Buyer Behaviour and Price Expectations: A Spatial Analysis of the Athens Residential Market

Abstract

Purpose – This paper examines the price setting behaviour over time and space in the Athens residential market. In periods of house price inflation asking prices are often based upon the last observed highest selling price achieved for a similar property in the same micro-location. However, in a falling market, prices may be rigid downwards and less sensitive to the most recent transaction prices, weakening spatial effects. Furthermore, the paper considers whether future price expectations affect price setting behaviour.
Design/methodology/approach – The paper employs a dataset of approximately 24,500 property values from 2007 until 2014 in Athens incorporating characteristics and locational variables. The authors begin by estimating a baseline hedonic price model using property characteristics, neighbourhood amenities and location effects. Following this, a spatio-temporal autoregressive (STAR) model is estimated. Running separate models, the authors account for spatial dependence from historic valuations, contemporaneous peer effects and expectations effects.
Findings – The initial STAR model shows significant spatial and temporal effects, the former remaining important in a falling market contrasting with previous literature findings. In the second STAR model, whilst past sales effects remain significant although smaller, contemporaneous and price expectations effects are also found to be significant, the latter capturing anchoring and slow adjustment heuristics in price setting behaviour.
Research limitations/implications – As valuations used in the database are based upon comparable sales, then in the recessionary periods covered in the dataset, finding comparables may have become more difficult, and hence this, in turn, may have impacted on valuation accuracy.
Practical implications – In addition to past effects, contemporaneous transactions and expected future values need to be taken in consideration in analysing spatial interactions in housing markets. These factors will influence housing markets in different cities and countries.
Social implications – The information content of property valuations should more carefully consider the relative importance of different components of asking prices.
Originality/value – This is the first paper to use transactions data over a period of falling house prices in Athens and to consider current and future values in addition to past values in a spatio-temporal context.

Keywords: Athens, housing market, Spatio-temporal autoregressive models

Introduction

The aftermath of the Global Financial Crisis (GFC) had a particularly long-lasting impact on Greece. The country's economy experienced a protracted period of recession and house prices fell significantly from their peak in 2008. Unlike other countries where recovery in housing markets began around 2012, Greece has been different with virtually no evidence of house price increases even by the end of 2017 (Bank of Greece).

Housing markets are also spatial and locational effects are important in determining values. Housing market literature has identified the importance of housing submarkets (Watkins, 2001; Whitehead, 1999). Watkins (2001) argues for a need to embrace submarket delineation where buyers perceive that submarkets are imperfectly substitutable locations. He notes, however, that there is no single widely accepted definition of submarkets. Some authors base submarkets on neighbourhoods while others consider dwelling type. Some have defined submarkets spatially linking contiguous areas (Ball and Kirwan, 1977). These authors further suggest that stock characteristics that can vary spatially may also contribute to imperfect substitutability across locations, or urban neighbourhoods. The debate in earlier literature thus has considered the relative importance of spatial and structural characteristics in submarket determination. Both factors were evident in research by Maclennan and Tu (1996), and by Adair et al (1996). However, researchers may still be unclear and not agree upon submarket boundaries that when constructed may appear arbitrary and imposed by the researcher. Watkins (2001) argues that, "it is possible to derive a set of necessary and sufficient conditions for submarket existence. If we follow post-Marshallian microeconomic theory, the extent of the market for an economic good will encompass all demanders and suppliers involved in the process of exchange who pay the market price for the good (Stigler and Sherwin, 1986). In order to apply this principle to an examination of the structure of the housing market, it is important to consider the underpinning processes that shape the interaction of supply and demand. Thus, …, "housing submarkets exist where the interaction between segmented demand, characterised by consumer groups, and segmented supply, characterised by product groups, generate price differences for some hypothetical standardised dwelling." (p2241)

In estimation and testing for existence of submarkets researchers employ standard hedonic regression modelling. Chow tests can then be employed to find if price differentials exist between segments or submarkets. Findings supporting clearly spatially defined submarkets are not always clear-cut as evidenced from Watkins (2001) when considering how locational and structural characteristics interact. Similar to his approach we begin with a spatially defined set of possible apartment submarkets in Athens.

However as contiguous locations, submarkets may interact with each other. For example, if certain submarkets have better amenities than others, they will tend to be more desirable and expensive. Potential buyers who cannot afford the most expensive neighbourhoods may choose instead the next best, and possibly adjacent neighbourhood. This implies correlation in submarket behaviour reflecting relative substitutability that could be captured in part in price setting behaviour. For example, there could be evidence of a leading submarket in which price change happened first before being transmitted to other contiguous submarkets in a distance-decay type of relationship or ripple effect over a given urban area (Wilson et al., 2011). This would further imply an autoregressive type of relationship and a clear time directionality and causation. Location effects in price setting behaviour would also be evident. The most recent sale may be used to anchor the next asking price in a given neighbourhood. This is also consistent with the sales comparison approach in price setting or valuation. It further reflects a clear directional relationship from past to current and expected future prices. The more proximate a transaction, the greater its impact on new price setting or valuation of similar properties in that location, again generating a distance-decay relationship. Thus, submarkets whilst imperfectly substitutable may remain spatially dependent and therefore ignoring spatial dependence can create omitted variable bias in model estimation.

Thanos and White (2014) note that in a growing market, sales prices can increase rapidly and diverge from asking prices. However, when the market moves into a downturn, asking prices are slow to adjust and may not even change for several quarters reflecting lagged adjustment of price expectations in the housing market. Hence price setting may no longer reflect recent transactions prices in the same neighbourhood and weaken spatial effects.

Neugebauer and Perote (2007) found that a winning bid in the housing market affects market actors' behaviour who interpret this as the price to be paid in the market. This implies that information on past observed transactions prices affects current (asking) prices consistent with the 'sales comparison' approach that may also reflect how estate agents set asking prices.

Secondly current house prices may be affected by contemporaneous effects arising from interactions between market participants. This is in a short time frame where searching, competing and bargaining occur before a final sale is agreed. These endogenous peer effects are captured by using spatially weighted prices of houses sold contemporaneously within that short time frame.

