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A model of regional housing markets in England and Wales

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Abstract

Purpose – We propose an economic model of housing markets. The model incorporates the macroeconomic relationships between prices, demand and supply. Since vacancy rates are not observable, the demand-supply mismatches are identified using a microeconomic model of search, matching and price formation. The model is applied to data on regional housing markets in England and Wales.

Design/methodology/approach – Economic theory combining macroeconomics and microeconomics together with new generation econometric methods for empirical analysis.

Findings – The empirical model, estimated for the ten government office regions of England and Wales, validates the economic model. We find that there is substantial heterogeneity across the regions, which is useful in informing housing and land-use policies. In addition to heterogeneity, the model enables us to better understand unrestricted inter-regional spatial relationships. The estimated spatial autocorrelations imply different drivers of spatial diffusion in different regions.

Research limitations/implications – In the nature of other empirical work, the findings are subject to specificities of the data considered here. The understanding of spatial diffusion can also be further developed in future work.

Practical implications – This paper develops a nice way of closing macroeconomic models of housing markets when complete demand, supply and pricing data are not available. The model may also be useful when data are available but with large measurement errors. The model comes together with corresponding empirical methods.

Social implications – Implications for the housing market and other regional policies are important. These are context-specific, but some implications for housing policy in the UK are provided in the paper as an example.

Originality/value – Unique housing market paper combining both macroeconomic and microeconomic theory as well as both theory and empirics. The rich framework so developed can be extended to much future work.

Keywords Housing markets, Search and matching, Spatial diffusion, Housing demand, Housing supply

Paper type Research paper

1. Introduction

Much has been written about how residential property markets function at the macroeconomic level, including price formation and inflation, demographic change,



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This paper is dedicated to the fond and loving memory of the late Chris Jensen-Butler. We thank Donald Haurin, Duncan Maclennan, Geoff Meen and Adrian Pabst for valuable comments on the paper. We also thank Hometrack and particularly David Catt for access to data used in this paper. The usual disclaimer applies. unemployment and productivity, and volatility and speculative consumption or bubbles; see, for example, Meen (2008), Favilukis *et al.* (2017), Hsieh and Moretti (2019), Maclennan and Long (2024) and White (2024). A substantial part of this research has focussed on urban housing markets, attempting to understand demand-supply mismatches, price-elasticities of demand and supply, the process of price formation and temporal evolution of housing prices and their volatility; see, Bhattacharjee *et al.* (2024) for a review. In this paper, we examine the way in which housing markets in the ten government office regions (GORs) in England and Wales operate by constructing an economic model that incorporates both the macroeconomic relationships between demand, supply and prices as well as the microeconomic processes of search and matching in housing markets. The model admits completely unrestricted spatial heterogeneity and autocorrelation across the regions and can therefore inform place-based policy and interregional diffusion of demand.

The approach enables a better characterisation of key features of the UK housing market, such as volatility, supply-demand mismatches and ripple effects. The model is estimated using monthly data for the period November 2000–May 2003, on house prices, time-on-the-market and degree of overpricing together with regional data on economic activity and neighbourhood characteristics. The estimated model incorporates heterogeneity across the different regions in England and Wales. The methodology proposed can be used to study regions as a whole as well as sub-markets, facilitating comparison of the effects of different policies such as improvement of transport infrastructure, quality of public services and jobs-skills trajectories on the housing market, either at national or regional levels. The results have important implications for policy for the housing market as a whole and for various sub-markets.

The paper is organised as follows: Section 2 offers a selective review of the empirical literature on housing markets, focussing on the UK and discusses the institutional background. The proposed structural model is presented in Section 3, followed by a description of the econometric model, methodology and data in Section 4. Section 5 discusses the empirical findings and conclusions are drawn in Section 6.

2. Studies of the UK housing market and the institutional backdrop

A substantial body of literature on the UK housing market has accumulated over the past four decades. Research illustrates a strong growth in prices and high volatility, reflecting mismatch between demand and supply, at least in a localised context (in terms of region and type of housing, for example), an extremely low and declining price-elasticity of supply and a lower response of demand to price signals as compared with changes in income; see, for example, Meen (2003) and Barker (2004).

The literature also reflects substantial and continuing inter-regional differences, both in prices and volatility. These spatial price differentials have been attributed to differences in features of the local economies (Muellbauer and Murphy, 1997) as well as to local supply constraints that limit the response of prices to changes in the economic environment (Meen, 2001, 2003; Barker, 2003; Muellbauer, 2003). The implications of inter-regional differences in housing markets in terms of reduced mobility (Cameron and Muellbauer, 1998) and growing spatial inequality (Barker, 2003) are also discussed.

