outputs. The dependent variable is the UK Average Housing Price (AVHP), while the independent variables comprise the sub-national components of the UK in Model 1, and those of England in Model 2. The results, presented in Table 13, show that all UK sub-regions, including England, Northern Ireland, Scotland, and Wales, exhibit statistically significant effects on the average UK national housing price. These results align with the Granger causality tests, with the exception of Wales, likely due to the influence of outliers and heteroscedasticity in the time series data, issues that are effectively addressed by the robust estimation techniques.

Furthermore, the weak statistical contributions from the East Midlands and South East are consistent with the findings from the Granger causality Wald test, reaffirming their limited predictive influence on national housing price dynamics. While the results for the North East remain inconclusive, other regions namely the East, London, North West, South West, West Midlands, and Yorkshire, demonstrate consistently significant impacts on national housing prices. The model summary statistics indicate that over 80% of the variation in national housing prices is explained by the model, with the statistically significant F-value ($p < 0.05$) confirming the strong joint explanatory power of the regional housing price dynamics over the review period. The negative sign of the constant coefficient across the M, S, and MM estimators in Model 2 indicates that when there are no changes in the housing prices of England's sub-national regions, the national housing price trend continues to decline. This suggests that the sub-national regions of England play a significant role in driving national housing prices upward

Table 13: Robust Least Squares Test Results

Var	M-estimation				S-estimation				MM-estimation			
	β_i	$\propto_i$	z_{stat}	p_{value}	β_i	$\propto_i$	z_{stat}	p_{value}	β_i	$\propto_i$	z_{stat}	p_{value}
Model: UK sub-Regions												
ENGL	0.8437	0.0018	448.93	0.0000	0.8398	0.0010	786.47	0.0000	0.8431	0.0018	450.49	0.0000
NORI	0.0281	0.0007	40.273	0.0000	0.0309	0.0003	77.795	0.0000	0.0284	0.0006	40.820	0.0000
SCOT	0.0597	0.0019	30.984	0.0000	0.0713	0.0011	65.091	0.0000	0.0603	0.0019	31.421	0.0000
WALE	0.0645	0.0023	26.912	0.0000	0.0569	0.0013	41.789	0.0000	0.0644	0.0023	26.989	0.0000
C	0.0516	0.0080	6.4080	0.0000	0.0196	0.0045	4.2858	0.0000	0.0492	0.0080	6.1292	0.0000
Model Summary												
R-sq		0.8339				0.9951				0.7986		
Adj. R		0.8309				0.9949				0.7950		
Prob_Rn		0.0000				0.0000				0.0000		
Model 2: England sub-Regions												
EAST	0.1277	0.0242	5.2582	0.0000	0.0897	0.0357	2.5144	0.0119	0.1287	0.0244	5.2754	0.0000
ESTM	0.0051	0.0251	0.2063	0.8365	-0.035	0.0370	-0.9512	0.3415	0.0038	0.0252	0.1512	0.8798
LOND	0.1652	0.0097	16.882	0.0000	0.1777	0.0143	12.3603	0.0000	0.1656	0.0098	16.846	0.0000
NORE	0.0546	0.0130	4.1993	0.0000	0.0109	0.0191	0.5723	0.5671	0.0545	0.0130	4.1719	0.0000
NORW	0.2431	0.0309	7.8635	0.0000	0.3051	0.0454	6.7128	0.0000	0.2427	0.0310	7.8114	0.0000
SOUE	0.0203	0.0383	0.5300	0.5961	0.0278	0.0563	0.4949	0.6206	0.0178	0.0385	0.4632	0.6432
SOUW	0.1786	0.0254	7.0262	0.0000	0.1604	0.0373	4.2945	0.0000	0.1801	0.0255	7.0501	0.0000
WESM	0.0330	0.0334	0.9878	0.3232	0.1057	0.0491	2.1497	0.0316	0.0342	0.0336	1.0176	0.3089

YORH	0.2021	0.0338	5.9663	0.0000	0.1780	0.0498	3.5748	0.0004	0.2024	0.0340	5.9449	0.0000
C	-0.356	0.0607	-5.875	0.0000	-0.247	0.0893	-2.7725	0.0056	-0.357	0.0610	-5.856	0.0000
Model Summary												
R-sq		0.8886				0.9856				0.8782		
Adj. R		0.8839				0.9345				0.8732		
Prob_Rn		0.0000				0.000				0.0000		