Current house prices may also reflect future expectations captured in the price setting behaviour of other similar properties current on the market and not yet sold. The effect includes the impact of strategic behaviour and anchoring affecting sales prices.

Kahneman and Tversky (1974) discuss the role of heuristics in decision making. These heuristics are cognitive shortcuts that reduce the cost of decision making. Kahneman and Tversky consider the importance of initial conditions when making decisions, such as in price setting behaviour. This is the anchoring effect where estimates of asking prices may depend upon recently observed prices for similar homes. Haurin et al., (2013) find that sellers set their asking price based upon their perceptions of expected future price changes and that asking prices were slow to adjust in falling markets.

The aim of this paper is to examine the impact of timing of the cycle and spatial effects in house price setting behaviour, capturing the impact of the sales comparison effect, the contemporaneous peer effect, and the future price expectations effect.

Literature Review of Spatial Analysis of Housing Markets

Developing from and based upon hedonic house price models, attempts have been made to take into consideration spatial dependence. Initial hedonic approaches tended to be cross-sectional but extension to include a time dimension added time dummy variables in ordinary least squares (OLS) models. In relation to relationships over space, early work included adding neighbourhood and location variables (Dubin and Sung, 1990; Li and Brown, 1980). Dubin (1988) estimated a covariance matrix of errors that was then used to extract unbiased standard errors. This was built upon distances between observations where the relationship would be stronger the shorter the distance. Thanos et al., (2016) note that "literature shows that the effect of misspecifying the temporal relations of spatio-temporal data can result in over-connected spatial weight matrices, which introduce serious biases to both testing for and the estimation of spatial autocorrelation models. "(p79)

Wilhelmsson (2002) examined spatial dependence in house prices using transactions data for Stockholm, Sweden. One interesting finding from this research was the selection of the spatial weights matrix which was found to impact upon the spatial effects estimated. Kim et al (2003) employed both the spatial autoregressive model and the spatial error model to examine the relationship between house prices and air quality in Seoul, South Korea. While the error term and house prices showed evidence of spatial autocorrelation, the authors found that the spatial autoregressive model was the preferred approach to estimation. Spatial dependence was found to be important and reduced the size of neighbourhood amenity impacts.

Brasington (1999) examined the impact of school quality on house price and applied a spatial autoregressive model capturing spatial autocorrelation in the dependent variable and independent variables. The results showed that there was significant spatial autocorrelation and thus the model had an improved fit compared to non-spatial modelling approaches.

Osland (2010) estimated a number of spatial models (including geographically weighted regression and mixed spatial Durbin model) using data for South West Norway. Spatial autocorrelation was found in the dependent variable (house price) and errors but the spatial error model was preferred over the spatial autoregressive model. Thus, capturing spatial effects was found by all of these authors to improve model performance. However, most authors had not considered temporal effects where data were collected over time. In relation to the direction of the relationship, spatial relations can be in all directions theoretically. In relation to time, relationships are from the past to the future and are therefore clearly directional. Thus, when analysing house price data, the spatio-temporal context must be considered as ignoring the unidirectional temporal relationships can bias estimates of spatial dependence (Anselin et al 2008; LeSage and Pace, 2009; Dubé and Legros, 2014) as well as biasing spatial weights matrices (Farber et al, 2009; Smith, 2009).

Spatio-temporal models have been developed in order to address these issues. Can and Megbolugbe (1997) address misspecification due to temporal relations by examining spatial relationships from proximate properties that are sold within the previous six months. They estimated a hedonic house price model and account for misspecification of the temporal component in the data. They used spatio-temporal autoregressive (STAR) models. Their spatial weight matrix included only the spatial effects from neighbouring properties and these were found to be statistically significant. Using condominium data from Singapore, Sun et al (2005) apply a Bayesian estimation approach for a two-order autoregressive spatio-temporal Durbin model. They included spatial effects from neighbouring properties but only those sold in six months before the sale of the specific property. They found that this estimator produced more robust coefficients addressing heteroscedasticity more efficiently in comparison with a non-spatial OLS estimator.

Pace et al (1998) consider both spatial and temporal dependence using a filtering approach. This method separates the spatial weights matrix into different matrices for spatial, temporal and spatio-temporal links respectively. The temporal weights matrix (T) is defined by a lower triangular matrix where all observations are chronologically ordered from the first row and column in the matrix. The matrix products ST (where S is a standard spatial weights matrix) and TS account for the indirect spatio-temporal effects respectively. Pace et al (2000) follow this same approach when examining house prices in Baton Rouge, US. As with their earlier paper, the spatio-temporal model reduced the median absolute error of estimation. Applying this approach to the Randstad, the Netherlands, Liu (2013) finds both spatial and temporal dependence but with the spatial dependence being much stronger.

Sun et al. (2005) construct a Bayesian estimation approach for a two order autoregressive spatio-temporal Durbin model. They suggest that this approach produces more robust coefficients as it efficiently detects and corrects heteroskedasticity when compared to OLS. However, they found a trade-off between the heteroskedastic robustness and the incorporation of spatial information into the model estimation. Nevertheless, they argue that it is more efficient to derive location and property specific indices by specifying a two order autocorrelation in a spatio-temporal Durbin model since price movements may vary across different development locations and at different times. Adopting a similar modelling specification, Tu et al. (2004) create the first spatio-temporal hedonic model applied to the office market, constructing transaction-based office price indices at the property level.

Nappi-Choulet and Maury (2009) apply a spatio-temporal Durbin model to office markets in Paris finding the existence of both spatial and temporal effects and that the dependence coefficients vary significantly with the date of transaction. In another paper, Nappi-Choulet and Maury (2011) apply spatial modelling to housing markets in Paris. They create sub-samples taking the closest spatial and temporal neighbours for a given house transaction. Their results find the presence of strong spatial and temporal heterogeneity. They find stronger spatial autogressiveness in the centre of Paris and that the price of certain housing attributes varies counter-cyclically.