Two other aspects of the UK regional housing markets have attracted considerable recent research attention. First, several hedonic and repeated sales models of regional prices have been constructed (Holmans, 1990; Ashworth and Parker, 1997; Rosenthal, 1999; Anselin and Lozano-Gracia, 2009; Anselin *et al.*, 2010; Bhattacharjee *et al.*, 2016, 2017). These models reflect not only geographically varying price effects but also substantial spatial dependence. Second, a number of authors have also studied the so-called ripple effects, by which house prices have a propensity to first rise in the South-East during an upswing and then spread out

Asian Journal of Economics and Banking to the rest of the UK over time (Meen, 1999; Cook and Holly, 2000; Cook, 2003; Bhattacharjee *et al.*, 2022). The existence of ripple effects reflects spatio-temporal dependence in regional house prices in the UK.

The above-mentioned literature acknowledges implicitly the strong spatio-temporal dependence in features of regional/local housing markets. Attempts are made to explain spatial diffusion, particularly in terms of neighbourhood characteristics such as crime rates, schooling, transport infrastructure and quality of public services (Meen, 2001; Gibbons and Machin, 2003, 2005; Cheshire and Sheppard, 2004; Gibbons, 2004; Bhattacharjee and Jensen-Butler, 2013), and social interactions and segregation (Meen and Meen, 2003; Bhattacharjee and Jensen-Butler, 2013). In this paper, we do not hypothesize *a priori* any fixed pattern of spatial diffusion and instead we estimate our models in a way that is consistent with the observed pattern of spatial dependence.

As noted above, the extensive recent literature on the UK housing market demonstrates a substantial and persistent mismatch between demand and supply, an extremely low and declining price-elasticity of supply, a low response of demand to price signals, substantial and continuing inter-regional differences in prices and volatility and ripple effects; see, for example, Meen (1996, 2003). These spatial differences have been attributed to differences in features of the local economies as well as to local supply constraints that limit the behaviour of prices as a response to changes in the economic environment (Meen, 2003).

Our economic model rests upon microeconomic theoretical foundations and allows both for heterogeneity across the regions and unrestricted spatial diffusion. There is a large literature on econometric methods to estimate regression models with spatio-temporal variation, both with and without spatially distributed lags; see, for example, Elhorst (2003), Baltagi *et al.* (2003), Giacomini and Granger (2004) and Kelejian and Prucha (2004). Applying these methods, our estimated models derived from the above economic model are useful in understanding the factors driving the regional housing markets in the UK, including regionspecific differences in economic activity and neighbourhood conditions.

3. A micro-founded model of housing markets

The economic model proposed here draws upon the literature on aggregate analysis of office space markets and on search and bargaining in market microstructure models of price-setting in residential housing markets.

3.1 Demand, supply and prices

Based broadly on research on rental office markets (Wheaton and Torto, 1993; Wheaton, 1990; Wheaton *et al.*, 1997; Hendershott *et al.*, 2002; Fuerst, 2004), we first consider an economic model consisting of three behavioural relationships (for price, demand and supply dynamics) linking exogenous variables to the housing market.

The price adjustment relationship (Relationship 1) relates rates of change in the realised value (price) (V_t) of housing properties to deviations of the vacancy rate (ν_t) from the natural vacancy rate (ν^{\star}) and deviations of the realised value from its equilibrium level (V_t^{\star}). This is essentially the rental adjustment model expressed in terms of values rather than rents, incorporating an extension proposed by Hendershott (1996) postulating an additional role for adjustment of the actual level of rent to the natural rent.

$$(V_t - V_{t-1}) / V_{t-1} = \gamma_1 (\nu^* - \nu_{t-1}) + \gamma_2 (V_t^* - V_{t-1}).$$
⁽¹⁾

Demand (D_t) is modelled as a function of realised value, housing market conditions and neighbourhood characteristics (Relationship 2). The market conditions include economic activity (Y_t -local and economy-wide income, unemployment, productivity and interest rates)

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and the neighbourhood characteristics include socioeconomic variables (X_t – quality of education and public services, crime, demographics, etc.).

$$D_t = \lambda_0 X_t^{\lambda_1} V_t^{\lambda_2} Y_t^{\lambda_3}, \tag{2}$$

where $\lambda_2 < 0$ is the price elasticity and $\lambda_3 > 0$ is income elasticity of demand.

In equilibrium, supply (S_t) is related to demand as

$$D_t \equiv (1 - \nu_t) S_t. \tag{3}$$

If vacancy rates (or occupancy rates) and supply were perfectly observed, the above three relationships (Equations (1), (2) and (3)) would form a recursive system and the structural relationships can be estimated (Hendershott *et al.*, 2002). This is the usual approach taken in the rental office market literature.

However, quality data on vacancy rates for the residential housing market in the UK are difficult to source. Further, even though data on supply of residential property are more readily available, there may not be perceptible changes in supply over time in many nonurban areas since investment in residential property is often highly localised and geographically not very widespread. Hence, it is probable that supply data may not contain much information on the temporal variation in the demand-supply balance in regional housing markets.

