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Impact of quality-led design on real estate value: a spatiotemporal analysis of city centre apartments

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ABSTRACT

This paper estimates the impact of quality design attributes on real estate value through empirical investigation of the owner-occupied multifamily residential sector. The methodological design is based on spatiotemporal modelling using a unique data-set of 424 Belfast City Centre apartments sold during the period 2000–2008. The key findings indicate that urban scale aspects of quality such as connectivity and vitality associated with building density add to real estate value. At the building level, quality features highly valued by home buyers are namely appropriateness of material quality, fenestration and massing to the surroundings. These key criteria are considered to have a significant visual perception compared to more complex concepts such as identity, material choice and overall condition. The contribution to knowledge involves extending the hedonic model to incorporate a wider selection of design quality variables; and improving estimation through the use of spatiotemporal modelling.

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Real estate value; design quality; spatiotemporal modelling; spatial econometrics; spatial weight matrices

1. Introduction

This paper investigates the impact of quality design attributes on the real estate market value of multi-family residential units through an empirical analysis of owner – occupied, inner-city apartments in a regional-tier UK city. The multi-family residential sector constitutes a crucial component in ensuring the viability of urban regeneration schemes by providing the initial income return necessary to finance the commercial components in mixed use city centre developments. The post-1999 urban renaissance agenda provided a significant improvement in design standards through the 'repopulation of and reinvestment in the major towns and cities' (Punter, 2010). Planning policies for increasing densities in urban cores, as a crucial factor of good design, have played a key role in shaping the built environment of UK cities at the turn of the millennium (Dunse, Thanos, & Bramley, 2013; Evans & Unsworth, 2012). While high-quality design is considered an essential element of successful urban core redevelopment projects the accrued value is of an intangible nature thus leading to wide scepticism about its economic value. This has led to a growing body of

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literature that investigates the economic value of design through hedonic modelling of real estate prices. The study presented in this paper focuses on the urban context of Belfast city centre and aims to advance knowledge by extending the hedonic model employing design quality variables and improving estimation through the use of spatiotemporal modelling techniques.

Quality design plays a key role in the production of a high standard built environment which in turn contributes to increased quality of life in towns and cities. This fact has found wide acceptance in the planning and design disciplines, however, research emphasises the importance of and need for empirical evidence on the economic value of building and urban features associated with high quality design. In this context, the main empirical advances are observed in hedonic modelling of property markets as the most appropriate tool for analysing implicit prices of composite goods based on the theoretical framework developed by Lancaster (1966) and Rosen (1974). In the existing body of knowledge only a small number of studies has focused on the modelling techniques that reduce bias in the parameter estimates for better statistical inference to help informed decision-making (Dubé & Legros, 2014; Pace, Barry, Gilley, & Sirmans, 2000; Smith & Wu, 2009; Sun, Tu, & Yu, 2005). Additional to its central aim of extending the property price equation to include design quality determinants, this paper builds upon previous hedonic studies based on design quality through an applied methodology that accounts for the spatial and temporal dimensions of property transaction data.

In the following section, the theoretical underpinnings of the paper are investigated. The third section includes a synopsis of the data-sets and discusses the construction of the variables for subsequent application in the models. The spatiotemporal methodology is the focus of the fourth section which details two key themes. Initially, we provide a detailed explanation of the specification of weight matrices for the spatiotemporal modelling of the real estate data-set. The paper then elaborates on the models and discusses the estimation of different variables employed in the empirical analysis. Finally, in part six of the paper we draw out the key conclusions and impacts on stakeholders/decision-makers.

2. Theoretical framework: hedonic prices, quality design and spatiotemporal dependence of multi-family residential units

Hedonic price theory has provided a well-grounded framework for empirical analysis in the real estate domain where the unit of analysis is a clearly differentiated product whose package of characteristics cannot be united (Lancaster, 1966; Rosen, 1974). Particularly in the residential property sector broader concepts of urban economic theory have also been adopted to extend this 'package of characteristics' beyond the property-specific one. A consolidated body of knowledge in the urban economic literature has underlined the importance of location amenities on house prices (see Gibbons & Machin, 2008 for a review). Previous studies have shown, among other factors, the positive impact of recreational amenities namely parks and open space (Anderson & West, 2006; Troy & Grove, 2008), the negative impact associated with increased crime rates (Gibbons, 2004) and the positive impact of school quality (Brasington & Haurin, 2006; Cheshire & Sheppard, 2004). Hedonic studies in a design context have exclusively focused on commercial real estate and adopted the use of officially designated measures of quality by controlling for specific national or local landmark status (Hough & Kratz, 1983) or have employed measures of quality derived from the opinion of experts (Vandell & Lane, 1989).

The subsequent body of knowledge in the field has adopted either of the above approaches estimating hedonic models through the use of the ordinary least square method which does not take into consideration the spatial dependence in real estate data resulting in potential estimation bias. The lack of control for spatial dependence constitutes the main drawback of previous studies in a design quality context which this paper attempts to address. Generally, this has been treated through controlling for possible rent gradients via distance to the centre or to various activities and by including submarket-specific dummies considered as spatial fixed effects. While the first approach controls for local amenities but not spatial dependence the second approach has been criticised for being unable to remove the spatial autocorrelation in the data (Anselin & Arribas-Bel, 2013). This has consequences for the adoption of spatial models and the ability to account for omitted variables with spatial dependence (LeSage & Pace, 2009). A comprehensive framework that considers different methodological issues in hedonic studies of design quality has been suggested by Nase, Berry, and Adair (2015). The authors call for, among others, a stronger theoretical basis in the construction of design quality variables, a more heuristic approach when specifying the nature of spatial interactions (see Corrado & Fingleton, 2012 for more details) and appropriate modelling of real estate data to account for the diverse nature of spatial and temporal dimensions (see Dubé & Legros, 2014 for more details).