Dubé and Legros (2013) develop a spatio-temporal weight matrix in which separate spatial and temporal weight matrices are multiplied using the Hadamard product. The application of the matrix ensures simultaneity between space and time so that the dynamic temporal effect is spatially modelled with the spatial effect temporarily adjusted within the unidirectional temporal framework. Their research found significant spatial effects. The potential over-connection identified in Smith (2009) when all observations are assumed to be simultaneously linked in a strictly spatial weights matrix is addressed with distance cut-offs. This is further tested by Dubé and Legros (2013) who suggest that a correctly specified spatio-temporal autoregressive (STAR) model can overcome this potential problem.

Thanos et al (2015) use spatial models based upon the Hadamard spatio-temporal matrix to estimate the impact of aviation noise exposure on the Athens housing market. They use robust Lagrange multiplier tests to choose between spatio-temporal autoregressive and the spatio-temporal error model specification. They find significant spatial autocorrelation in the error terms. They interpret this as being due to new houses that are a large part of their dataset with spatial effects being unobserved effects from new house building and urban infrastructure improvements in the urban area, rather than coming from past house prices. Thanos et al (2016) again use the Hadamard spatio-temporal matrices to estimate spatial dependence in house prices in Aberdeen, Scotland. Using the auction system that dominates urban housing transactions in strong markets in Scotland the authors measure three different spatio-temporal dependences in house prices; the comparable past sales effect, future expectation effect, and contemporaneous effect. The findings from this study suggested that spatio-temporal effects of comparable past sales tended to decrease when the future expectations and contemporaneous peer effects are considered all together, in comparison to considering only the comparable past sales effect. Spatio-temporal models were found to outperform the spatial only model and significant differences between two specifications were found in the constant and the time dummy variable coefficients. They suggested that the temporal effects were erroneously captured by the time dummy variables in the spatial only model.

Following Kuminoff and Jarrah (2010) spatially specific amenities are linked to house location and hence each house is a unique bundle of local amenity values and its own characteristics. Changes in the economy and preferences also make house prices change over time. Considering the comparable sales approach, in establishing the price of the property, buyers will examine similar properties in the same neighbourhood with the same amenity attributes. Houses further away will be discounted and their asking prices seen as less relevant.

Hyun and Milcheva (2018) estimate a spatio-temporal autoregressive model of the apartment market in Seoul, South Korea, using data covering a full economic cycle between 2006 and 2015. Their research notes the importance of considering temporal causality within a model of spatial relationships where "spatial dependence can be defined as a unidirectional effect from the past transactions to the present transaction, but not from future transactions … (Op. Cit., p37). Hyun and Milcheva find that spatial dependence in property prices is significantly higher in the boom than bust period, hence varying over an economic cycle. Thus, neighbouring property prices are reasonable benchmarks in rising markets but become less relevant in falling markets. They relate this to the concept of loss aversion. In a falling market, sellers will be less likely to drop price for a sale. Loss aversion is the key component of prospect theory (Kahneman and Tvesky 1974, 1979). Key to this is the asymmetric impact on utility (or welfare) of equal value gains and losses. A loss has a greater (negative) utility impact than an equal sized gain. In the housing market, sellers want to avoid losses in a falling market so may hold on to the property for longer. In this situation, information on adjacent properties (similar properties in the same submarket) is less relevant in a falling market. Loss aversion keeps sellers in their homes (longer duration on-the-market) reducing move probabilities (Genesove and Mayer 1997; Anenberg 2011). Sellers either do not, or are slow to adjust price expectations in a falling market, anchoring on past (higher) observed transaction prices (see Thanos and White (2014) for this effect in the Aberdeen housing market and Haurin et al., (2013) in the Belfast housing market).

Stamou et al., (2017) examine house prices in Athens using spatial analysis and estimate a range of different spatial models (including spatial general, autoregressive, spatial Durbin, spatial error models) and weighting schemes to find the best fit based upon evaluation criteria. Given the lack of publicly available datasets for house prices and characteristics, they collect information from real estate agencies and amass over 11,000 observations for properties on the market in September 2013. They found that their spatial general model fitted best (on criteria including the Akaike Information Criterion), where this model includes both the spatial lag term and spatial correlated error.

More recently, Nikitidou et al., (2021) analyse the determinants of residential property prices in Athens using property characteristics and macroeconomic determinants. They employ data from 2011 to 2016 although they do not explicitly consider spatial interactions. The find that both hedonic characteristics and macroeconomic variables are significant determinants of price.

Spatial and Temporal Modelling

Hedonic analysis of housing markets usually regresses the house transaction price on characteristics which may include the property's location:

$$P_i = X_i\beta + \varepsilon_i \tag{1}$$

where P_i is the price of the ith house, X_i is a vector of exogenous variables, β is a vector of parameters and ε_i is a stochastic disturbance term. In this linear OLS hedonic regression, the house price depends on its characteristics but not on prices of nearby properties, in contrast to spatial models. In the case where two properties, i and j, are neighbouring spatial dependence could take the form:

$$P_i = \rho \sum_j^n w_{ij} P_j + X_i\beta + \varepsilon_i, \tag{2}$$

where w_{ij} is the spatial dependence relationship between houses i and j and the interaction term $w_{ij}P_j$ is a spatially lagged price of house i's neighbouring house j on the spatial dependence relations. The term immediately to the right of the sigma sign is a linear combination of spatially lagged prices of property i's adjacent properties. The parameter ρ represents the spatial dependence of property i's price on a linear combination of its neighbouring property prices. W is a spatial weights matrix and the spatial autoregressive process can take the following form:

$$P = \rho WP + X\beta + \varepsilon \tag{3}$$

A key issue is to define spatial weights within the spatial weights matrix. Weights may be based upon a Euclidean distance function where all observations up to a given distance are defined as being neighbouring and all others are non-neighbouring. Logically and crucial in spatial relationships is the idea that closer properties have a greater impact on each other than those further away. The inverse distance function of the spatial weights matrix, S_{ij}, ensures that the distance-decay function gives closer houses higher weights than those further away. The main diagonal elements in the matrix S have a zero value so that properties are not considered to be neighbours to themselves. The spatial weights matrix is normalised to have row sums of unity forming a spatial lag of linear combination of values from neighbouring observations (Can and Megbolugbe, 1997: Dubé and Legros, 2014). Following the row-standardisation process, the spatial weight matrix forms a row stochastic matrix and the sum of the weights in each row is equal to one permitting the spatial relationship to be measured as a weighted average across the neighbouring houses (Anselin, 1988).