3.2 Price-setting

Given these features of the residential housing market, we look into the literature on search, bargaining and price-setting in housing markets to identify other observed characteristics of the housing markets that may inform demand-supply mismatches.

The literature on search and bargaining models (Wheaton, 1990; Yavas, 1992; Arnold, 1999; Krainer, 2001; Anglin *et al.*, 2003) highlights the way in which an initial list price is set, and the final (realised) price is determined through repeated search and bargaining by both the seller and the buyer, and the time-on-the-market that it takes to find a successful match. The trade-offs between time-on-the-market and setting the initial listing price (equivalently, the degree of overpricing) play important roles in this price-setting process. A higher list price (V_t^L) discourages potential buyers and increases time-on-the-market (TOM_t) , while a lower initial list price not only reduces time-on-the-market but also simultaneously reduces the final price.

Broadly following Anglin *et al.* (2003), the degree of overpricing (DOP_t) is modelled as follows:

$$\ln DOP_t \equiv \ln V_t - \ln V_t^L = \alpha_0 + \alpha_1 X_t + \alpha_2 \ln Y_t + \alpha_3 \ln D_t, \tag{4}$$

where X_t denotes neighbourhood characteristics typically included in a hedonic model.

Further, time-on-the-market will decrease with the degree of overpricing and increase with vacancy rate; this negative effect of the degree of overpricing on time-on-the-market may be magnified in a market niche with a smaller list price variance. We propose to use the price determination process and the relationship between time-on-the-market and degree of overpricing (Relationship 4) to identify the wedge between demand and supply in residential markets.

$$\ln TOM_{t} = \beta_{0} + \beta_{1} \ln Y_{t} + \beta_{2} \ln DOP_{t} + \beta_{3} \ln(1 - \nu_{t}).$$
(5)

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The above five relationships (Equations (1), (2), (3), (4) and (5)) describe our proposed micro-AJEB founded model of demand and supply in a regional housing market.

> Following Anselin (1988, 2002), we model spatial variation using a spatial regime model that allows for unrestricted heterogeneity across the regions and a completely unrestricted pattern of spatial diffusion. In other words, our regression models are estimated based on flexible descriptions of spatial diffusion in both cross-regressive variables (spatially distributed lags) and spatial errors.

4. Econometric methodology

The structural parameters of the system of simultaneous equations given by the relationships above can be estimated in the presence of known spatial and temporal dependence. When vacancy rates and supply are observed. Relationships 1–3 form a recursive system. When these are observed imperfectly, as in our case, this information may be recovered from variation in time-on-the-market and degree of overpricing and the relationship between the two. The reduced form equations of the endogenous variables can be estimated and the structural parameters recovered. This, of course, is assuming that the spatial and temporal autocorrelation in the errors and the nature of spatially distributed lags have been modelled using an appropriate specification of the diffusion process.

4.1 Empirical model

We estimate our structural relationships in first differences. This renders each of demand, supply, prices, degree-of-overpricing and time on the market stationary across the temporal dimension, while nonstationary (or non-granular) and stationary dynamics over space can be modelled using spatial regression models with common factors (Pesaran and Tosetti, 2011; Bhattacharjee et al., 2022, 2024). Here we use a spatial regime model with heterogeneity across the regions and completely unrestricted (nonparametric) spatial autocorrelations.

Supply and demand both have temporal variation. Demand is endogenously determined but supply is exogenous, and we assume that the natural value (V_t^{\star}) is fixed in the short run.

$$V_{\star}^{\bigstar} = V^{\bigstar}$$

Growth of prices (realised value) is determined by growth rates of the occupancy rate (1 - 1)vacancy rate or growth of demand relative to supply), natural value and (time-)lagged realised value. Since $\Delta V_t^{\star} = 0$, and $\Delta \ln(1 - \nu_t) \equiv \Delta \ln D_t - \Delta \ln S_t$, we have: $\Delta V_t = r_t \Delta \ln(1 - \nu_t) + r_t \Delta V^{\star} + r_t \Delta V_t + \epsilon_t$

$$\Delta V_t = \gamma_1 \Delta \ln(1 - \nu_{t-1}) + \gamma_2 \Delta V_t^* + \gamma_3 \Delta V_{t-1} + \epsilon_{1t}$$

= $\gamma_1 \Delta \ln D_{t-1} + \gamma_3 \Delta V_{t-1} - \gamma_4 \Delta \ln S_{t-1} \epsilon_{1t}$ (6)
 $0 < \{\gamma_1, \gamma_3\}, \quad \gamma_4 = \gamma_1.$