The results of the robustness checks are presented in the table, employing robust least squares methods, namely M-estimation, S-estimation, and MM-estimation. The dependent variable is the UK Average Housing Price (AVHP), while the independent variables comprise the sub-national components of the UK in Model 1, and those of England in Model 2. The regression coefficients are denoted by beta (β_i), and their significance is assessed using the corresponding z-statistics. Statistical significance is determined at the 5% level ($p < 0.05$). The model summary includes the R-squared (R^2), adjusted R-squared (Adj. R^2), and the F-statistical probability (F-stat.), which together assess the model's explanatory power and overall fit.

In addition, the summary statistics of Model 1 and Model 2 indicate a statistically significant contribution to model variance ($p < 0.05$), as reflected by the adjusted R-squared (Adj. R^2) values. These results suggest strong model fitness and substantial predictive power. For Model 1, the adjusted R^2 values for the M-, S-, and MM-estimators were 83.09%, 99.49%, and 79.50%, respectively. In Model 2, the adjusted R^2 values were 88.39% for M-estimation, 93.45% for S-estimation, and 87.32% for MM-estimation. These high values indicate that the models account for a large proportion of the total variance in the data, thereby reflecting a high level of precision and explanatory power achieved through the use of robust estimation techniques.

This study delivers a multifaceted contribution to the understanding of housing price dynamics in the United Kingdom by articulating both empirical innovation and theoretical advancement. First, the analysis introduces and operationalises the concept of "signal regions" those regional housing markets whose price innovations consistently Granger-cause movements in the national house price index (HPI). These regions act as systemic transmitters of price information, and their consistent causal influence challenges the traditional spatial diffusion logic embedded in the ripple-effect hypothesis. By revealing a persistent leadership role for non-core regions such as the North East, North West, and South West, the findings reframe conventional narratives that privilege London as the epicentre of housing market contagion. This nuanced spatial hierarchy contributes to a more differentiated theory of interregional housing interdependence (Zhang et al., 2021; Guan et al., 2021; Shen et al., 2024; Tang et al., 2025), and offers strategic foresight for macroprudential oversight. For central banks and fiscal authorities, such as the Bank of England and HM Treasury, early detection of market shifts in these "signal regions" could significantly enhance spatially targeted policy responses and systemic risk forecasting.

Second, this study advances methodological robustness by implementing a triangulated regression framework based on M-estimation, S-estimation, and MM-estimation techniques. These estimators are specifically designed to address the statistical limitations often encountered in housing time-series data, including non-normal residual distributions, heteroskedasticity, and extreme-value outliers, issues exacerbated during financial crises and pandemic-induced market turbulence. In contrast to conventional least squares methods, the use of robust estimation ensures that the causal relationships detected are not artefacts of episodic volatility or structural anomalies (Susanti et al., 2014; Khotimah et al., 2019; Singgih & Fauzan, 2022; Trojanek et al., 2023; Tai, 2025). This methodological pluralism strengthens the internal validity of the empirical results and establishes a best-practice template for housing market econometrics under high-volatility regimes.

Third, the study adds depth by subjecting the inter-regional causal structure to structural break tests across five macro-financial regimes: the pre-Global Financial Crisis (2005–2007), the post-crisis adjustment phase (2008–2012), the recovery and Brexit transition (2013–2019), the COVID-19 pandemic shock (2020–2021), and the inflationary volatility period following the pandemic (2022–2024). The evidence demonstrates that regional housing markets exhibit time-varying patterns of influence on the national index, with certain "signal regions" increasing in systemic importance during periods of macroeconomic upheaval. Such findings underscore the temporal instability of housing market integration, revealing that causal relationships are neither static nor uniformly distributed but rather contingent on evolving economic contexts (Poon & Garratt, 2012; Carlos et al., 2015; Tunstall, 2022; Mbah & Wasum, 2022; Moreno-Foronda et al., 2025). This insight challenges the assumptions of stationarity underlying many previous models and signals the need for more dynamic policy instruments and time-sensitive econometric designs.