However, given that temporal relations are unidirectional, not considering such relationships would lead to over-connection problems in a spatial weight matrix that consequently would cause bias in the estimation of spatial dependence (Farber et al 2009). A spatio-temporal weight matrix can be calculated in which a separate temporal weight matrix with unidirectional time causality is multiplied by a standard spatial weight matrix using the Hadamard product (Thanos et al., 2016). The values on the leading diagonal of the temporal matrix, T, are zero and also the upper triangular elements have zero values, whereas the lower triangular have positive values. A spatio-temporal weight matrix W, is formed by multiplying the spatial weight matrix S with the temporal weight matrix T using the Hadamard product. This matrix has chronological ordering and spatially and temporally closer neighbouring observations (nearer in time and space) have a greater impact (weight) than others.

Spatio-temporal dependence has been introduced into hedonic price models by the spatio-temporal autoregressive (STAR) model, and the spatio-temporal error model (STEM). The implicit assumption in the STAR model is that house prices are affected by spatio-temporal weighted average prices of neighbouring houses specified in the spatio-temporal weight matrix. Therefore, the STAR model includes a vector of spatio-temporally lagged house prices as an explanatory variable in addition to standard hedonic variables that describe property-specific and neighbourhood-specific characteristics. As its name suggests, the STEM considers spatio-temporal dependence in the error terms. The assumption in STEM is that omitted variables in hedonic models are spatio-temporally correlated and therefore not independent of each other, the effect being captured within the error term.

Into a hedonic price model, the STAR model incorporates a spatio-temporal autoregressive term that is an interaction term between an exogenous spatio-temporal weight matrix and a vector of dependent variables. The general format is in (3) above. The spatial models can be used to capture behaviour in real estate markets. Realtors will use a comparable sales approach when setting asking prices. The most recent sale price of a similar property may anchor the asking price for a given property and can be captured in the autoregressive term in the STAR model. This is particularly useful for our study as the pricing variable is house valuations. STAR models thus correspond more closely to how the real estate market functions. Thus failing to consider spatio-temporal dependence in the dependent variable would lead to biased estimates and inaccurate interpretation of other hedonic variable coefficients within the model (LeSage and Pace, 2009).

The STEM model takes the following functional form:

$$\begin{aligned} P &= X\beta + \varepsilon \\ \varepsilon &= \lambda W\varepsilon + u \end{aligned} \tag{4}$$

where λ is the scalar parameter of spatio-temporal autoregressive effects for the random error ε. The spatial coefficient, λ, captures spatio-temporal dependence in omitted variables. In the housing market it may be possible that unobserved location characteristics, (e.g., amenities), could exhibit spatial dependence to another unobserved variable so there are no longer uncorrelated error terms. Ignoring this would cause biased parameter estimates, misleading significance levels, and loss of efficiency.

Anselin (1999) considers four related models where: a) dependence relates to neighbouring locations in different time periods; b) dependence relates to the same and neighbouring locations in different time periods; c) with both a time and spatially lagged dependent variable; and d) where all forms of dependence are possible:

$$y_{it} = \lambda y_{it-1} + \rho[Wy_t]_i + \gamma[Wy_{t-1}]_i + f(z) + \mu_{it} \tag{5}$$

where *f(z)* includes regressors that can be lagged over both time and space, $[Wy_{t-1}]$ is the i^{th} element of the spatial lag vector applied to observations on the dependent variable in the last time period, and $[Wy_t]_i$ is the i^{th} element of the spatial lag vector in the current time period.

Given that the dataset has both time and space components, a spatiotemporal autoregressive (STAR) model is specified based upon (5). Properties sold in any given time period will have a transactions price that is a function of its characteristics that include its locational amenities (that may also reflect agglomeration economies) within the neighbourhood (or submarket) and neighbouring properties sold in the same time period and some weighted average of proximate spatiotemporal properties sold in past periods only. We nest both autoregressive and error models via spatial dependence in the dependent variable and the error term. Hence from (5) the error specification takes the form as expressed in (6) below.

$$\mu = \rho W \mu + \upsilon \tag{6}$$

Where υ is assumed to have zero mean and constant variance and is essentially the same as (4).

The buyer has information on the characteristics of the relevant property and the price history of comparables in addition to information on comparable properties contemporaneously on the market with the property in question. Furthermore, the buyer may interact with other buyers and sellers in the market. This is captured by the price of an alternative property, P_{ht}, where h is the spatial neighbour. This is a short run effect that has a significant price effect.

The three effects on price (the past sales, contemporaneous and expectations effects) imply an autoregressive model leading to a STAR model of:

$$P_{it} = \alpha + \psi \sum_{j=1}^{J} w_{ij} P_{j(t-p)} + \varphi \sum_{m=1}^{M} w_{im} P^*_{m(t+q)} + \rho \sum_{h=1}^{H} w_{ih} P_{ht} + \sum_{k=1}^{K} \beta_k x_{ikt} + \varepsilon_{it}$$

(7)

In this equation the parameters ψ, φ, and ρ capture the comparable sales, sellers' expectations, and the contemporaneous peer effects respectively. To combine time and spatial distances between observations i and j, we multiply the spatial distance dij with time distance tij:

$$w_{ij} = f(d_{ij}) \times f(t_{ij})$$

(8)

This leads us to a Hadamard (or Schur) product of two matrices of the same dimension.

Next, spatio-temporal weights matrices need to be constructed. Data are ordered chronologically. Spatial links, s_{ij}, between observations (i and j) reflect the intensity of the spatial relationship captured by the Euclidian distance d_{ij}.