In turn, demand growth is explained by change in local (neighbourhood characteristics), growth rate of house prices and change in (local) income or other demand side indicators for local market conditions:

$$\Delta \ln D_t = \lambda_1 \Delta X_t - \lambda_2 \Delta \ln V_t + \lambda_3 \Delta \ln Y_t + \epsilon_{2t}.$$
(7)

Listing price, V_t^L (= $V_t DOP_t$), depends on local neighbourhood characteristics, market conditions and demand. Hence, the degree-of-overpricing is modelled by:

$$\Delta \ln DOP_t = \alpha_1 \Delta X_t + \alpha_2 \Delta \ln Y_t + \alpha_3 \Delta \ln D_t - \alpha_4 \ln V_t + \epsilon_{3t}, \tag{8}$$

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$$\alpha_4 = 1.$$

Likewise, time on the market is modelled as:

$$\Delta TOM_t = \beta_1 \Delta Y_t + \beta_2 \Delta \ln DOP_t - \beta_3 \Delta \ln D_t + \beta_4 \ln S_t + \epsilon_{4t},$$

$$\beta_4 = \beta_3.$$

Under this simple structure without spatial diffusion, and assuming that we have one measure for each of the exogenous variables, we examine the identifiability of the individual equations (relationships). Here we have four endogenous variables ($\Delta \ln V_t$, $\Delta \ln D_t$, $\Delta \ln DOP_t$ and ΔTOM_t) and six exogenous or lagged endogenous variables ($\Delta \ln D_{t-1}$, $\Delta \ln S_{t-1}$, $\Delta \ln V_{t-1}$, ΔX_t , $\Delta \ln Y_t$ and $\Delta \ln S_t$).

All four simultaneous equations are overidentified so that the structural parameters in each relationship can be recovered using two-stage least squares. Efficiency can be improved and weak identification mitigated by including multiple indicators for neighbourhood characteristics and local market conditions.

In addition to spatial heterogeneity, we model spatial autocorrelation or diffusion of demand shocks ϵ_{2t} . Specifically, we allow spatial spillover of the shocks using a spatial error model with spatial autoregressive errors (Anselin, 1988, 1999, 2002). With the errors organised as a $n \times 1$ vector \mathbf{e}_2 collecting values across the *n* regions, this model is written as:

$$\mathbf{e}_2 = \rho \mathbf{W} \mathbf{e}_2 + \eta, \tag{10}$$

where **W** is a ($n \times n$) spatial weight matrix with zero diagonal elements and the off-diagonal elements representing spatial spillovers between regions. This paper is agnostic about the drivers of spatial diffusion, that is, **W** is treated as unknown *a priori*.

4.2 Methodology

In the first stage of our estimation procedure, we estimate the four structural equations individually for each region. This allows for heterogeneity in the relationships across the regions, both in region or fixed effects (intercept heterogeneity) and slope heterogeneity, and in the relevant choice of indicators for neighbourhood characteristics and market conditions; in this final aspect, it has the flavour of high-dimensional model selection (Cai *et al.*, 2019). In other words, we assume a spatial regime model (Anselin, 1988) with a completely general form of heterogeneity across the spatial units. This kind of heterogeneity is reasonable in our context, since our regions are large and it is expected *a priori* that the functioning of housing markets in different regions will be heterogeneous. Under this model, we estimate our structural equations separately for each region using two-stage least squares, and then combine these individual region-specific models, assuming a very general form of spatial diffusion.

For the errors, we assume a spatial autoregressive (SAR) model with an unspecified structure of spatial autocorrelations determined by an unknown spatial weights matrix. Following Fiebig (1999), we estimate the structural equation for demand using seemingly unrelated regressions (SURE) (Zellner, 1962) and recover the nonparametric estimate of the spatial covariance matrix of the reduced form errors from the first stage of this two-stage least squares procedure. As emphasized by Anselin (1999), this approach is very general and does not require any specification of spatial processes or any functional form for the distance decay. In other words, this estimation methodology is nonparametric and makes no assumption about the drivers of spatial diffusion in demand.

Thus, we place special emphasis on the spatial diffusion of demand, which is important in understanding the spatial structure of housing markets. If desired, a similar procedure can also be used to understand the nature of spatial externalities in prices, *DOP* and *TOM*.

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4.3 Data

Our empirical analysis covers housing markets in England and Wales over the period November 2000–May 2003. Because of the distinct nature of the Scottish housing market, particularly in relation to price formation, Scotland is not included in the current analysis. The basic spatial units of analysis are the ten GORs[1] in England and Wales (Figure 1). Data on regional housing markets for the period were collected or estimated on a monthly basis.

Monthly data on local housing markets at three-digit postcode level were obtained from Hometrack, an independent property research and database company in the UK. The variables included are:



Figure 1. Government office regions (GORs) in England and Wales

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- (1) Average number of views;
- (2) Average time on the market (TOM) and
- (3) Average final to listing price ratios (reciprocal of DOP).

