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Abstract

We propose and estimate 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. The empirical model, estimated separately for each of the 10 government office regions in England and Wales, validates the economic model. However, we find substantial heterogeneity across the regions, which is potentially useful in informing housing and land-use policies. In addition, the model allows completely unrestricted inter-regional spatial relationships. The estimated spatial autocorrelations imply different drivers of spatial diffusion in different regions, the understanding of which can be improved by further work.

Keywords: Housing markets; Search and matching; Spatial diffusion; Housing demand; Housing Supply.

JEL Classification: R21; R31; R33; C31.

1 Introduction

Much has been written on how residential property markets function at the macroeconomic level, including price formation, inflation and volatility. 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. In this paper, we examine the way in which housing markets in the 10 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 pattern of spatial autocorrelation, and therefore can be extended to include spatial effects such as interregional diffusion of demand.

The approach permits 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 to 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. This methodology enables comparison of the effects of different policies such as improvement of transport infrastructure, quality of public services and employment opportunities on the housing market, either at national or region level. 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 examines other approaches to the study of housing markets and discusses the institutional background. The underlying structural model is presented in Section 3, followed by description of the econometric methodology in Section 4. The data are described in Section 5, Section 6 discusses the empirical results, and conclusions are drawn in Section 7.

2 Studies of the housing market and the institutional background

A substantial literature on the UK housing market has accumulated over the past two 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 lower response of demand to price signals as compared with changes in income (Meen, 2003; Barker, 2004).

The literature also reflects substantial and continuing inter-regional differences, both in terms of prices and volatility. These spatial price differences 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; Barker, 2003, incorporating inputs from Meen (2003) and 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) have been discussed in the literature.

Two other aspects of the UK regional housing markets have attracted considerable research attention. Several hedonic and repeated sales models of regional prices have been constructed (Holmans, 1990; Ashworth and Parker, 1997; Rosenthal, 1999). These models reflect not only geographically varying price effects, but also substantial spatial dependence. Several 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 to the rest of the UK over time (Meen, 1999; Cook and Holly, 2000; Cook, 2003). The existence of ripple effects reflects spatio-temporal dependence in regional housing prices in the UK.

The above literature abounds in implicit acknowledgement of 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), and social interactions and segregation (Meen and Meen, 2003). In this paper, we do not hypothesize *a priori* any fixed pattern of spatial diffusion, and estimate our models in a way that is consistent with any 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, low response of demand to price signals, substantial and continuing inter-regional differences in prices and volatility, and ripple effects (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 a microeconomic theoretical foundation and allows both for heterogeneity across the regions and arbitrary nature of spatial diffusions. The estimated models derived from this economic model can thus be used to understand the factors driving the regional housing markets in the UK, including region-specific differences in economic activity and neighbourhood conditions.

3 A Micro-founded Model of Housing Markets

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

3.1 Demand, Supply and Prices

Based broadly on work of earlier researchers on rental office markets (see Wheaton and Torto, 1993; Wheaton, 1990; Wheaton *et al.*, 1997; Hendershott *et al.*, 2002; and Fuerst, 2004), we begin with an economic model consisting of three behavioural relationships (for price adjustment, demand and supply) 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^*) and deviations of the realised value from its equilibrium level (V_t^*). This is essentially the rental adjustment model expressed in terms of values rather than rents, and incorporating an extension proposed by Hendershott (1996) postulating an additional role for adjustment of the actual level of rent to the natural rent.

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

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) and the neighbourhood characteristics include socio-economic variables (X_t; quality of education and public services, 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 $\lambda_3 > 0$ may be regarded as the income elasticity.

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)) become recursive 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 obtain. 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 non-urban areas since investment in residential property is often highly localized 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 about demand-supply mismatches.

The literature on search and bargaining models (see, for example, Wheaton, 1990; Yavas, 1992; Arnold, 1999; Krainer, 2001; and Anglin *et al.*, 2003) highlights the way in which the initial list price is set, 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 an appropriate buyer. The trade-offs between time-on-the-market and setting the initial listing price (equivalently, the degree of overpricing) play crucial 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 reduces time-on-the-market but also simultaneously reduces the final price.

Broadly following Anglin *et al.*(2003), we have:

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

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

Further, it has been argued that time-on-the-market decreases with the degree of overpricing and increases with vacancy rate; this negative effect of the degree of overpricing on time-on-the-market may be magnified in a market niche with smaller list price variance. Here, we shall use the price-determination process and the relationship between time-on-the-market and degree of overpricing (Relationship 4) to identify the gap between demand and supply in residential markets.

$$\ln TOM_t = \beta_0 + \beta_1 . \ln Y_t + \beta_2 . \ln DOP_t - \beta_3 . \ln(1 - \nu_t). \qquad (5)$$

The above five relationships (Equations (1), (2), (3), (4) and (5)) describe a micro-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 regression error.