$s_{ij} = e^{-d}$ if $i \neq d_{ij} \neq d_c$ (9)
$s_{ij} = 0$ if $i = j$ or $d_{ij} > d_c$

Where d_c is the cut-off distance that can be fixed for all observations of variable for each observation. However fixed cut-off distances can be problematic particularly in areas of high sale density with many spatially close transactions. Alternatively in other areas there may be observations with no neighbours which can occur in thin markets and / or in recessionary markets in which sellers adopt a wait-and-see attitude. To take account of this we take a cut-off distance to be equal to the average distance for each observation, so $d_c = \bar{d}_i$. Additionally, and as in Thanos et al (2016), this is not a linear effect but a non-linear dissipation to overcome the problem of over-connection as discussed by Smith (2009). The spatial weights matrix can then be written as:

$$\boldsymbol{S} = \begin{bmatrix} 0 & s_{12} & s_{13} & \cdots & s_{1N_R} \\ s_{21} & 0 & s_{23} & \cdots & s_{2N_R} \\ s_{31} & s_{32} & 0 & \cdots & s_{3N_R} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{NN_R1} & s_{N_R2} & S_{N_R3} & \cdots & 0 \end{bmatrix} \quad (10)$$

This matrix can also be written as:

$$\boldsymbol{S} = \begin{bmatrix} S_{11} & S_{12} & S_{13} & \cdots & S_{1R} \\ s_{21} & S_{22} & s_{23} & \cdots & s_{2R} \\ s_{31} & s_{32} & S_{33} & \cdots & s_{3R} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ s_{R1} & s_{R2} & S_{R3} & \cdots & S_{RR} \end{bmatrix} \quad (11)$$

Here, for example, the top left term S_{11} shows spatial connection between transactions that take place in the first time period. The leading diagonal captures spatial connections for contemporaneous transactions. The lower triangular captures spatial connections between transactions in the past to transactions in the present. The upper triangular captures connections between future transactions and the present.

A temporal weights matrix can be constructed in a similar manner. However due to directionality in time, the matrix is not symmetric but instead takes the following form:

$$\underline{T} = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ T_{21} & 0 & 0 & \cdots & 0 \\ T_{31} & T_{32} & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ T_{R1} & T_{R2} & T_{R3} & \cdots & 0 \end{bmatrix} \tag{12}$$

12 would capture the effect of past selling prices on current prices. If there were contemporaneous effects[1], these would be captured in non-zero values (set to one) on the leading diagonal and zeros for all other matrix positions, which we can label as $\ddot{T}$. Further, if current valuations of properties influence future transactions price expectations, then the matrix in (12) would contain non-zero elements above the leading diagonal, labelled as $\overline{T}$ However, valuations are not in themselves transactions prices but it seems likely that valuations are backward looking at actual transaction prices (seeking comparable evidence) and this would anchor future valuations. In addition, valuations in Greek housing markets are close to actual transactions values. We combine spatial and temporal weights matrices taking the Hadamard product. This permits us to test the effect of past valuations, current valuations, and expectations of future prices effects. Hence there are three spatio-temporal matrices in which the spatial matrix is the same but the temporal matrix is different to capture these different potential relationships. So:

$\underline{W} = S \odot \underline{T}$ comparable sales effect (13)

$\ddot{W} = S \odot \ddot{T}$ Contemporaneous peer effect (14)

$\overline{W} = S \odot \overline{W}$ effect of sellers' expectations (15)

Data and Model

The dataset[2] employed contains 24,468 observations on house/apartment values for Athens. However, in contrast to Stamou et al., (2017), the dataset has a clear temporal as well as spatial dimension. The period covered is 2007 to 2014, a period mainly of recession due to the impact following from the GFC. This is shorter than the period covered by Nikitidou et al., (2021), although with more observations and explicit use of the spatial dimension of the data. One caveat to note is that the number of transactions fall as the economic crises deepened which implies that for some submarkets with lower transactions, samples sizes may be very small and given the heterogeneity of the housing stock can therefore be unrepresentative and therefore provide potentially biased results in model estimation. Also, as the data are valuations, we do not have transactions prices. However, historically valuations have tended to be very close to actual transactions prices. This is consistent with work by Adair et al (2004) who find similar results in UK commercial real estate. Figure 1 below shows the evolution of values across Athens submarkets from 2007 to 2014. There is a clear downward trend particularly from 2011 onwards to the end of the sample period. The rate of change in prices based upon data from the Bank of Greece is presented in figure 2. Price change has been negative since 2009 with the largest falls in price being in 2012 and 2013 and provisional data from 2017 suggest it was still to record any positive price change.

[1] This would refer to valuations taking place with the average selling time for a property. This itself will be time varying over a given economic cycle. We take this contemporaneous period to be equal to one quarter.

[2] The authors are grateful to Eurobank Property Services for providing the dataset used in this paper.

Normally real estate agents set asking prices on the basis of recently observed selling prices. Asking prices can affect final sale prices as well as reflecting the seller's motives. This price may be equal to the seller's reservation price and if so, the seller would accept the first offer that reaches or exceeds this level. In a falling market, sellers may be reluctant to sell for below their asking price exhibiting a loss aversion tendency or the possibility that they are slow to learn new market information that might affect their willingness to accept a given offer. This is consistent with the idea that prices are sticky downwards. Because of loss aversion, homeowners will delay a transaction or decide not to sell their property when the market is cooling and wait until the market recovers. Sellers may have adopted the anchoring heuristic (see Kahneman and Tversky, 1974) where they fix their expected selling or reservation price upon the most recently observed price for similar properties in their location ignoring changes in the direction of the market. Scott and Lizieri (2012) use an experimental methodology to capture consumer behaviour. They found that individuals were heavily influenced by anchor values even when given accurate valuation information. They further found that the anchor could influence subsequent appraisals. Thus, the anchoring and adjustment heuristic was found to be important in valuing houses and that these potentially biased anchors could have a long-term impact on behaviour and perceived values.

In a rising market house sellers and buyers would be willing to agree on a transaction price based upon comparables of neighbouring properties thus inducing strong spatial dependence in actual transactions prices. However, in a falling market buyers and sellers may not take recent transactions into consideration showing a weak relationship with recent transactions prices in the same neighbourhood. Hence spatial dependence would be stronger in growth periods than in recessionary periods.