The Hometrack data are based on a compilation of monthly responses to a questionnaire from about 3,500 major estate agents in England and Wales. Like other survey-based housing market information in the UK, the reliability of these data depends critically on the representativeness of the selected estate agents, an issue that has not been addressed sufficiently in the literature. These data were used elsewhere (Bhattacharjee and Jensen-Butler, 2013) to study inter-regional spillovers in prices and housing demand.

For the purposes of the current paper, the data are unique in providing information on time on the market and degree-of-overpricing, which provide a unique opportunity to combine the macroeconomic dimension with the process of search, matching and price formation at the microeconomic level. The data also have good coverage in terms of both the spatial and temporal dimensions.

We validate the Hometrack data against related information from other sources. We also augment these data with quarterly information on sales price and number of sales by type of property for each county and local/unitary authority, collected from the HM Land Registry of England and Wales.

Additional regional spatio-temporal data were collected on various dimensions, including:

- (1) Supply: Housing stock (Source: Office of the Deputy Prime Minister (ODPM) and the Office of National Statistics (ONS));
- (2) Demand: Proportion of local authority and RSL dwellings having low demand (Source: ODPM); property transactions (Source: HM Land Registry and Inland Revenue); supply minus vacant housing (Source: ODPM) and average number of views per week (Source: Hometrack);
- (3) Neighbourhood characteristics: Percentage of unfit houses (Source: ODPM); crime rates (Source: ODPM); crime detection rates (Source: Home Office); percentage of university acceptances to applications (Source: Universities and Colleges Admissions Service (UCAS)); percentage of population of 16–24 year olds attending university (Source: UCAS); best value performance indicators (Source: ODPM) and
- (4) Market conditions: Average weekly household income (Source: ONS); unemployment rate (Source: Labour Force Survey (LFS)) and proportion of population claiming income support (Source: ONS).

We used monthly data on prices, degree-of-overpricing and time on the market, averaged for each region, from a detailed level of geographical and temporal disaggregation to estimate the parameters of the model. Our structural model of housing markets in England and Wales is estimated using monthly data at the three-digit postcode level, augmented with other information at the level of the government office regions. Under the assumption of a spatial regime model (Anselin, 1988), we allow heterogeneity across the regions. In other words, the models are estimated separately for each region, based on three-digit postcode-level data within the region. The residuals (at the three-digit postcode level) from these ten regional models for demand are used to estimate the cross-regional spatial covariance matrix (of dimension 10×10) used in the second stage of the SURE estimation.

The estimated model is multi-regional and enables analysis of housing markets in single regions and in conurbations. The estimated structural equation for demand, where demand depends on sales price, local neighbourhood characteristics and market conditions, Asian Journal of Economics and Banking incorporates unrestricted forms of spatial diffusion. The estimated cross-region spatial covariance matrix is then used to interpret the nature of spatial diffusion of demand across the GORs. For prices, *DOP* and *TOM*, we assume a random coefficients model and report mean group estimates combining evidence across the regions (Pesaran and Smith, 1995).

5. Results

A set of demand equations were estimated using the number of views per week as the dependent variable [2], measures of realised value (price), neighbourhood characteristics (unfit houses, access to education and crime detection rates) and indicators of market conditions (claimant counts and household income). The equations were estimated using two-stage least squares, where a proxy realised value was obtained from predictions using a number of instrumental variables, including supply, lagged endogenous variables, neighbourhood characteristics and market conditions.

Separate demand equations were estimated for each region and for England and Wales together. This permits study of unrestricted heterogeneity in the demand relationship across the regions, which is reasonable in the present context. It is well-known that, because correlations are low, instrumental variables methods can lead to poor results in cross-sectional analysis; see Bound *et al.* (1995) for further information. We consider the F-statistics of the first stage regressions for each of the endogenous variables in our model, and verify that the instruments in our estimated model are well-specified.

The estimates of the structural equation (Equation (7)), presented in Table 1, show substantial heterogeneity across the ten GORs in England and Wales. The effect of price changes on demand is, as expected, negative for all the regions. However, the coefficient shows substantial slope heterogeneity across the regions; in fact, estimated price elasticities are very small and not statistically significant at the 5% level for Wales and for Yorkshire and the Humber.

Neighbourhood characteristics have an important effect on demand. However, as with prices, the nature of this effect is heterogenous across the different regions. Demand in all regions is positively related to access to education; the coefficients are statistically significant at the 5% level in all regions except the South East (where the *p*-value is 0.096). This finding is in line with the conclusions of other studies concerning the effect of access to education on house prices; see Gibbons and Machin (2003), among others. The share of unfit houses is negatively related to demand in all regions except Wales, though the coefficients are not statistically significant for London, the East Midlands and the East of England. Crime detection has a positive effect on demand for housing in Yorkshire and the Humber.