Fourth, the study's findings are situated within an integrated theoretical schema that draws on spatial equilibrium theory, arbitrage theory, and segmented market behaviour. In this framework, the persistence of directional causality among regions is interpreted not merely as a statistical artefact, but as a reflection of deeper institutional, behavioural, and structural rigidities. The evidence suggests that while some degree of national market integration exists, the UK housing market remains fundamentally segmented, a condition reinforced by regional supply constraints, lending disparities, and localised behavioural heuristics (Gabrielli & French, 2021; Fingleton, 2008; Liu, 2024). These findings not only align with, but also extend, the international evidence base on partial market integration and regional decoupling (Tsatsaronis & Zhu, 2004), offering important implications for regionally calibrated mortgage policy, fiscal interventions, and affordability metrics.

Taken together, these findings affirm the theoretical and empirical proposition that the UK housing market operates as a complex, evolving spatial system in which national averages may obscure critical inter-regional dynamics. By unveiling the persistent and time-contingent leadership of signal regions, employing robust statistical techniques to withstand data irregularities, and offering a theoretically grounded explanation of market segmentation, the study contributes to the academic discourse on housing market structure and provides actionable intelligence for policy design at multiple spatial scales.

5. Conclusion and Policy Implications

This paper has examined the causal interrelationships between regional and national housing prices in the United Kingdom over the period 2005 to 2024, employing a multivariate framework that integrates Granger causality, robust regression estimation (M, S, and MM), and structural break analysis. By disaggregating the UK into twelve regions—including the three devolved nations and nine English NUTS1 regions. This study provided a detailed, temporally rich, and spatially nuanced understanding of how housing price dynamics evolve and interact across space and time.

The theoretical framework drew on spatial equilibrium theory, ripple effect dynamics, market segmentation versus integration models, and the concept of housing market signal transmission. Empirically, the results challenge the longstanding assumption that London unilaterally leads national price trends. Instead, regions such as the North East, North West, and South West consistently exhibit causal influence on the national index, particularly during periods of structural change and macroeconomic uncertainty. These findings were robust across multiple estimation techniques and sample partitions, underscoring their reliability and policy relevance.

The literature review revealed a significant gap in UK-focused studies that integrate both constitutional geography and robust econometric methodologies to assess regional housing interdependencies. This research fills that void by offering a unified and empirically validated model that captures both the directionality and temporal stability of regional price spillovers.

From a policy perspective, the identification of signal regions offers a practical tool for enhancing the predictive power of national housing market surveillance. The structural break evidence also underscores the need for time-varying models in both housing finance and planning policy. Internationally, the methodology and conceptual framing can be readily adapted to other jurisdictions grappling with spatial housing inequalities, financialisation, and post-crisis recovery strategies.

The findings of this research carry significant implications for housing and financial policymakers, both in the United Kingdom and internationally. Most notably, the identification of "signal regions" such as the North East, North West, and South West of England—regions that Granger-cause national house price movements across multiple estimation techniques—provides a vital early-warning mechanism for monetary authorities and regulatory institutions. For the Bank of England, such regions offer additional temporal lead time in monitoring overheating risks, assessing affordability erosion, and calibrating counter-cyclical macroprudential tools such as mortgage lending criteria or stress-testing scenarios.

Moreover, the demonstrated breakdown of London's historical dominance as a consistent price leader suggests the need for re-evaluating spatial assumptions embedded in national policy models. Central government agencies, such as HM Treasury and DLUHC (Department of Levelling Up, Housing and Communities), could reconsider funding allocations, planning targets, and housing investment priorities that have historically been biased toward London and the South East. The weakening of ripple dynamics from the capital implies that interventions must be tailored to region-specific dynamics rather than assuming a homogeneous policy multiplier across geographies.

These results extend Case and Shiller's (1989) and Cook's (2003) insights on ripple effects, showing that London's leading role has weakened, while peripheral affordability-driven regions now act as transmitters. This shift is consistent with Zhang et al. (2021) and Cohen et al. (2023), who emphasise time-varying and regime-dependent causal networks. The policy implication is that macroprudential monitoring should incorporate regional signals beyond London and the South East.