4 Econometric Methodology

The structural parameters of the system of simultaneous equations given by the relationships described earlier 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. Several recent papers (see, for example, Elhorst, 2003; Baltagi *et al.*, 2003; Giacomini and Granger, 2004; Kalejian and Prucha, 2004) discuss econometric methods for estimating regression models with spatio-temporal variation, both with and without spatially distributed lags.

We estimate our structural relationships in first differences. This approach renders each of demand, supply, prices, degree-of-overpricing and time on the market stationary across the temporal dimension, while non-stationarity over space can be dealt with using a spatial model. Here we use a spatial regime model with heterogeneity across the regions and completely unrestricted (nonparametric) spatial autocorrelations.

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

$$V_t^* = V^*$$

Change in realised value (price) is explained by change in occupancy rate (1- vacancy rate), change in natural value, and lagged change in realised value. Since $\Delta \ln V_t^* = 0$, and $\Delta \ln(1-\nu_t) \equiv \Delta \ln D_t - \Delta \ln S_t$, we have:

$$\begin{aligned} \Delta \ln V_t &= \gamma_1 \Delta \ln(1-\nu_{t-1}) + \gamma_2 \Delta \ln V_t^* + \gamma_3 \Delta \ln V_{t-1} + \epsilon_{1t} \\ &= \gamma_1 \Delta \ln D_{t-1} + \gamma_3 \Delta \ln V_{t-1} - \gamma_4 \Delta \ln S_{t-1} + \epsilon_{1t}, \end{aligned} \tag{6}$$

$$0 < \{\gamma_1, \gamma_3\} < 1, \gamma_4 = \gamma_1.$$

Change in demand is explained by change in local (neighbourhood characteristics), change in price, and change in (local) income or other indicators of local market conditions.

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

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

$$\Delta \ln DOP_t = \alpha_1 \Delta X_t + \alpha_2 \Delta \ln Y_t + \alpha_3 . \Delta \ln D_t - \alpha_4 \Delta \ln V_t + \epsilon_{4t}, \tag{8}$$

$$\alpha_4 = 1$$

Time on the market is given by:

$$\Delta TOM_t = \beta_1 \Delta \ln Y_t + \beta_2 \Delta \ln DOP_t - \beta_3 \Delta \ln D_t + \beta_4 \Delta \ln S_t + \epsilon_{5t}, \qquad (9)$$

$$\beta_4 = \beta_3.$$

Under this simple structure without spatial diffusion, and assuming that we have one measure for each of the exogenous variables, we examine identifiability of the individual equations (relationships). Here we have 4 endogenous variables ($\Delta \ln V_t$, $\Delta \ln D_t$, $\Delta \ln DOP_t$ and ΔTOM_t) and 6 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 the four simultaneous equations are overidentified, so that the structural parameters in each relationship can be recovered using two-stage least squares. Identifiability is not affected by including multiple indicators for neighbourhood characteristics and local market conditions.

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 the sense of intercept heterogeneity (or heterogeneity in spatial fixed effects) and slope heterogeneity, and in the choice of indicators for neighbourhood characteristics and market conditions. 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 there is no *a priori* reason to believe that the functioning of housing markets in different regions will be homogeneous. 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.

We assume a spatial autoregressive (SAR) model with unspecified structure of spatial autocorrelations determined by an unknown spatial weights matrix. Following Fiebig (1999), we estimate the structural equation for demand in a seemingly unrelated regressions (SURE) framework (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.

In this paper, we place special emphasis on the spatial diffusion of demand, since the diffusion of demand is important in understanding the spatial structure of housing markets. However, the same procedure can also be used to understand the nature of spatial externalities in prices, DOP and TOM.

5 The Data

Our empirical analysis covers housing markets in England and Wales over the period November 2000 to May 2003. Because of the special nature of the Scottish housing market, particularly in relation to the process of price-formation, Scotland is not included in the current analysis. The basic spatial units of analysis are the ten government office regions in England and Wales (Figure 1). Data on regional housing markets for the period have been collected or estimated on a monthly basis.

Monthly data on local housing markets at 3-digit postcode level were obtained from Hometrack, an independent property research and database company in the UK. The variables included are:

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

The Hometrack data are based on 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 which has not been addressed sufficiently in the literature. In the context of this paper, the data are unique in providing information on time on the market and degree-of-overpricing, which provide an 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.

The Hometrack data are compared with 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 HM Land Registry of England and Wales.