The impact of neighbourhood characteristics on demand across the different GORs, as well as heterogeneity in these relationships, have important implications for housing policy. Access to education affects housing demand significantly across all the regions of England and Wales, while crime detection has an important effect in Yorkshire and the Humber. The quality of housing stock, measured by the proportion of unfit houses, has significant negative effects on housing demand in the regions South East, South West, North West, Yorkshire and the Humber and the North East.

As in the case of price changes and neighbourhood characteristics, market conditions also affect demand for housing; the strength and nature of the effect vary across the regions. Demand is negatively related to claimant counts in all the regions and is positively related to income in Yorkshire and the Humber. However, the effect of market conditions on demand is not statistically significant, at the 5% level, in the South East, East Midlands, North West and Yorkshire and the Humber.

In Table 1, we also report, as a benchmark, the results for England and Wales as a whole. As expected, because of substantial heterogeneity across the regions, these results are only

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Regressors	Coeff	Std.Err	Coeff	Std.Err	Coeff	Std.Err	Economics and
	London		South East		South West		Banking
$\Delta \ln \widehat{V}_{4}$	-2.266***	0.651	-8.965***	2.304	-4.360***	1.206	
ΔX_{1t}	-1.871	1.265			-10.439^{***}	3.517	
$\Delta X_{1,t-1}$			-8.702 ***	2.237			
ΔX_{2t}			6.946*	4.173			1
$\Delta X_{2,t-1}$	34.853 ***	9.640			83.215***	21.389	155
ΔY_{1t}			-0.082	0.117	-0.579^{***}	0.222	
$\Delta Y_{1,t-1}$	-0.690***	0.198	0.001 ***	0.010	0.150***	0.040	
Intercept	-0.002	0.029	-0.061	0.018	-0.153°	0.046	
	Fast of Fngland		Fast Midlands		West Midlands		
$\Delta \ln \hat{V}$	-6.941***	1.866	-4.863***	1.803	-18.238**	9.223	
ΔX_{1t}			-7.934	6.232			
$\Delta X_{1,t-1}$	-0.212	2.346					
ΔX_{2t}	12.032**	5.476	52.665***	14.161			
$\Delta X_{2,t-1}$					18.356***	6.378	
$\Delta Y_{1,t-1}$	-0.990^{***}	0.301	-0.044	0.133	-1.092^{***}	0.353	
Intercept	0.083*	0.048	0.028	0.022	0.237*	0.132	
	North West		Yorks and Humber		North Fast		
$\Delta \ln \hat{V}$	-15.903***	3.921	-1.192	0.781	-12.568***	3.161	
ΔX_{1t}	-2361***	0.678	-7563^{***}	2852	-4561^{***}	1 262	
ΔX_{2t}	99.869***	25.319	89.555***	23.018	73.461***	23.772	
ΔX_{3t}^{2t}			0.192**	0.076			
ΔY_{1t}	-0.034	0.118					
$\Delta Y_{1,t-1}$					-2.066^{***}	0.556	
ΔY_{2t}	· · · · · · · · ·	0.038	0.842				
Intercept	0.052	0.016	0.080	0.036	0.218	0.059	
	Wale	s			All regio	ms	
$A \ln \hat{V}$	-0.532	1.172			-52.995***	12.426	
$\Delta m v_t$ ΔX_{14}					-0.370***	0.106	
ΔX_{2t}					12.696***	3.414	
$\Delta X_{2,t-1}$	38.998***	13.141					
$\Delta Y_{1t}^{2,r}$	-0.949^{***}	0.273					
$\Delta Y_{1,t-1}$					-0.336***	0.097	
Intercept	-0.062**	0.028			0.831***	0.214	

Note(s): Dependent variable: $\Delta \ln D_i$, Regressors – V: Predicted price (instrumented); X_1 : Unfit houses %; X_2 : University acceptances as % of applications; X_3 : Crime detection %; Y_1 : Benefit claimants per '000 Population and Y_2 : Logarithm, average weekly household income. Statistical significance at conventional levels is reported for reference: *** 1% level; ** 5% level and * 10% level Source(s): Authors' own work

 Table 1.

 2SLS estimates,

 structural equation for

 demand

indicative (Pesaran and Smith, 1995). Nevertheless, the results represent reasonably well the direction and strength of the underlying regression relationships. We also estimated the structural relationship for demand allowing for region-specific fixed effects; the results were very similar.

Like the structural equation for demand, we also estimated equations for price (Equation (6)), degree-of-overpricing (Equation (8)) and time on the market (Equation (9)), both for each individual region and for England and Wales as a whole. There is substantial heterogeneity across the regions, both in the specification and in the strength of the relationships; this implies that the estimated coefficients are only indicative.