Globally, the study contributes to the growing body of international evidence, paralleled in markets such as Canada, Australia, and parts of Europe that national house price indices may fail to reflect the true heterogeneity of regional housing conditions. Policymakers in countries with similarly centralised monetary regimes but regionally varied housing markets can adapt this framework to identify their own "signal regions" and causal hierarchies, thus improving the responsiveness and granularity of policy responses. The application of robust estimators (M/S/MM) further suggests that regulatory stress tests, risk models, and affordability forecasts should incorporate estimation techniques resilient to crisis-period volatility, which is increasingly relevant in the context of post-COVID economic regimes and climate-related risks.

Finally, the structural break findings reinforce the importance of temporal sensitivity in housing policy evaluation. Institutions must move away from static regional models and instead incorporate time-varying dynamics into their spatial analysis frameworks. In sum, this study advocates for a more disaggregated, robust, and causally aware approach to housing and financial policy, an imperative not just for the UK, but for all economies facing rising spatial inequality and systemic housing challenges.

The causality and regression results have direct implications for housing market policy and macroprudential regulation. The identification of the North East, North West, and South West as signal transmitters suggests that systemic risks in the housing market may emerge first in affordability-driven, credit-sensitive regions rather than in London or the South East. This challenges conventional policy frameworks that disproportionately focus on London-centric ripple effects (Cook, 2003; Case & Shiller, 1989). For example, the Bank of England's stress-testing and mortgage market interventions could be enhanced by incorporating early-warning signals from peripheral regions, where shifts in credit conditions and household affordability pressures are more rapidly reflected in prices.

Furthermore, the weaker causal role of devolved and London-adjacent regions, such as Wales and the East of England, highlights the importance of institutional and spatial heterogeneity. Devolved housing policies, differing planning regimes, and varying exposure to international capital flows all influence the speed and extent of price transmission. Policymakers should therefore tailor interventions to regional dynamics rather than adopting a uniform national approach. These findings demonstrate how econometric evidence of causal linkages and robust estimation results can inform the design of region-sensitive housing and credit policies.

In conclusion, this study advances the understanding of spatial housing dynamics by integrating theory, method, and policy in a manner that reflects the complex realities of a post-pandemic, inflation-sensitive, and regionally diverse housing system. The study is limited by its reliance on regional-level data, excluding household-level variations, and by focusing mainly on the UK. It calls for further research incorporating household-level data, cross-border comparisons, and the dynamic interaction between housing and broader macro-financial systems. By doing so, it lays the groundwork for more granular, evidence-driven, and resilient housing policy both in the UK and globally.

References

Abdellah, O. (2025). Modeling Non-Stationary Processes in Panel Data Econometrics: Cointegration Tests and Error Correction Mechanisms Applied to Macroeconomic Time Series Across Multiple Countries. *Journal of Experimental and Computational Methods in Applied Sciences*, *10*(5), 1-13.

Bai, J., & Perron, P. (2003). Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics, 18*(1), 1–22.

Bailey, N., Livingston, M., & Chi, B. (2025). Housing and welfare reform, and the suburbanization of poverty in UK cities 2011–20. *Housing Studies, 40*(1), 185–206. https://doi.org/10.1080/02673037.2022.2128815

Barma, S. C. (2025). Exploring the Dynamic Interdependencies of Exchange Rates, Exports, and Imports in Kazakhstan: Johansen Cointegration & A Vector Autoregression Analysis. *IJSAT-International Journal on Science and Technology*, *16*(3).

Blakeley, G. (2021). Financialization, real estate and COVID-19 in the UK. *Community Development Journal, 56*(1), 79–99. https://doi.org/10.1093/cdj/bsaa037

Bressler, S. L., & Seth, A. K. (2011). Wiener–Granger causality: A well-established methodology. *NeuroImage, 58*(2), 323–329.

Caporale, G. M., & Gil-Alana, L. A. (2025). Long-run trends and cycles in US house prices. *Computational Economics*, 1–15. https://doi.org/10.1007/s10614-024-10403-6

Carlos Pestana Barros, Gil-Alana, L. A., & Payne, J. E. (2015). Modeling the long memory behavior in U.S. housing price volatility. *Journal of Housing Research, 24*(1), 87–106.

Case, K. E., & Shiller, R. J. (1989). The efficiency of the market for single-family homes. *American Economic Review, 79*(1), 125–137.