Genesove and Mayer (2001) suggest that loss aversion homeowners would have an incentive to attenuate losses by deciding upon a reservation price that exceeds the level they would set in the absence of a loss. Using data for the Boston condominium market the authors find that owners subject to nominal losses tend to set higher asking prices. This study and Anenberg (2011) suggest that sellers become locked into their houses because of loss aversion during market downturns. Haurin et al (2013) examine list and selling price over a housing cycle to understand the sellers' housing transactions strategy and how it relates to the strength of the housing market. Using data from Belfast, UK, they find that sellers' loss aversion behaviour is reflected in the high list-to-sale price ratio. Sellers didn't adjust their expectations downwards and set high list prices and were seen to be waiting for the market to return to normal levels.

Thanos and White (2014) consider buyer and seller behaviour in a dataset for Aberdeen, Scotland that contains both asking and selling price information. In the Scottish system, most sale prices are above asking prices and achieved by sealed bidding process in which buyers compete against each other without knowing the price offers made by their competitors but are aware of the number of potential bidders. Where there are no competitors or the seller has had no offers in two or three months the sellers tend to set 'fixed prices' in which case the property normally sells when an offer of this value is received. As the dataset used by Thanos and White (2014) covered the beginning of the period of falling house prices, they were able to see how buyers and sellers behaved. They noted that sellers were slower to adjust prices when the market began to fall. This could perhaps have also reflected the sales comparison approach adopted by sellers' agents who would tend to set an asking price taking the most recent highest selling price into consideration, thus being anchored on this value. Buyers however seemed more aware of market conditions and were less willing to make higher offers for houses. The outcome of this fed into lower transactions volumes per time period and longer durations on the market for sellers.

Figure 1: House Prices in Athens & Suburbs, 2007 – 2014

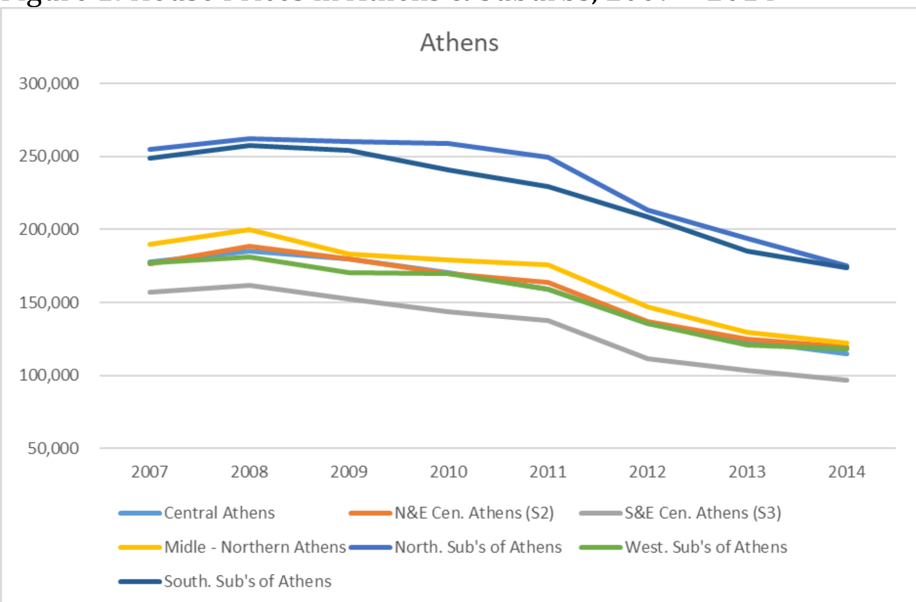
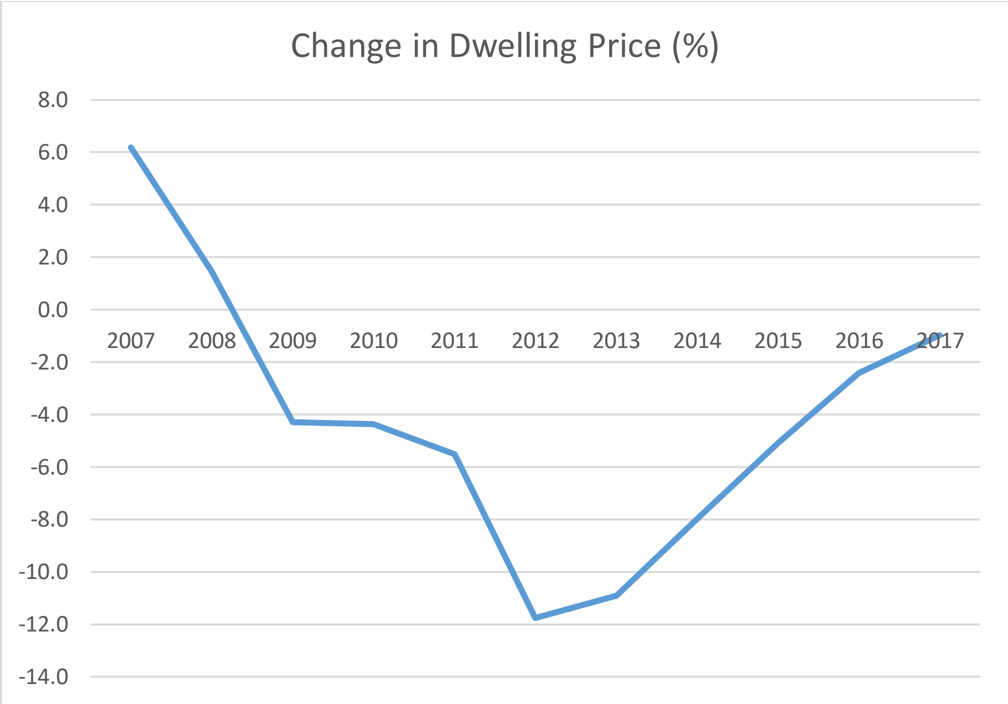


Figure 2: Annual Percentage Change in Dwelling Prices



Source: Bank of Greece

The relationship between spatial dependence and house price dynamics has been examined at regional (metropolitan) level (e.g., Clapp and Tirtiroglu, 1994). However, there exists relatively little research analysing housing dynamics at household level mainly due to the lack of availability of transactions data and relatedly the lack of information on characteristics and infrequency of transactions. The application of this study to Athens residential data combines characteristics, transactions volume and coverage over time provides a relatively unique dataset upon which to analyse spatio-temporal relations. In addition, the time period, as noted above, covers mainly a period of falling house prices.