Modelling issues are of particular importance in parameter estimations of hedonic studies and significant contributions in this context have been made in the field of spatial econometrics. The case for spatial hedonic models mentioned earlier is finding increasing acceptance within the real estate literature, however the treatment of the spatial interaction effects through the specification of the spatial weight matrix is its most critiqued aspect. The first critique is the lack of theory in the a priori specification of the spatial weight matrix by researchers (Corrado & Fingleton, 2012; Gibbons & Overman, 2012; Harris, Moffat, & Kravtsova, 2011). The second critique is the specification of cross-sectional spatial weight matrices for property transactions generally appearing in data-sets that have been described as spatial data pooled over time (Dubé & Legros, 2014). This specification does not account for the unidirectional time dependence in real estate data and incorrectly implies that house prices can be influenced by future transactions.

A growing body of literature is addressing this issue through 'spatiotemporal' models that account for both the space and time dimension of spatially dependent data observed over a period of time. The first studies in this context are those of Pace, Barry, Clapp, and Rodriquez (1998) and Pace et al. (2000) applied in the single-family residential sector. The approach employed by Pace involves specifying different weighting schemes for space and time and subsequently, through matrix multiplication, applying two filters for space first and then time and for time first and then space. This methodology was extended to multifamily residential units by Sun et al. (2005) through separately accounting for neighbourhood and building-specific effects that arise in this sector. Their model further divided the spatial weight matrix into building and neighbourhood, respectively; and applied the same spatiotemporal filtering, resulting in a model that could suffer from over-parameterisation and multicollinearity issues in small to medium data-sets. This issue was further addressed by Smith and Wu (2009) who proposed a unit by unit (also known as Hadamard) multiplication of the weight matrices. As the data are ordered temporally, time dependence

Table 1. Variable names, descriptions and statistics.

Variable name	Description	Min.	Max.	Mean	SD
Price (Y)	Apartment transaction price in £ (in log form)	10.7986	12.4212	11.6304	0.3517
Age	Age of apartment in years (in log form)	1.0986	3.2189	2.2211	0.3902
Area	Area of apartment in m^2 (in log form)	3.7550	4.7877	4.2081	0.1585
Garage	Dummy variable for presence of a garage	0.0	1.0	.073	.2606
Bedrooms	Number of bedrooms in apartment	1.0	4.0	1.856	.5463
Receproom	Number of reception rooms in apartment	1.0	2.0	1.014	.1183
Floorno	Number of floors in the building where the transaction took place (building height proxy)	3.0	10.0	6.849	1.3336
Finishing	Appropriateness of exterior finishing to the surroundings	2.0	5.0	2.847	.9290
Identity	Appropriateness of building identity to the surroundings	2.0	5.0	3.363	.9725
Materialqual	Appropriateness of used material's quality to the surroundings	1.0	4.0	2.920	.8383
Fenestration	Appropriateness of façade fenestration to the surroundings	2.0	4.0	2.698	.6934
Massing	Appropriateness of building massing to the surroundings	1.0	5.0	2.882	1.2127
Height	Appropriateness of building's height to the surroundings	1.0	4.0	3.233	.6908
Condition	Overall building condition's appropriateness to the surroundings	1.0	4.0	2.396	.8186
Connect	Connectivity index (as % points) (proxy for urban form accessibility) (Equation 1)	34.1270	40.0000	35.4223	1.4645
BpR	Building footprint to plot ratio (as % points) (proxy for urban density)	19.3989	93.5821	52.1273	21.8077
Attindex	Attraction index: interaction of apartment units with selected commercial node (Equation 2)	1.9044	13.1040	4.7481	3.0939
Dgreen	Distance to active green area (× 100 m)	2.5025	12.8848	6.6731	3.1912
NearST	Distance to the nearest train station (× 100 m)	1.6122	13.2209	6.6421	3.4878
PWdist	Distance to peace wall (in Cupar Way) (× 100 m)	7.73	23.71	16.2967	4.58017
yr2000	Transaction year dummy	0.0	1.0	.120	.3257
yr2001	Transaction year dummy	0.0	1.0	.031	.1726
yr2002	Transaction year dummy	0.0	1.0	.108	.3114
yr2003	Transaction year dummy	0.0	1.0	.116	.3201
yr2004	Transaction year dummy	0.0	1.0	.186	.3898
yr2005	Transaction year dummy	0.0	1.0	.061	.2402
yr2006	Transaction year dummy	0.0	1.0	.130	.3364
yr2007	Transaction year dummy	0.0	1.0	.101	.3022
yr2008	Transaction year dummy	0.0	1.0	.146	.3538
N		424			

could be restricted so that prices can be influenced only through past transactions. In the analysis of apartment units a final consideration was suggested by Dubé and Legros (2014) who adopt the spatiotemporal weighting framework resulting from the Hadamard matrix product to restrict multidimensional spatial interactions to same period transactions. For unidirectional spatiotemporal effects, the authors combine the neighbourhood and building weight matrices so that the former are represented by a distance decay function with a cut-off point and same building transactions are given a weight of one. In the empirical analysis detailed later in this paper we adopt the latter approach.

3. Data and variable description

The residential transaction database used in this empirical study was obtained from the records of the Ulster University Quarterly House Price Index (NIQHPI). It comprises 424 multi-family residential (apartment) units transacted in the City of Belfast (postcode areas BT1 and BT2) during the period 2000–2008.[1] The data-set includes information on transaction price, area, transaction year,[2] age of the property, presence of a garage, number of bedrooms, reception rooms and floor area. In a relatively new (sub)market which shows a high consistency with regard to floor area the latter three variables are used as proxies for interior subdivision quality. More specifically, larger properties offer better opportunities for diversity in design which increases end user options concerning utility maximisation. When coupled with the variables number of bedrooms and number of reception rooms, the combined outcomes gives an insight to the end user preferences for overall [living] space and its arrangement (subdivision design) in city centre apartments. A detailed description of all the variables generated including their respective statistics is given in Table 1.