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

- **Supply**: Housing stock (Source: Office of the Deputy Prime Minister (ODPM) and the Office of National Statistics (ONS);

- **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); Average number of views per week (Source: Hometrack);

- **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

- **Market conditions**: Average weekly household income (Source: ONS); unemployment rate (Source: Labour Force Survey (LFS)); Proportion of population claiming income support (Source: ONS).

Figure 1: **Government Office Regions (GORs) in England and Wales**

Data on average prices, degree-of-overpricing and time on the market at a detailed level of geographical and temporal disaggregation are used to estimate the parameters of the model. Our structural model of housing markets in England and Wales is estimated using monthly data at the 3-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 3-digit postcode level data within the region. The residuals (at the 3-digit postcode level) from these 10 regional models 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 permits 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, incorporates arbitrary forms of spatial diffusion. The estimated cross-region spatial covariance matrix is used to interpret the nature of spatial diffusion of demand across the GORs.

6 Results

A set of demand equations has been estimated using number of views per week as the dependent variable[1], and 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 are estimated using two-stage least squares, where a surrogate realised value is obtained from predictions using a number of instrumental variables including supply, lagged endogenous variables, neighbourhood characteristics and market conditions.

[1] We experimented with several other measures of demand.

Table 1: Estimates, Structural Equation for Demand[2]

	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
	London		South East		South West	
$\Delta \ln \widehat{V}_t$	-2.266	0.000	-8.965	0.000	-4.360	0.000
ΔX_{1t}	-1.871	0.139			-10.439	0.003
$\Delta X_{1,t-1}$			-8.702	0.000		
ΔX_{2t}			6.946	0.096		
$\Delta X_{2,t-1}$	34.853	0.000			83.215	0.000
ΔY_{1t}			-0.082	0.485	-0.579	0.009
$\Delta Y_{1,t-1}$	-0.690	0.000				
const.	-0.002	0.945	-0.061	0.000	-0.153	0.001
	East		East Midlands		West Midlands	
$\Delta \ln \widehat{V}_t$	-6.941	0.000	-4.863	0.007	-18.238	0.048
ΔX_{1t}			-7.934	0.203		
$\Delta X_{1,t-1}$	-0.212	0.928				
ΔX_{2t}	12.032	0.028	52.665	0.000		
$\Delta X_{2,t-1}$					18.356	0.004
$\Delta Y_{1,t-1}$	-0.990	0.001	-0.044	0.740	-1.092	0.002
const.	0.083	0.086	0.028	0.200	0.237	0.073
	North West		Yorks & Humber		North East	
$\Delta \ln \widehat{V}_t$	-15.903	0.000	-1.192	0.127	-12.568	0.000
ΔX_{1t}	-2.361	0.000	-7.563	0.008	-4.561	0.000
$\Delta X_{1,t-1}$						
ΔX_{2t}	99.869	0.000	89.555	0.000	73.461	0.002
ΔX_{3t}			0.192	0.012		
ΔY_{1t}	-0.034	0.774				
$\Delta Y_{1,t-1}$					-2.066	0.000
$\Delta \ln Y_{2t}$			0.038	0.964		
const.	0.052	0.001	0.080	0.027	0.218	0.000
	Wales				All regions	
$\Delta \ln \widehat{V}_t$	-0.532	0.650			-52.995	0.000
ΔX_{1t}					-0.370	0.000
ΔX_{2t}					12.696	0.000
$\Delta X_{2,t-1}$	38.998	0.003				
ΔY_{1t}	-0.949	0.000				
$\Delta Y_{1,t-1}$					-0.336	0.000
const.	-0.062	0.028			0.831	0.000

[2] $\widehat{V}$: Predicted price; X_1: Unfit houses %; X_2: Univ. acceptances / applications %; X_3: Crime detection %; Y_1: Claimant / '000 Pop.; Y_2: Log, Average Weekly HH income.

Separate demand equations are estimated for each region and for England and Wales together. This permits 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 a recent discussion of this issue). Following the literature, we check 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 10 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, price elasticity is not significant at the 5 percent 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 different across the different regions. Demand in all regions is positively related to access to education; the coefficients are significant at the 5 percent level in all regions except 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 significant for London, 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 some potentially 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 detrimental 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 varies 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 significant, at the 5 percent level, in the South East, East Midlands, North West and Yorkshire and the Humber.

Table 2: 2SLS Estimates – Structural Equations for Prices, Degree-of-Overpricing and Time on the Market[3]

	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
	Prices		Degree-of-Overpricing		Time on the market	
$\Delta \ln \widehat{V}_t$			0.041	0.528		
$\Delta \ln \widehat{D}_t$			0.002	0.062	-2.129	0.000
$\Delta \ln \widehat{DOP}_t$					66.109	0.000
$\Delta \ln S_t$					0.274	0.714
$\Delta \ln V_{t-1}$	0.073	0.000				
$\Delta \ln (S_{t-1}/D_{t-1})$	-0.003	0.000				
ΔX_{4t}			-0.003	0.006		
$\Delta Y_{1,t-1}$					-0.328	0.012
$\Delta \ln Y_{2t}$			0.053	0.000		
const.	0.015	0.000	-0.000	0.827	-0.016	0.033

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 indicative. Nevertheless, the results represent reasonably 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.