A spatio-temporal autoregressive model is applied in which a spatially lagged dependent variable is added into a hedonic house/apartment price model. Considering spatial and temporal dimensions simultaneously ensures that the spatial spillover effect in house prices occurs from recently sold properties to future sales and not vice versa.

Method

The first step in this analysis is to estimate a baseline hedonic price model using property characteristics, neighbourhood amenities and location effects. Next the STAR takes the following form:

$$p = \rho \ddot{W} p + \psi \underline{W} p^* + \varphi \overline{W} p^* + X\beta + \varepsilon \qquad (16)$$

Where p is a vector of apartment values and X captures a matrix of hedonic variables accounting for property specific and locational characteristics. The spatio-temporal weight matrices are included with $\ddot{W}$, $\underline{W}$, and $\overline{W}$ that represent the spatial-temporal weights matrices capturing the contemporaneous peer effect, the comparable past sales effect, and the sellers' expectations effect respectively.

Table 1 below presents descriptive statistics on property value and characteristics included in the baseline hedonic models.

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation
Survey Value (€)	187589	155794
Natural Log of Survey Value	12.142	11.956
Useable Residence Area (m^2)	95.868	48.830
House	0.037	0.189
Apartment	0.035	0.184
Med Heat	0.736	0.441
Gas Heat	0.235	0.424
Good Build	0.604	0.489
Very Good Build	0.077	0.266
1 Bedroom	0.248	0.431
2 Bedrooms	0.473	0.499
3 or more bedrooms	0.259	0.438
1 Bathroom	0.593	0.491
2 or more Bathrooms	0.389	0.488
Built in 1950s	0.034	0.180
Built in 1960s	0.126	0.332
Built in 1970s	0.252	0.434
Built in 1980s	0.156	0.363
Built in 1990s	0.128	0.334
Built in 2000s	0.298	0.457
Distance from CBD (km)	6.763	4.479
Elevator	0.41	0.491
Tourist Hotspot	0.08	0.267
View	0.09	0.291

The data cover 2007 to 2014 during which time the real estate market shows significant price reductions. The models in table 2 use standard hedonic variables indicated in table 1 as a baseline function. In estimation we use one bedroom, one bathroom, and properties built in the 1950s as the reference categories. Although not included in the spatio-temporal models, the number of transactions varies significantly over the time period. These fall from over 3,000 in 2007 to just over 1,000 in 2011 and 2012 before rising to 4,075 in 2013 and then falling to 2,975 in 2014. These may reflect change in market sentiment and sellers' expectations over the period, becoming negative, reflected in the falling number of valuations, and then becoming more positive again, reflected in the growing number of valuations. The peak in 2013 may also reflect decisions by those who had decided wait a few years previously to come back to the market. Although transactions volumes decrease somewhat in 2014, they remain above the value just before the financial crisis impacted on the Greek economy.

Table 2 presents the STAR models for Athens apartment values and has a sample size of 24,446. The model extends the baseline hedonic (results of which are presented in table A1 in the appendix) by addition of spatio-temporal weights matrices. Diagnostics reported for the baseline hedonic model in addition to the adjusted R^2 are the Akaike and Bayesian information criterions. In addition, Lagrange multiplier tests for spatial error

(LM error) and a missing spatially lagged dependent variable (LM lag) are also presented as well as versions of the tests that are robust to the other being present. The results were statistically significant indicating the presence of these spatial effects.

In addition to characteristics and the spatial and temporal weights, the STAR models include year dummies (relative to 2007). Referring to the first two left-hand columns of results, the model has quite high explanatory power and the hedonic characteristics have the expected signs a priori. In relation to spatial and temporal parameters these are statistically significant and with respect to coefficient size, the spatial coefficient is bigger in absolute terms than most year dummies indicating that spatial relations remain relatively important even in a falling market in which sellers may be loss averse. To the best of our knowledge this has not been investigated previously for the Athens residential market. It may also be a result present in other housing markets across different cities and countries.

Insert Table 2 about here

The two last columns of table 2 repeat the same hedonic model and identify separate past sales/valuation effects, the contemporaneous peer effect and the effect of future expectations. Coefficient estimates seem quite stable and statistically significant with the expected signs. Only houses are not statistically significant in each of the model specifications. The time dummies behave similarly in both models with coefficients becoming significantly negative as the economic crisis and housing market worsens. This is also reflected in the fall in transactions volumes in the Athens housing market.

The second STAR model separating the three spatio-temporal effects show significant and different results for each. The coefficient on the past sales effect is larger in the STAR 1 model than in the STAR 2 model when the latter also includes the past sales, contemporaneous and expectations effects. It may be reasonable to assume that part of their effect was captured in the past sales effect when these other effects were not considered in the STAR 1 model. This and the statistical significance of the contemporaneous and expectations effects highlights the importance of taking these into consideration. From the second STAR model, the past sales effect coefficient of 0.145 suggests that a €10,000 price increase in the last period will cause a price rise of €1,450 in the following period. The impact of spatially weighted prices of other properties sold contemporaneously is captured in the coefficient on ρ, 0.269. In this a €10,000 price shock to the mean value in the neighbourhood will change the value of a given house by €2,690.

Property valuations reflect comparable evidence and as discussed reflect heuristics of anchoring and slow adjustment. These feed into expectations formation mechanisms and then into sellers' behaviour. The expectations effect, φ, tries to capture this effect. The nature of the dataset means that we can use valuations to proxy expected future transactions prices. This effect was found to be statistically significant but smaller than the past and contemporaneous sales effects. In this case an increase in valuation of €10,000 would increase expected sales prices by €540 in the neighbourhood. However, we may note some caution as prices are often sticky downwards and the effect may not be symmetric over growing and falling markets. In addition, in boom market conditions, future expectations may cause prices to exceed the present discounted value of the net return on the housing asset. In this situation the coefficient on φ would be biased.