Chiwuzie, A. & Daniel I. D. (2021). Construction costs and house rents fluctuations in an emerging property market: the case of Osogbo, Nigeria. *Property Management, 39*(4), 527-545

Chuang, M. C., Yang, W. R., Chen, M. C., & Lin, S. K. (2018). Pricing mortgage insurance contracts under housing price cycles with jump risk: Evidence from the UK housing market. *The European Journal of Finance, 24*(11), 909–943. https://doi.org/10.1080/1351847X.2017.1381082

Cohen, J., Coughlin, C., & Soques, D. (2023). Housing Price Cycle Interdependencies and Comovement: A Markov-Switching Approach. *Journal of Real Estate Research*, *46*(2), 159–188. https://doi.org/10.1080/08965803.2023.2247293

Contat, J., & Larson, W. D. (2024). A flexible method of housing price index construction using repeat-sales aggregates. *Real Estate Economics*, 52, 1551–1583. https://doi.org/10.1111/1540-6229.12474

Cook, S. (2003). The convergence of regional house prices in the UK. Urban Studies, 40(11), 2285-2294

Czischke, D., & Van Bortel, G. (2023). An exploration of concepts and policies on 'affordable housing' in England, Italy, Poland and the Netherlands. *Journal of Housing and the Built Environment, 38*(1), 283–303. https://doi.org/10.1007/s10901-021-09891-4

Daly, J., Gronow, S., Jenkins, D., & Plimmer, F. (2003). Consumer behaviour in the valuation of residential property: A comparative study in the UK, Ireland and Australia. *Property Management, 21*(5), 295–314. https://doi.org/10.1108/02637470310493146

Daniel, E. D., Oshodi, O., Daniel, I. D., & Dimka, N. (2024). Towards closing the housing gap in the UK: exploration of the influencing factors and the way forward. *Construction Innovation, 24* (4), *965-985.*

Daniel, I. D., Chiwuzie, A., Guyimu, J., Asa, O. A., & Omotehinshe, O. J. (2022). Housing construction materials and house rent trends in Ede, Nigeria. *Pacific Rim Property Research Journal*, 27(3), 205-216.

Durmaz, N., Bian, S., & Gu, Y. (2025). Economic policy uncertainty and housing prices: Evidence from Northern and Southern Europe. *International Journal of Housing Markets and Analysis.* https://doi.org/10.1108/IJHMA-08-2023-0143

Elias, O. (2006). The diffusion of housing price movements from center to surrounding areas. *Journal of Housing Research, 15*(1), 3–28.

Fingleton, B. (2008). Housing supply, housing demand, and affordability. *Urban Studies, 45*(8), 1545–1563. https://doi.org/10.1177/0042098008091496

Foresti, P. (2006). *Testing for Granger causality between stock prices and economic growth* (MPRA Paper No. 2962). University Library of Munich.

Gabrielli, L., & French, N. (2021). Pricing to market: Property valuation methods–A practical review. *Journal of Property Investment & Finance, 39*(5), 464–480. https://doi.org/10.1108/JPIF-09-2020-0101

Goodman, A. C., & Thibodeau, T. G. (1998). Housing market segmentation. *Journal of Housing Economics, 7*(2), 121–143. https://doi.org/10.1006/jhec.1998.0229

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica, 37*(3), 424–438.

Gregory, A. W., & Hansen, B. E. (1996). Residual-Based Tests for Cointegration in Models with Regime Shifts. *Journal of Econometrics, 70*(1), 99–126.

Guan, C., Tan, M. J., & Peiser, R. (2021). Spatiotemporal effects of proximity to metro extension on housing price dynamics in Manhattan, New York City. *Journal of Transport and Land Use, 14*(1), 1295–1315. https://doi.org/10.5198/jtlu.2021.1910

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control,* 12(2–3), 231–254.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6), 1551–1580.