Data obtained from the NIQHPI did not include information on exterior building characteristics. To address this issue data from field observations were used. Subsequently, a group of local experts (architects/urban designers) was employed to assess the appropriateness of a building to its surroundings for seven different categories on a 5-grade Likert scale (see Nase, Berry, & Adair, 2013 for more details). The seven categories are namely choice of material (*finishing*), external façade *identity*, quality of material used (*materialqual*), *fenestration* that relates to the whole appearance/composition of a building frontage in relation to window/bay levels, repetition etc. *massing* that relates to the external architectural form and size of a building, *height* (in floors) and building *condition*. The latter was included following discussions with the experts whereas the other six were included based on the literature review. Detailed information on the scoring process is given in Appendix 1.

The transacted properties were geocoded in a GIS framework following identification of their exact address. This enabled spatial analysis and the computation of various urban form proxies and distance control variables. The first category comprises indices widely used in planning and design such as building to plot ratio (BpR). This is a direct indicator of building density and in core urban areas BpR can be used as a proxy for the amount of open space within a block. *Connect* is another variable constructed using GIS and measures the connectivity of the surroundings of a property. The variable is generated using the gamma (γ) index for the spinal pattern of connectivity as explained by Taaffe, Gauthier, and O'Kelly (1996) given by the formula:

$$\gamma = \frac{\#\text{nodes} - 1}{3 * (\#\text{nodes} - 2)} \tag{1}$$

where nodes are the street/segment intersections. The spinal pattern gamma values range between $1/3 \leq \gamma \leq 1/2$ for #nodes ≥ 4. This pattern is particularly used in this study to represent city centre urban block networks by accounting for simplicity in the system and the lack of appeal of dead ends as explained in Appendix 2. To estimate this index we employ the 'emergent neighbourhood model' developed by Mehaffy, Porta, Rofè, and Salingaros (2010) for historic urban cores. According to this model the pre-motorised urban fabric is shaped by the 5 min walking distance rule that denotes the distance pedestrians are willing to walk to engage in daily activities. This results in *neighbourhood units* shaped by edges approximately 400 m long. We apply this model to Belfast City Centre to estimate the connectivity index for each *emergent neighbourhood* and use the values to generate the variable *Connect*.

Based on urban economic theory, we control explicitly for distance to active green areas,[3] distance to main public transport nodes (nearest train stations) and additionally for local idiosyncrasies through the distance to the peace wall in Cupar Way. The impact of retail activity on apartment prices is captured through the attraction index which is generated using the interaction of an activity centre's attraction power and the distance of the observed property to this centre (Equation 2). A similar variable is employed by Des Rosiers, Theriault, and Menetrier (2005) to measure the potential attraction power of a shopping centre. It is based on Reilly's (1931) model that relates shopping centre size, distance of a cluster to that centre and the population in the cluster. The attraction index generated in this paper employs observed attraction power as measured by weekly footfall figures obtained by Belfast City Centre Management. It is a measure of the interaction between a commercial activity node in the city centre and observed transactions and is given by the formula

$$\text{Attindex} = \frac{\text{FF}}{\text{centre\_area/block\_area}} * \frac{100}{\text{Dist}} \qquad (2)$$

where $\frac{\text{FF}}{\text{area}}$ is the customer drawing power of the activity centre (expressed as weekly average footfall) weighted by centre area (given as a ratio of centre area/area of urban block where shopping centre is situated). We construct attraction indices of three different activity foci aiming to capture the impact of centre attractiveness based on different footfall values. However, given the small size of our study area and the relative distances of the apartment buildings to these foci we expect these indices to be somewhat correlated. A final consideration regards school quality as urban economic literature has clearly demonstrated its impact on house prices. Our study area includes higher educational institutions (such as regional colleges) but does not include primary or secondary schools. The latter are important in household location due to the fact that in the UK pupils are admitted according to school catchment areas. Based on the above, we do not explicitly control for distance to schools in our models which are described in the following section. We return to this issue in section 5 when analysing model outcomes.

4. Methods

The methodology in this paper falls within the 'specific-to-general' approach (Elhorst, 2014) that starts with the estimation of the base model utilising an ordinary least squares (OLS) routine. Subsequently, it tests more general nesting spatial models through classic tests well established in the spatial econometrics literature and complements them with Bayesian posterior tests. When analysing spatial dependence we start by comparing the hedonic base model OLS estimation outcomes with Maximum Likelihood (ML) estimation of the Spatial Error (SEM) Model, and then focus on the Spatial Autoregressive (SAR) Model where we additionally test for different spatiotemporal dependence.

4.1. Weight matrix specification: accounting for building, multidirectional space and unidirectional time effects

In modelling multi-family residential property transactions, additional challenges have been pointed out relating to accounting for building and neighbourhood specific effects separately (Sun et al., 2005). As noted earlier, based on the need for filtering both space first and then time and time first and then space the resulting model might suffer from over-parametrisation (Pace et al., 2000; Sun et al., 2005). In small to medium data-sets such as the one employed in this paper over-parameterisation can be a significant issue regarding degrees of freedom and multicollinearity. A crucial issue in spatial econometrics is that weight matrix specification has received a strong critique from different authors for the lack of robust theoretical underpinnings (Gibbons & Overman, 2012; Harris et al., 2011). Special emphasis relates to calls for practitioners to specify weight matrices based more on economic theory (Corrado & Fingleton, 2012). To appropriately address these issues in weight matrix specification we pay particular attention to the multidirectional nature of spatial effects and the unidirectional nature of the time dependence (Dubé & Legros, 2014).