Since our main focus here is on the demand relationship, we do not present these heterogenous model estimates here. Instead, we aggregate the regional estimates and present only the mean group estimates (Pesaran and Smith, 1995) for the structural equations averaged across regions in England and Wales (Table 2). These estimates represent the direction and strength of the regression relationships for the different regions.

The rental adjustment model for prices is well-specified, with house prices strongly and positively related to lagged prices and strongly and negatively related to lagged vacancy rates. As indicated by our structural model, the degree-of-overpricing is positively related to prices and demand; however, neither of these effects is statistically significant at the 5% level. Degree-of-overpricing is strongly and positively related to income and strongly and negatively related to crime rates; see also Gibbons (2004).

Consistent with the structural model, time on the market is strongly and positively related to degree-of-overpricing and is strongly and negatively related to growth in demand. Since supply is highly inelastic, growth in supply has positive effect but is not statistically significant. Changes in market conditions, as measured by an increase in claimant counts, have a negative effect; this reflects a stronger effect on time on the market from the demand side, where higher-income households tend to wait longer for a good match before buying a house.

As a first approach towards identification of the pattern of spatial autocorrelation across the regions, we estimate the structural equation for demand in a seemingly unrelated regression (SURE) framework (Zellner, 1962). In this approach, the spatial covariance matrix is estimated non-parametrically, that is, without specifying an explicit spatial process or functional form for distance decay (Fiebig, 1999; Anselin, 1999). Separate equations are estimated for each region and we allow the unexplained variation in demand to be contemporaneously correlated across the regions. This approach is consistent with the spatial regime model (Anselin, 1988) in that it allows heterogeneity in the demand relationship across the ten GORs in England and Wales. Further, in admitting correlated errors across the regions, the approach allows for completely unrestricted spatial autocorrelation. In other words, this assumes a very general treatment of a spatial error model, which is aligned with the spatial lag model (Anselin, 1988).

Regressors	Coeff Std.Err Prices		Coeff Degree-of-ove	Std.Err rpricing	Coeff Std.Err Time on the market		
$ \Delta \ln \widehat{V}_{t} \Delta \ln \widehat{D}_{t} \Delta \ln \widehat{DOP}_{t} \Delta \ln S_{t} \Delta \ln V_{t-1} \Delta \ln V_{t-1} $	0.073***	0.020	0.041 0.0021 ★	0.065 0.0011	-2.129 *** 66.109 *** 0.274	0.589 16.992 0.748	
$\begin{array}{l} \Delta \ln \frac{y_{l-1}}{D_{l-1}} \\ \Delta X_{4t} \\ \Delta Y_{1,t-1} \\ \Delta \ln Y_{2t} \\ \text{Intercept} \end{array}$	-0.0034 0.015 ***	0.0010	-0.0033 *** 0.053 *** -0.0004	0.0012 0.015 0.0018	-0.328^{***} -0.016^{**}	0.131 0.008	

Table 2.

2SLS estimates, structural equations for prices, degree-ofoverpricing and time on the market **Note**(s): Dependent variables: $\Delta \ln V_b \Delta \ln DOP_b$, and ΔTOM_b respectively. Regressors – \hat{V} : Predicted price (instrumented); \hat{D} . Predicted demand (instrumented); \hat{DOP} . Predicted degree-of-overpricing (instrumented); \hat{S} : Supply; V: Price; D. Demand, X_4 : Crime rate (notifiable offences per 1,000 households); Y_1 : Benefit claimants per '000 Population and Y_2 : Logarithm, average weekly household income. Statistical significance at conventional levels is reported for reference: ******* 1% level; ****** 5% level and ***** 10% level **Source(s)**: Authors' own work

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Regions	Е	EM	L	NE	NW	SE	SW	W	WM	YH	Asian Journal of Economics and
A. Errors	s, Spatial co	ovariance i	matrix								Banking
E	0.014										
EM	0.013	0.023									
L	0.008	0.011	0.011								
NE	0.021	0.034	0.018	0.094							
NW	0.003	0.006	0.003	0.006	0.020						157
SE	0.010	0.010	0.007	0.018	0.001	0.010					
SW	0.003	0.002	0.003	-0.002	0.009	0.002	0.010				
W	0.023	0.036	0.019	0.100	-0.009	0.022	-0.013	0.152			
WM	0.006	0.010	0.008	0.016	0.005	0.006	0.004	0.133	0.011		
YH	0.028	0.041	0.024	0.100	-0.003	0.024	-0.006	0.131	0.018	0.142	
B. Errors	, Spatial co	orrelation i	matrix								
E	1										
EM	0.736	1									
L	0.647	0.702	1								
NE	0.577	0.736	0.560	1							
NW	0.185	0.280	0.221	0.141	1						
SE	0.832	0.692	0.680	0.607	0.100	1					
SW	0.232	0.146	0.272	-0.074	0.612	0.173	1				
W	0.493	0.598	0.474	0.834	-0.171	0.579	-0.331	1			
WM	0.473	0.631	0.724	0.509	0.358	0.552	0.359	0.329	1		
YH	0.622	0.709	0.607	0.869	-0.050	0.633	-0.160	0.892	0.446	1	
Note(s): NW: Nort Humber	Region at thWest; SE	bbreviatior 2: South Ea rs' own wo	ns. E: East ast; SW: So rk	of England; outhWest; W	EM: East : Wales; W	Midlands M: West	s; L: Greate Midlands a	r London; and YH: Y	NE: Norf orkshire	th East; and the	Table 3. Spatial error covariances and correlations