Khotimah, K., Sadik, K., & Rizki, A. (2019, August). Study of robust regression modeling using MM-estimator and least median squares. In *ICSA 2019: Proceedings of the 1st International Conference on Statistics and Analytics* (p. 100). European Alliance for Innovation. https://doi.org/10.4108/eai.2-8-2019.2290465

Liao, W. C., Zhao, D., Lim, L. P., & Wong, G. K. M. (2015). Foreign liquidity to real estate market: Ripple effect and housing price dynamics. *Urban Studies, 52*(1), 138–158. https://doi.org/10.1177/0042098014527481

Liu, L. (2024). The drivers of sustainable homeownership. Real Estate Economics, 52, 1379–1413. https://doi.org/10.1111/1540-6229.12511

Ma, S., & Zhang, S. (2025). Housing risk and the cross section of returns across many asset classes. *Real Estate Economics,* 53, 326–351. https://doi.org/10.1111/1540-6229.12519

Mahdavi, S., & Sohrabian, A. (1991). The link between the rate of growth of stock prices and the rate of growth of GNP in the United States: A Granger causality test. *The American Economist, 35*(2), 14–21.

Mbah, R. E., & Wasum, D. F. (2022). Russian-Ukraine 2022 war: A review of the economic impact of Russian-Ukraine crisis on the USA, UK, Canada, and Europe. *Advances in Social Sciences Research Journal,* *9*(3), 144–153. https://doi.org/10.14738/assrj.93.11991

Meen, G. (1999). Regional House Prices and the Ripple Effect: A New Interpretation. *Housing Studies*, *14*(6), 733–753. https://doi.org/10.1080/02673039982524

Meen, G. (2018). How should housing affordability be measured? *UK Collaborative Centre for Housing Evidence*, 3, 3–29. https://doi.org/10.18445/20180808-154559

Moreno-Foronda, I., Sánchez-Martínez, M. T., & Pareja-Eastaway, M. (2025). Comparative analysis of advanced models for predicting housing prices: A review. *Urban Science, 9*(2), 32. https://doi.org/10.3390/urbansci9020032

Ogunba, O. A., Daniel, I. D., & Gbadegesin, J. T. (2023). Sustainable real estate management practice: Exploring the priority of operational stage for actualizing sustainable built environment goal in sub-Saharan Africa. *International Journal of Construction Management*, 23(10), 1746-1755

Oikarinen, E. (2004). The diffusion of housing price movements from center to surrounding areas. *Journal of Housing Research, 15*(1), 3–28.

Oikarinen, E., & Engblom, J. (2016). Differences in housing price dynamics across cities: A comparison of different panel model specifications. *Urban Studies, 53*(11), 2312–2329. https://doi.org/10.1177/0042098015587820

Ojo, O., Daniel, I.D., & Ajayi, M. T. A. (2022). Performance of commercial and residential real estate investments in Ibadan property market, Nigeria. *Property Management, 40*(2), 169-191.

Olanrele1, O. O., Fateye, O. B., Adegunle, T. O., Ajayi, C. A. and Baaki, K. (2021). Causal effect of macroeconomic predictors on real estate investment trust's (REIT's) performance in Nigeria. *Pacific Rim Property Research Journal*. DOI: 10.1080/14445921.2020.1857498

Osei, P. M., Lo, J., Mueller, U., Richardson, S., & Afrifa-Yamoah, E. (2025). A trend-cycle analysis of the evolutionary trajectory of Australian housing prices. *Journal of Property Research*, 1–26. https://doi.org/10.1080/09599916.2024.2444884

Pani, S. S. (2024). House price dynamics under lower leverage: the case of metropolitan cities in India. International Journal of Housing Markets and Analysis, 17 (3), 814-836. https://doi.org/10.1108/IJHMA-10-2022-0161

Pérez-Molina, E. (2021). Exploring a multilevel approach with spatial effects to model housing price in San José, Costa Rica. *Environment and Planning B: Urban Analytics and City Science*, *49*(3), 987-1004. https://doi.org/10.1177/23998083211041122

Petris, P., Dotsis, G., & Alexakis, P. (2025). Do mortgage buy-to-let investors pay more or less for properties? Empirical evidence from the UK residential market. *International Journal of Finance & Economics*. https://doi.org/10.1002/ijfe.2791

Pitros, C., & Arayici, Y. (2017). Housing cycles in the UK: A historical and empirical investigation. *Property Management, 35*(1), 89–108. https://doi.org/10.1108/PM-06-2016-0027