This approach starts by ordering the data temporally with the oldest transaction first and the newest transaction in the last row. We consider two weight matrices that model multidirectional space relations (**M**) and unidirectional spatiotemporal relations (**U**). The matrix **M** is constructed using the pairwise distance between two transactions (d_{ij}) and **U** based on the combined interaction of the time elapsed between two transactions (τ_{ij}) and their distance. The multidirectional spatial interactions are restricted to the transactions that took place in the same time period resulting in a block diagonal spatial weight matrix. We assign weights to the general elements of **M** (m_{ij}) based on the distance between two transactions (d_{ij}) according to the scheme detailed in Equation (3) below.

$$m_{ij} = \begin{cases} \exp(-\nu\, d_{ij}) & \text{if}\, d_{ij} \leq \bar{d} \,\&\, \tau_i = \tau_j \\ 1 & \text{if}\, d_{ij} = 0\, \forall\, i \neq j \,\&\, \tau_i = \tau_j \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where $\bar{d}$ is a distance cut-off value (in kilometres) and ν is any positive exponent. We take $\nu = 1$ for a spatial weighting scheme specification based on the negative exponential distance function. This matrix combines the building and neighbourhood effects by assigning a weight of 1 to transactions in the same building and a distance decaying weight to transactions in different buildings. The latter is based on the first law of geography, often associated with Tobler (1970), which states that interaction in space is stronger between two objects that are closer than those that are further apart from each other.

Initially, the temporal weight matrix **T** is constructed to contain elements (t_{ij}) based on the time elapsed between transactions i and j. When modelling time effects in spatiotemporal models the literature seems to have reached agreement in considering only previous transactions (unidirectional dimension) by employing lower triangular weight matrices[4] (Dubé & Legros, 2014; Pace et al., 1998; Smith & Wu, 2009; Thanos, Bristow, & Wardman, 2012). However, when deciding on a cut-off point in time these studies adopt an approach based on specifications that best fit the data and information detail. More specifically, Pace et al. (1998) consider 5 years back in time while Dubé and Legros (2014) and Thanos et al. (2012) work on a quarterly basis. The latter study does not specify a cut-off point but provides a time decay rate based on the inverse of the time elapsed (in quarters) between two transactions. Consequently, transactions two years apart would be weighted 87.5% less than transactions in the same period. We try to approximate this time decay rate and, considering the time period level of detail in our data-set, we believe the weighting scheme expressed in Equation (4) best fits our data.

$$t_{ij} = \left(\left|\tau_i - \tau_j\right| + 1\right)^{-\nu} \tag{4}$$

where ν is any positive exponent. In testing for robustness of results to weight matrix specification we consider two cases, one based on $\nu = 2$ and the other for a faster temporal decay where $\nu = 3$.[5]

Specification of the spatiotemporal weight matrix is based on the two weighting schemes described above. For our purpose we use the negative exponential distance matrix **S** without any time restrictions or distance cut-off and the time weight matrix also with no cut-off. To obtain our spatiotemporal matrix **U** we use the unit by unit multiplication of these two matrices ($U = S \odot T$), referred to earlier as the Hadamard product, which ensures a combined space and time weight in the final matrix (Dubé & Legros, 2014; Smith & Wu, 2009). Additionally, this multiplication also ensures that **U** is lower triangular accounting for the unidirectional effect of time where only past transactions are allowed to influence sale prices. To model the market actors' behaviour we consider nearest spatiotemporal neighbours in **U** and set the other values to zero.[6] To test for robustness of results to weight matrix specification we examine weights based on the more widely used 5, 10 and 15 nearest neighbours supplemented with the intermediary specifications of 8 and 12 neighbours. These are considered for the two temporal decay rates described above for a set of 10 competing spatiotemporal weights under investigation. Both **M** and **U** are row stochastic – each row sums to 1.

4.2. Spatial model specifications and effect estimation

As noted earlier, model specification in this paper follows the specific-to-general approach starting with the estimation of the standard hedonic base model estimated by OLS (Equation 5)

$$\boldsymbol{Y} = \alpha\boldsymbol{\iota} + \boldsymbol{X}\beta + \boldsymbol{D}\delta + \varepsilon \tag{5}$$

$$\varepsilon \rightarrow \boldsymbol{iid}(0, \sigma^2\boldsymbol{I})$$

where **Y** is the $n \times 1$ vector of observations on the dependent variable, $\boldsymbol{\iota}$ is an $n \times 1$ vector of ones related to the constant $\boldsymbol{\alpha}$ to be estimated. **X** is an $n \times k$ matrix of hedonic property characteristics, $\boldsymbol{\beta}$ is a $k \times 1$ vector of parameters to be estimated associated with these characteristics, $\boldsymbol{D}$ is a $n \times (t-1)$ matrix of time period dummies and $\boldsymbol{\delta}$ is a $(t-1) \times 1$ vector of time dummy parameters to be estimated and $\boldsymbol{\varepsilon}$ is the $n \times 1$ vector of error terms with all elements assumed to be independent and identically distributed (*iid*) with mean zero and variance σ^2. In this annotation n = number of observations in the data-set, k = number of hedonic property characteristics (explanatory variables), t = number of time periods in the data-set and the $(t-1)$ dimension takes into consideration the omission of the first time period dummy for use as reference.

Subsequently, we consider two spatial model specifications namely SAR and the SEM. The SAR specification accounts for spatial dependence through the lagged dependent variable, spillover effects of neighbouring transactions in space. Its general form is given in Equation (6)

$$\boldsymbol{Y} = \rho\boldsymbol{W}\boldsymbol{Y} + \alpha\boldsymbol{\iota} + \boldsymbol{X}\beta + \boldsymbol{D}\delta + \varepsilon \tag{6}$$

where $\boldsymbol{\rho}$ is the spatial autoregressive parameter vector of dimensions $n \times 1$, $\mathbf{W}$ is the $n \times n$ spatial weight matrix that models the spatial dependence structure in the data and all other annotations are as above. The SEM specification on the other hand accounts for spatial dependence in the error terms associated mainly with omitted variable bias that might be spatially correlated with the dependent variable (Equation 7).

$$\begin{aligned} \boldsymbol{Y} &= \alpha \boldsymbol{\iota} + \boldsymbol{X}\beta + \boldsymbol{D}\delta + \boldsymbol{u} \\ \boldsymbol{u} &= \lambda \boldsymbol{W}\boldsymbol{u} + \varepsilon \end{aligned} \tag{7}$$

where $\mathbf{u}$ are heteroskedastic (spatially autocorrelated) disturbances (of dimensions $n \times 1$), λ is the spatial error parameter vector of dimensions $n \times 1$, ε is white noise (*iid* $n \times 1$ vector) and $\mathbf{W}$ is the $n \times n$ spatial weight matrix.