[3] $\widehat{V}$: Predicted price; $\widehat{D}$: Predicted demand; $\widehat{DOP}$: Predicted degree-of-overpricing; S: Supply; V: Price; D: Demand; X_4: Crime rate (Notifiable offences per 1,000 households); Y_1: Claimant / '000 Pop.; Y_2: Log, Average Weekly HH income.

Like the structural equation for demand, we also estimate 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. Since our major focus here is on the demand relationship, we present only the estimates for the structural equations for England and Wales (Table 2). As in the case of the structural relationship for demand, heterogeneity across the regions implies that the estimated coefficients are only indicative. However, as earlier, they accurately represent the direction and strength of the regression relationships for the different regions.

The rental adjustment model for prices is well-specified, with price changes being strongly and positively related to lagged changes in prices, and strongly and negatively related to lagged vacancy rates.

As indicated by our structural model, degree-of-overpricing is positively related to prices and demand; however, neither of these effects is significant at the 5 percent 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 increase in demand. The effect of change in supply is positive but not significant, which can be related to the fact that supply is highly inelastic. The effect of changes in market conditions, as measured by increase in claimant count, is negative; this reflects a stronger effect on time on the market from the demand side where higher-income households would 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 regressions (SURE) framework (Zellner, 1962). In this approach, the spatial covariance matrix is estimated non-parametrically, (*i.e.*, 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 10 GORs in England and Wales. Further, in admitting correlated errors across the regions, the approach allows for completely unrestricted kinds of spatial autocorrelation. In other words, this is a very general treatment of a spatial error model, which is consistent with the spatial lag model (Anselin, 1988).

Table 3: Spatial Error Covariances and Correlations[4]

A. Errors, Spatial Covariance Matrix

	E	EM	L	NE	NW	SE	SW	W	WM	YH
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					
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 Correlation Matrix

	E	EM	L	NE	NW	SE	SW	W	WM	YH
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

[4] E: East of England; EM: East Midlands; L: Greater London; NE: North East; NW: North West; SE: South East; SW: South West; W: Wales; WM: West Midlands; YH: Yorkshire & the Humber.

Table 3 A presents the estimated spatial covariance matrix of the residuals across the 10 regions. The spatial correlation matrix derived from this covariance matrix (Table 3 B) shows some interesting spatial characteristics. The results in Table 3 B, in combination with those in Table 1, have interesting implications for region-specific housing policy.

The patterns of spatial correlation across the 10 GORs indicate that spatial patterns in demand are, in some cases, explained by contiguity and geographical distance. These include: South East and East; Yorkshire and the Humber and North East; and East Midlands and East.

However, there are possible alternative explanations for some spatial autocorrelations. The high correlation between Wales, North East and Yorkshire and the Humber may represent the peripheral component of a centre-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 perhaps regarded as substitutes in the choice of housing location. This suggests that the regional markets are segmented in social terms, implying that while London is attractive for certain social 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 West Midlands and East Midlands. Perhaps London is relatively more attractive for some social or ethnic groups. Meen and Meen (2003) point to the importance of social interactions and segregation in understanding housing markets.

Thus, the pattern of spatial correlations provide interesting insights into the drivers of spatial diffusion in demand. 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 makets including ripple effects (Meen, 1996). While our analysis in this paper is indicative, the nature of spatial diffusion of demand requires more careful and detailed consideration, and is a future research task.

7 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. Even though there is substantial heterogeneity in the structure of housing markets across the different regions, the proposed economic model describes the structure of housing markets in each of the regions satisfactorily. Further, we find significant spatial relationships in demand between government office regions in England and Wales, many of which appear to be readily interpretable, though a simple interpretation in terms of contiguity and distance is clearly insufficient.

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 in 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 process through which housing demand in any one region is transformed by demand from other regions. In future research, we intend to develop methods for the analysis of processes of spatial diffusion, with a view to understanding 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.

Further extensions to this line of research will include construction of spatial weights matrices that incorporate different drivers of spatial diffusion, based not only on contiguity and distance, but also concepts like population or economic potential, and social and cultural distances. We also intend to extend the analysis to a lower level of spatial disaggregation involving 104 NUTS-3 regions in England and Wales as well as to extend our modeling approach to include temporal aspects, which will facilitate understanding of features such as ripple effects.

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