Table 3A presents the estimated spatial covariance matrix of the residuals across the ten regions. The spatial correlation matrix derived from this covariance matrix (Table 3B) shows some interesting spatial characteristics. While formal tests to negate strong spatial dependence along the lines of Pesaran (2015) are difficult because of the small spatial dimension, no dominant units are apparent. The results in Table 3B, in combination with those in Table 1, have interesting implications for region-specific housing policy.

The patterns of spatial correlation across the ten GORs indicate that spatial patterns in demand are, in some cases, explained by contiguity and geographical distance. These include: South East and the East of England; Yorkshire and the Humber and North East and East Midlands and East (the East of England).

However, there are possible alternative explanations for some spatial autocorrelations. The high correlation between Wales, the North East and Yorkshire and the Humber highlights the peripheral component of a core-periphery structure. One possible interpretation is that an external shock affects the periphery as a whole differently, and in some senses uniformly, compared to other regions.

It is interesting to note that the spatial errors for Greater London are not strongly correlated with the adjacent regions, South East and East. These two regions can therefore be regarded as substitutes in the choice of housing location; see also Bhattacharjee *et al.* (2022). This suggests that the regional markets are segmented in social terms, implying that while London is attractive for certain social or ethnic groups, these groups are less attracted by the housing markets in the East and South East. This view is also supported by the high spatial correlations between Greater London and the two regions of the West Midlands and East Midlands. Meen and Meen (2003) point to the importance of social interactions and segregation in understanding housing markets.

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Thus, the pattern of spatial correlations provides interesting insights into the drivers of spatial diffusion in demand. While our analysis in this paper is indicative, the nature of spatial diffusion of demand requires more careful and detailed consideration. Explicit estimates of the spatial weights matrix offer similar interpretations (Bhattacharjee and Jensen-Butler, 2013). Understanding the nature of spatial diffusion is important for the design and conduct of region-specific housing policy as well as for understanding features of the UK housing markets, including ripple effects (Meen, 1996; Cook and Holly, 2000; Bhattacharjee *et al.*, 2022). This leaves substantial scope for future research.

6. Conclusion

In this paper, we propose an economic model of regional housing markets in England and Wales, incorporating both the macroeconomic relationships between prices, demand and supply and a microeconomic model of search, matching and price formation. We estimate this micro-founded model of regional housing markets in England and Wales, incorporating heterogeneity across the regions and unrestricted patterns of spatial interactions. Notwithstanding substantial heterogeneity in the structure of housing markets across the different regions, the proposed economic model describes well the structure of housing markets in each of the regions. Further, we find significant spatial relationships in demand between GORs in England and Wales, many of which are readily interpreted, though a simple understanding in terms of contiguity and distance is clearly inadequate.

By incorporating heterogeneity at different levels, the approach potentially enables improved prediction of demand and prices in regional housing markets. Further, the approach also permits evaluation of the effects of spatially asymmetric shocks on the housing markets in all regions. The methodology allows heterogeneity in the specification of spatial diffusion in different regions and identifies region-specific drivers in the housing market. Hence, the methodology is useful both for explaining how regional housing markets function and in the evaluation of region-specific housing policy.

The work in this paper suggests several extensions and paths of model development. The estimated spatial autocorrelations across the regions indicate several distinct channels of spatial diffusion of demand. However, further work is necessary to identify the spatial processes through which housing demand in any one region is transformed by demand from other regions. A nuanced combination of how diffusion in the different regions is driven by different factors, including contiguity, distance, peripherality, position in the urban hierarchy as well as social and ethnic composition, requires further research.

Finally, in this work, we took housing supply as exogenous because it is largely driven by planning and other policy constraints. Housing supply in the UK is inadequate, particularly for some social and ethnic groups, and the gap between demand and supply varies substantially across the regions. Further research is needed to understand regional housing supply and housebuilding, its determinants and implications for housing and regional policy.

Notes

- 1. Also denoted NUTS1 or ITL1 regions.
- 2. We also experimented with several other measures of demand, and findings are qualitatively similar.

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