To appropriately model real estate transaction data, the third type of model specified is the spatiotemporal autoregressive (STAR) model that accounts for both spatial and temporal dependence in the data. We now slightly modify the general specification in (6) using the matrix annotation described in the previous subsection ($\mathbf{M}$ = multidirectional; $\mathbf{U}$ = unidirectional) and introducing the subscript (t) to describe the time periods. The model outlined in Equation (8) underlines that house prices sold at a particular time period are determined by a set of utility bearing property characteristics (assumed to be constant over time), neighbouring (including transactions in the same building and those within a predefined boundary) house prices sold in the same period and weighted average of nearest spatiotemporal neighbour house prices sold in the previous period(s) only.

$$\boldsymbol{Y}_t = \rho \boldsymbol{M}\boldsymbol{Y}_t + \psi \boldsymbol{U}\boldsymbol{Y}_{(t-1)} + \alpha \boldsymbol{\iota} + \boldsymbol{X}_t\beta + \boldsymbol{D}\delta + \varepsilon_t \tag{8}$$

The STAR model captures the multidirectional spatial spillovers through the parameter $\boldsymbol{\rho}$ and the dynamic spatiotemporal dependence through the parameter $\boldsymbol{\psi}$. Based on the above specification the STAR model needs to eliminate the first period data in the data-set to ensure that prices are determined by previous transactions only (Dubé & Legros, 2014). This results in a final set of 373 observations for the empirical analysis detailed in the next section[7] since in the original database (N = 424) properties sold in the first time period amounted to 12% of the total (Table 1).

As a final consideration in the specific-to-general approach we specify a 'general' model that nests the autoregressive and error models through spatial dependence in both the dependent variable and the error terms (Equation 9). Regarding terminology, the general form of this model has been described as the SAC, SARAR or Kelejian-Prucha model (Elhorst, 2014; Kelejian & Prucha, 1998; LeSage & Pace, 2009). We use the STARAR term to ensure terminology continuity of spatiotemporal model specification throughout the paper.

$$\begin{aligned} \boldsymbol{Y}_t &= \rho \boldsymbol{M}\boldsymbol{Y}_t + \psi \boldsymbol{U}\boldsymbol{Y}_{(t-1)} + \alpha \boldsymbol{\iota} + \boldsymbol{X}_t\beta + \boldsymbol{D}\delta + \boldsymbol{u}_t \\ \boldsymbol{u}_t &= \lambda \boldsymbol{M}\boldsymbol{u}_t + \varepsilon_t \end{aligned} \tag{9}$$

Since the ultimate goal of this analysis is the exact estimation of the impact of utility bearing descriptive variables (and particularly the specified quality design attributes) on value we now turn our attention to this issue. Hedonic theory has focused on the appropriate estimation of marginal effects (willingness to pay) of any explanatory variable x_r through the partial derivative of expected values of y with respect to changes in x_r given as: $\partial y/\partial x_r$. In OLS (and SEM) models this specification might as well correspond to the point estimates of β but it is not the case in presence of spatial dependence in the dependent variable. For the model specified in (6) the reduced form is given in Equation (10).

$$\boldsymbol{Y} = (\boldsymbol{I} - \rho \boldsymbol{W})^{-1} (\alpha \boldsymbol{\iota} + \boldsymbol{X}\beta + \boldsymbol{D}\delta + \varepsilon) \tag{10}$$

where $(\boldsymbol{I}\text{-}\rho\mathbf{W})^{-1}$ is the spatial multiplier term and $\boldsymbol{I}$ is the identity matrix of dimension $n \times n$. As it can be observed, this equation does not describe a linear relationship between y and the non-spatial multiplier right hand side terms. Under these conditions LeSage and Pace (2009) have suggested using the elements of the matrix of partial derivatives of expected values of y with respect to changes in the rth explanatory variable in $\mathbf{X}$.

Based on the matrix expression of the spatial multiplier as an infinite sequence: $I_n + \rho \mathrm{W} + \rho^2 \mathrm{W}^2 + \rho^3 \mathrm{W}^3 + \ldots$, it can be seen that the first term (I_n with ones only in the diagonal and zeros elsewhere) represents direct effect of a change in $\mathbf{X}$. The second term (ρW with diagonal elements set to zero to avoid units being their own neighbours) represents an indirect effect of a change in $\mathbf{X}$ of the first order neighbours (power is = 1) and other terms represent second and higher order neighbours' direct and indirect effects (Elhorst, 2014). Consequently, the correct interpretation of spatial models is based on direct and indirect effect estimates that are given as a scalar summary measure of the diagonal and off-diagonal elements of the matrix of partial derivatives as explained above. More specifically, for any variable x_r in $\mathbf{X}$ the direct effects are given as the average of diagonal elements of the matrix $(\mathbf{I}\text{-}\rho\mathbf{W})^{-1}\beta_r$ and the indirect effects are given as the average of off-diagonal elements of the matrix $(\mathbf{I}\text{-}\rho\mathbf{W})^{-1}\beta_r$ (LeSage & Pace, 2009, 2014). We use scalar summaries to report effect estimates in our empirical analysis in the next section.

5. Empirical analysis

The starting point of the empirical analysis is the standard hedonic model shown in (5). We estimate the base model with the OLS method and proceed with a twofold analysis. First, we compare the OLS outcomes with the standard SEM and SAR models. The estimation results are shown in Table 2 and indicate the high significance of the spatial parameters in both models. Additionally, the log-likelihoods of the spatial models are significantly larger than the OLS one with the SAR model exhibiting the highest. Second, we use the OLS residuals to analyse the presence of spatial autocorrelation through Moran's I tests and for the classic Lagrange Multiplier (LM) tests to analyse the nature of spatial dependence. In order to test for robustness of results to weight matrix specification we employ an empirical approach informed by the physical characteristics of the data. A preliminary investigation indicates that the longest distance between two observations in the data is approximately 1.9 km (no cut off) and the cut-off threshold that ensures each observation has at least one neighbour is 1.2 km[8] in the block diagonal specified $\mathbf{M}$. Based on this information, we consider eight different specifications of $\mathbf{M}$ starting with the full spatial interaction (no cut-off) and decreasing the bandwidth by 100 m.