Conclusions

The role of spatial relationships in residential markets cannot be overlooked. While urban housing areas are characterised by segmentation in the form of housing submarkets, spatial interrelationships remain important in explaining house and apartment prices. Previous research has focused on housing markets in different countries including, for example, the UK, the U.S., and South Korea. As data for housing markets in Greece remain scarce with limited data available on prices and characteristics, only a few studies have analysed markets here with only a handful examining the Athens market. Our study extends analysis of spatio-temporal relationships here. For Athens using the spatio-temporal autoregressive model, the results indicate that both spatial and temporal effects are important factors in the residential market. While loss-aversion theories based upon Kahneman and Tversky suggest that sellers may be prepared to wait until the market improves and the normal spatial linkages weaken in recessions, results for the Athens market suggest otherwise. Interestingly, this contrasts with some of the other literature examining falling markets. It may be that the prolonged nature of the fall in house prices impacts behaviour and causes sellers expectations eventually to change. This may be further evidenced by the fact that the number of homes going onto the market rises significantly in 2013 and in 2014 remained significantly above the market trough in 2011 and 2012.

The second version of the STAR model additionally contributes to the literature showing explicitly the past sales effect, contemporaneous sales effects and expectations effects. The model shows similar results for the property characteristics and time dummies as STAR Model 1. However, this model additionally shows separate and statistically significant effects for past sales, contemporaneous sales and expectations. These seem logical in that past sales evidence would impact current valuations and that there would be information spillovers contemporaneously impacting on spatially proximate valuations currently. Furthermore, anchoring effects would mean that current valuations would affect future value expectations. Thus, in this model also, the role of behaviour in markets in as important as in STAR model 1.

Given the behavioural component to price setting behaviour in housing markets, it is reasonable to assume that the past sales, contemporaneous spatially proximate sales, and the expectations effects would operate in other housing markets. This would be a fruitful avenue for future research in extending spatio-temporal modelling of housing markets.

Further work may also more carefully consider the information content in valuations as contained in our dataset as we do not have asking and selling prices or the difference between them. Also, as valuations are based upon comparable sales then in recessionary periods covered in the dataset, finding comparables may have become more difficult and hence this in turn may have impacted on valuation accuracy. Nevertheless, there is a clear spatial pattern and evidence of the use of heuristics in pricing behaviour.

Table 2: STAR Models Results

	STAR Model 1		STAR Model 2	
	Coefficient	Standard Error	Coefficient	Standard Error
Constant	7.776	3.221	4.555	2.132
Useable Residence Area	0.019	0.000	0.021	0.000
Living Area Squared	-3.402E-5	0.000	-3.532E-5	0.000
House	-0.066	0.016	-0.067	0.015
Apartment	0.020	0.019	0.022	0.019
Med Heat	0.107	0.017	0.110	0.017
Gas Heat	0.148	0.018	0.144	0.018
Good Build	0.152	0.019	0.156	0.018
Very Good Build	0.256	0.029	0.259	0.029
Bed2	0.071	0.022	0.074	0.022
Bed3p	0.053	0.016	0.055	0.016
Bath2p	0.052	0.020	0.053	0.020
Built in 1950s	-0.411	0.099	-0.404	0.098
Built in 1960s	-0.401	0.113	-0.407	0.112
Built in 1970s	-0.348	0.098	-0.342	0.098
Built in 1980s	-0.251	0.111	-0.248	0.111
Built in 1990s	-0.163	0.051	-0.159	0.051
Distance from CBD	0.018	0.004	0.019	0.004
Elevator	0.114	0.045	0.116	0.044
Touristic Hotspot	0.360	0.103	0.363	0.102
View	0.166	0.074	0.162	0.074
2008	0.015	0.006	0.011	0.006
2009	0.010	0.008	0.008	0.007
2010	-0.018	0.008	-0.019	0.007
2011	-0.064	0.012	-0.079	0.011
2012	-0.226	0.089	-0.238	0.087
2013	-0.353	0.104	-0.364	0.103
2014	-0.449	0.106	-0.398	0.105
Spatial	0.324	0.006		
Temporal	0.226	0.007		
Space and Time	0.101	0.021		
Spatial Error	1.224	0.099		
ψ comparable past sales			0.145	0.082
φ expectations effect			0.054	0.021
ρ contemporaneous effect			0.269	0.123
R^2	0.803		0.803	
Log Likelihood	33070.629		33079.084	
AIC	-65767.232		-65783.974	

BIC	-65486.394		-65503.136	
No of Observations	24,468		24,468	

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Appendix

Table A1: Baseline Hedonic Model for Log of Valuation Dependent Variable

	Coefficient	Standard Error
Constant	10.484	0.014
Useable Residence Area	0.019	0.000
Living Area Squared	-3.298E-5	0.000
House	-0.118	0.010
Apartment	-0.089	0.011
Med Heat	0.094	0.010
Gas Heat	0.140	0.011
Good Build	0.150	0.020
Very Good Build	0.232	0.029
Bed2	0.070	0.023
Bed3p	0.052	0.016
Bath2p	0.050	0.019
Built in 1950s	-0.434	0.099
Built in 1960s	-0.438	0.115
Built in 1970s	-0.383	0.105
Built in 1980s	-0.274	0.112
Built in 1990s	-0.149	0.053
Distance from CBD	0.018	0.000
Touristic Hotspot	0.369	0.006
Elevator	0.115	0.044
View	0.168	0.076
2008	0.020	0.006
2009	0.014	0.007
2010	-0.018	0.007
2011	-0.064	0.013
2012	-0.218	0.008
2013	-0.358	0.106
2014	-0.456	0.108
Adjusted R^2	0.776	
AIC	-65509.920	
BIC	-65237.082	
LM Lag	266.086***	
Robust LM Lag	126.155***	
LM Error	95.712***	
Robust LM Error	35.554***	
No. of Observations	24,468	

*** indicates significance at the 1% level