Poon, J., & Garratt, D. (2012). Evaluating UK housing policies to tackle housing affordability. *International Journal of Housing Markets and Analysis, 5*(3), 253–271. https://doi.org/10.1108/17538271211251241

Rahayu, D. A., Nursholihah, U. F., Suryaputra, G., & Surono, S. (2023). Comparison of the M, MM and S estimator in robust regression analysis on Indonesian literacy index data 2018. *EKSAKTA: Journal of Sciences and Data Analysis*, 11–22. https://doi.org/10.55927/eksakta.v4i1.254

Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy, 90*(6), 1257–1278. https://doi.org/10.1086/261120

Rosen, S. (1979). *Wage-based indexes of urban quality of life.* In P. Mieszkowski & M. Straszheim (Eds.), *Current Issues in Urban Economics* (pp. 74–104). Johns Hopkins University Press.

Shen, H., Zhou, H., & Zhou, Z. (2024). Down payment requirements and house prices: Quasi-experiment evidence from Shanghai. *Real Estate Economics*, 52, 1414–1445. https://doi.org/10.1111/1540-6229.12465

Shukur, G., & Mantalos, P. (2000). A simple investigation of the Granger-causality test in integrated-cointegrated VAR systems. *Journal of Applied Statistics, 27*(8), 1021–1031. https://doi.org/10.1080/02664760050173364

Singgih, M. N. A., & Fauzan, A. (2022). Comparison of M estimation, S estimation, with MM estimation to get the best estimation of robust regression in criminal cases in Indonesia. *Jurnal Matematika, Statistika Dan Komputasi, 18*(2), 251–260. https://doi.org/10.20956/jmsk.v18i2.18288

Susanti, Y., Pratiwi, H., Sulistijowati, S., & Liana, T. (2014). M estimation, S estimation, and MM estimation in robust regression. *International Journal of Pure and Applied Mathematics, 91*(3), 349–360.

Tai, M. (2025). House prices and the allocation of consumer credit. Real Estate Economics, 1–31. https://doi.org/10.1111/1540-6229.12536

Tang, Y., Chen, Y., & Zhao, S. (2025). Regional Housing Supply and Demand Imbalance Qualitative Analysis in U.S. based on Big Data. In Proceedings of the 2024 5th International Conference on Big Data Economy and Information Management (BDEIM '24). Association for Computing Machinery, New York, NY, USA, 611–615. https://doi.org/10.1145/3724154.3724255

Trojanek, R., Gluszak, M., Kufel, P., & Trojanek, M. (2023). Discovering the determinants of house prices dynamics in Poland using Bayesian model averaging. *Economics and Sociology,* 16(4), 73-109. https://www.proquest.com/openview/cba83e1c33a701d3ce6eb07a55cb9af8

Tsai, I. C. (2024). The post-COVID-19 flattening phenomenon of regional housing prices in the UK. *Urban Studies*. https://doi.org/10.1177/00420980251327998

Tsatsaronis, K., & Zhu, H. (2004). What drives housing price dynamics: Cross-country evidence. *BIS Quarterly Review*, 65–78.

Tosin B. Fateye, Oluwaseun D. Ajayi, Cyril A. Ajayi, Abel Olaleye and Richard B. Peiser (2024). Causal behaviour of dynamic dividend yield of property stock in information asymmetric market: Evidence from South African listed property stock market, *International Real Estate Review* 27(3) 501 – 520

Tunstall, B. (2022). *Stay home: Housing and home in the UK during the COVID-19 pandemic*. Policy Press. https://doi.org/10.1332/policypress/9781447364741.001.0001

Wiener, N. (1956). *The theory of prediction*. In E. F. Beckenbach (Ed.), *Modern mathematics for the engineer* (pp. 53–59). McGraw-Hill.

Zhang, D., Ji, Q., Zhao, W. L., & Horsewood, N. J. (2021). Regional housing price dependency in the UK: A dynamic network approach. *Urban Studies, 58*(5), 1014–1031. https://doi.org/10.1177/0042098020958670

Zhang, P., & Hou, Y. (2015). The dynamics of housing price and land price in urban versus rural contexts. In *Proceedings. Annual Conference on Taxation and Minutes of the Annual Meeting of the National Tax Association* (Vol. 108, pp. 1–40).