Approaches that select weight matrices in a similar fashion have been criticised for picking up only the 'local best' specification and being able to select the right one only if it is included in the considered subset (Harris et al., 2011). Our empirical approach aims to address this issue by considering an exhaustive set of options (from maximum connectivity to the theoretically accepted, least connected weight matrix) with context-based in-between alternatives (cut-off increments). Moran's I test statistics indicate that the hypothesis of no

Table 2. Hedonic and spatial model comparisons.

Variable	Model 1 Hedonic (OLS)		Model 2 SEM (ML)		Model 3 SAR (ML)	
Constant	1.5332	(1.8328)	3.0714**	(3.4862)	−1.4176	(−1.6753)
Age	−0.1312*	(−2.3588)	−0.1644**	(−3.0613)	−0.1241*	(−2.4979)
Area	0.9155*	(12.6764)	0.8427**	(12.3922)	0.8054**	(12.1854)
Garage	0.1761*	(3.6562)	0.1930**	(4.4050)	0.2111**	(4.8876)
Bedrooms	−0.0108	(−0.4963)	−0.0016	(−0.0774)	0.0083	(0.4216)
Receproom	0.1357	(1.7292)	0.1741*	(2.4100)	0.1682*	(2.3957)
Floorno	0.0594**	(3.8029)	0.0429*	(2.8552)	0.0343*	(2.3914)
Finishing	0.0823**	(2.9538)	0.0529	(1.9259)	0.0432	(1.7071)
Identity	0.1172**	(3.0372)	0.0817*	(2.1308)	0.0447	(1.2421)
Materialqual	0.3195**	(9.7516)	0.2394**	(6.1798)	0.1749**	(5.0190)
Fenestration	0.1102**	(3.0104)	0.1102**	(3.1965)	0.0909**	(2.7652)
Massing	0.0724**	(3.5583)	0.0675**	(3.4033)	0.0769**	(4.2348)
Height	0.0328	(1.3987)	0.0140	(0.5887)	0.0079	(0.3748)
Condition	0.0214	(0.6128)	0.0293	(0.8707)	0.0312	(1.0008)
Connect	0.0681**	(2.9810)	0.0574*	(2.5617)	0.0654**	(3.2051)
BpR	0.0102**	(5.7598)	0.0077**	(4.4278)	0.0067**	(4.0656)
Attindex	−0.0392**	(−2.7200)	−0.0408**	(−2.8341)	−0.0471**	(−3.6494)
Dgreen	−0.0898**	(−4.5197)	−0.0807**	(−4.0771)	−0.0882**	(−4.9730)
NearST	0.0220*	(2.5806)	0.0201*	(2.1370)	0.0289**	(3.7711)
PWdist	0.0757**	(7.6161)	0.0647**	(6.4809)	0.0566**	(6.1024)
yr2002	−0.0058	(−0.1151)	0.0577	(0.4684)	0.0527	(1.1633)
yr2003	0.1260*	(2.5254)	0.1721	(1.4025)	0.1846**	(4.1258)
yr2004	0.0556	(1.1846)	0.0969	(0.8203)	0.1056*	(2.5103)
yr2005	0.1744**	(3.2972)	0.2234	(1.6761)	0.1878**	(3.9737)
yr2006	0.4421**	(8.7191)	0.5057**	(4.1295)	0.3189**	(6.4205)
yr2007	0.6397**	(11.9617)	0.6657**	(5.3196)	0.4682**	(8.5984)
yr2008	0.4555**	(9.0797)	0.4825**	(3.9844)	0.3387**	(6.9931)
Lambda (λ)			0.6581**	(8.9581)		
Rho (ρ)					0.4279**	(7.5933)
Sigma^2 (σ^2)	0.0210		0.0176		0.0167	
R^2	0.8494		0.8634		0.8706	
Log-likelihood	18.9413		218.4580		231.9330	
N	373		373		373	

Notes: t values are in parentheses, * and ** denote 5% and 1% significance levels respectively. Multidirectional spatial weight matrix **M** based on negative exponential distance with 1.2 km cut-off.

Table 3. Moran's I tests for spatial autocorrelation in the OLS residuals.

M specification	1.9 km	1.8 km	1.7 km	1.6 km	1.5 km	1.4 km	1.3 km	1.2 km
Moran's I	0.0404	0.0415	0.0383	0.0426	0.0581	0.0732	0.0789	0.0950
Moran's I-statistic	16.7135	16.5283	14.9900	14.8962	16.1798	17.3529	15.7179	16.1742
Marginal probability	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Mean	−0.0279	−0.0280	−0.0281	−0.0285	−0.0289	−0.0291	−0.0298	−0.0306
SD	0.0041	0.0042	0.0044	0.0048	0.0054	0.0059	0.0069	0.0078

spatial autocorrelation in the residuals can be rejected for all specifications of **M** providing strong evidence for the need to control for spatial externalities through spatial econometric models (Table 3). The LM tests point towards the spatial lag (SAR) model for all different cut-off distances (Table 4).[9] Additionally, in selecting the most appropriate **M** for our study we consider those that maximise the test statistics (Boots & Dufournaud, 1994). The results indicate that the matrix with the 1.2 km cut-off best describes the multidirectional spatial relation with the combined building effects in the data. To additionally support the choice of **M**, Bayesian posterior model probabilities are compared (LeSage & Pace, 2009).[10] As the results indicate, the two candidates are the matrices with 1.3 and 1.2 km cut-off points.

Table 4. LM tests for type of spatial dependence and general tests for multidirectional spatial weight matrix (**M**) specification.

	Weight specification							
Tests	No cut-off (1.9 km)	1.8 km	1.7 km	1.6 km	1.5 km	1.4 km	1.3 km	1.2 km
LM test no spatial lag	37.9472	34.9251	29.7284	28.6771	42.9065	49.2513	69.7060	77.0109
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Robust LM test no spatial lag	33.8396	29.1800	24.9843	21.9840	30.3701	31.3528	48.5134	51.2744
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LM test no spatial error	7.0701	7.1839	5.9187	6.7383	12.6273	19.6143	21.6617	29.6569
	(0.008)	(0.007)	(0.015)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
Robust LM test no spatial error	2.9625	1.4388	2.9625	1.1746	0.0910	1.7158	0.4691	3.9204
	(0.085)	(0.230)	(0.085)	(0.278)	(0.763)	(0.190)	(0.493)	(0.048)
Posterior model probability (with SAR model)	0.0001	0.0000	0.0000	0.0000	0.0002	0.0012	0.1980	0.8005

Notes: LM tests use the OLS residuals from Model 1 (p-values are in parentheses). Posterior Bayesian probability tests are performed with the Bayesian estimation results of the model in (6) based on 2000 sample draws with the first 500 discarded for burn-in (LeSage & Pace, 2009).

The latter matrix shows posterior probability more than four times the previous one hence, indicating that the best specification for **M** is the 1.2 km cut-off option.

Following the selection of the multidirectional matrix the analysis focuses on the spatiotemporal weight matrix **U** which models the combined spatial and building effects considering the fact that apartment prices at any given time are only influenced by past transactions. More specifically, real estate agents value properties at time period t based on the average of transactions that happened at period $t-1$ hence the justification for using row-standardised matrices of nearest neighbours (LeSage & Pace, 2009). Our combined spatiotemporal weight allows for higher weighting if transactions took place in the same building while accounting for the time elapsed between these observed transactions. In order to provide more empirical and/or theoretical context to weight matrix specification we follow LeSage and Pace (2009) who argue that, in valuing properties, real estate agents consider the average price of between 5 and 10 comparable properties sold in the market during previous period(s). The specification of **U** follows this evidence and, in adopting a more heuristic approach as in the case of **M**, we test for 5, 8, 10, 12 and 15 nearest neighbours (NN) with two time decay rates of $v = 2$ and $v = 3$ as explained in (4).

Table 5 (Models 4–8) shows the outcomes of five spatiotemporal autoregressive models estimated with the same **M** as specified in (3) with $\bar{d} = 1.2$ km and different **U** based on the number of nearest spatiotemporal neighbours. The spatiotemporal parameter (ψ) is significant in all the five models but shows decrease in significance levels for over and under-connected matrices (15 and 5 nearest neighbours, respectively), reinforcing the importance of our context-based approach in weight specification.[11] Overall, the spatiotemporal model performance has increased from the purely spatial model (Model 3) albeit to a relatively low degree as can be seen from the log-likelihood values. The agreement of the estimates across various specifications is indicative of a lack of dramatic misspecification particularly with regards to omitted variables spatially correlated with the dependent variable. These outcomes further support our initial decision not to explicitly control for distance to schools considering their absence in the study area.

Table 5. Spatiotemporal specification, STAR and STARAR model estimation comparison.

Variable	Model 4 (STAR+5NN)		Model 5 (STAR+8NN)		Model 6 (STAR+10NN)		Model 7 (STAR+12NN)		Model 8 (STAR+15NN)		Model 9 (STARAR+12NN)	
Utility-bearing attributes (X)												
Age	−0.1237*	(−2.5014)	−0.1248*	(−2.5456)	−0.1332**	(−2.7289)	−0.1457**	(−2.9801)	−0.1369**	(−2.7528)	−0.1433**	(−3.0439)
Area	0.8011**	(12.1880)	0.7958**	(12.1983)	0.7880**	(12.1265)	0.7735**	(11.8738)	0.7928**	(1.2021)	0.7607**	(11.8804)
Garage	0.2076**	(4.8301)	0.2041**	(4.7820)	0.1998**	(4.7019)	0.1840**	(4.3007)	0.2050**	(4.7657)	0.1768**	(4.1554)
Bedrooms	0.0064	(0.3290)	0.0122	(0.6278)	0.0178	(0.9176)	0.0269	(1.3630)	0.0212	(1.0406)	0.0340	(1.7634)
Receproom	0.1706*	(2.4424)	0.1639*	(2.3662)	0.1591*	(2.3088)	0.1566*	(2.2777)	0.1507*	(2.1461)	0.1565*	(2.3018)
Floorno	0.0354*	(2.4767)	0.0380**	(2.6745)	0.0396**	(2.7941)	0.0397**	(2.8131)	0.0379**	(2.6385)	0.0351*	(2.5395)
Finishing	0.0446	(1.7719)	0.0469	(1.8735)	0.0445	(1.7866)	0.0451	(1.8189)	0.0444	(1.7639)	0.0436	(1.8523)
Identity	0.0448	(1.2518)	0.0533	(1.4955)	0.0576	(1.6211)	0.0625	(1.7604)	0.0540	(1.4986)	0.0461	(1.3520)
Materialqual	0.1850**	(5.2886)	0.1917**	(5.5012)	0.1880**	(5.4374)	0.1794**	(5.2410)	0.1754**	(5.0444)	0.1643**	(5.0804)
Fenestration	0.0917**	(2.8041)	0.0978**	(3.0094)	0.1013**	(3.1287)	0.1041**	(3.2192)	0.1049**	(3.1505)	0.0912**	(2.9118)
Massing	0.0769**	(4.2537)	0.0799**	(4.4481)	0.0826**	(4.6142)	0.0856**	(4.7785)	0.0770**	(4.2668)	0.0846**	(5.0173)
Height	0.0040	(0.1872)	0.0065	(0.3094)	0.0093	(0.4450)	0.0133	(0.6404)	0.0114	(0.5405)	0.0069	(0.3503)
Condition	0.0278	(0.8935)	0.0305	(0.9899)	0.0356	(1.1624)	0.0466	(1.5143)	0.0358	(1.1527)	0.0465	(1.5804)
Connect	0.0643**	(3.1706)	0.0641**	(3.1828)	0.0601**	(2.9975)	0.0625**	(3.1312)	0.0633**	(3.1196)	0.0655**	(3.4526)
BpR	0.0068**	(4.1369)	0.0074**	(4.5137)	0.0076**	(4.6340)	0.0081**	(4.8792)	0.0070**	(4.2535)	0.0076**	(4.7164)
Attindex	−0.0445**	(−3.4429)	−0.0440**	(−3.4456)	−0.0446**	(−3.5166)	−0.0500**	(−3.9526)	−0.0509**	(−3.9293)	−0.0520**	(−4.3828)
Dgreen	−0.0853**	(−4.8204)	−0.0836**	(−4.7602)	−0.0834**	(−4.7759)	−0.0876**	(−5.0476)	−0.0897**	(−5.0847)	−0.0894**	(−5.4927)
NearST	0.0282**	(3.6943)	0.0289**	(3.8225)	0.0291**	(3.8766)	0.0313**	(4.1679)	0.0291**	(3.8192)	0.0316**	(4.7420)
PWdist	0.0559**	(6.0592)	0.0577**	(6.2948)	0.0592**	(6.4695)	0.0615**	(6.7099)	0.0583**	(6.2957)	0.0572**	(6.5135)
Spatial & spatiotemporal parameters												
Rho (ρ)	0.4327**	(7.7260)	0.4273**	(7.6537)	0.4304**	(7.7420)	0.4274**	(7.7502)	0.4189**	(7.4258)	0.4625**	(9.2654)
Lambda (λ)											−0.5272	(−1.9559)
Spatiotemporal (ψ)	0.0598*	(1.9619)	0.1047**	(3.1619)	0.1346**	(3.7588)	0.1620**	(4.0650)	0.1007*	(2.2102)	0.1712**	(4.3963)
Constant	−2.1467*	(−2.3282)	−2.7687**	(−2.9481)	−3.0462**	(−3.2571)	−3.4125**	(−3.5568)	−2.4763*	(−2.5618)	−3.6750**	(−4.3816)
Time controls (D)												
yr2002	0.0413	(0.9092)	0.0390	(0.8689)	0.0363	(0.8115)	0.0338	(0.7576)	0.0488	(1.0822)	0.0251	(0.7621)
yr2003	0.1804**	(4.0448)	0.1920**	(4.3394)	0.1998**	(4.5274)	0.2140**	(4.8196)	0.2105**	(4.5686)	0.2041**	(6.2381)
yr2004	0.1103**	(2.6305)	0.1173**	(2.8128)	0.1207**	(2.9086)	0.1255**	(3.0272)	0.1223**	(2.8744)	0.1186**	(4.0716)
yr2005	0.1925**	(4.0914)	0.2199**	(4.6077)	0.2384**	(4.9383)	0.2602**	(5.2512)	0.2406**	(4.5585)	0.2518**	(6.8096)
yr2006	0.3078**	(6.1900)	0.3069**	(6.2409)	0.3051**	(6.2348)	0.3055**	(6.2819)	0.3164**	(6.4235)	0.2779**	(7.5196)
yr2007	0.4408**	(7.8691)	0.4323**	(7.8462)	0.4243**	(7.7176)	0.4227**	(7.7490)	0.4516**	(8.2675)	0.3869**	(8.6842)

(*Continued*)

Table 5. (*Continued*).

Variable	Model 4 (STAR+5NN)		Model 5 (STAR+8NN)		Model 6 (STAR+10NN)		Model 7 (STAR+12NN)		Model 8 (STAR+15NN)		Model 9 (STARAR+12NN)	
yr2008	0.3152**	(6.3439)	0.3058**	(6.2389)	0.2972**	(6.0678)	0.2903**	(5.9295)	0.3172**	(6.4645)	0.2654**	(6.9381)
Model fit statistics												
Sigma^2 (σ^2)	0.0166		0.0163		0.0161		0.0160		0.0165		0.0157	
R^2	0.8719		0.8739		0.8753		0.8761		0.8722		0.8783	
Log-likelihood	233.8510		236.8667		238.8707		240.0175		234.3574		241.5136	
Test for specification of (U)												
Posterior probability $v = 2$	0.0014		0.0237		0.1795		0.5268		0.0036			
Posterior probability $v = 3$	0.0018		0.0260		0.0630		0.1723		0.0019			
N	373		373		373		373		373		373	

Notes: t-values are in parentheses, * and ** denote 5% and 1% significance levels respectively. Reported results for models 4–8 are with unidirectional spatiotemporal weight matrix **U** based on the $v = 2$ temporal weight decay (4) and multidirectional spatial weight matrix **M** based on negative exponential distance with 1.2 km cut-off. In Model 9, we employ **U** based on 12 nearest neighbours (U12) and use the same weight matrix **M** for both dependent variable and error term autoregression processes.

We employ Bayesian posterior model probabilities to select the most appropriate **U** and Table 5 outcomes indicate that this is the specification with 12 nearest neighbours (NN) and a relatively slower temporal decay rate ($v = 2$, Equation (4)). It has an overall posterior probability of .527 (among 10 models) which is almost three times higher than the two other second best candidates (10NN with $v = 2$ and 12NN with $v = 3$). In light of these results, our preferred model is Model 7 (Table 5). This is a spatiotemporal autoregressive (STAR) model with combined multidirectional building and spatial effects restricted to the same time period with 1.2 km cut-off threshold and unidirectional spatiotemporal effects based on 12 nearest neighbours (both in space and time) with a relatively moderate temporal decay rate. Additionally, estimation consistency across the wide specification spectrum of **M** and **U** is in line with recent claims that estimation sensitivity to changes in the weight matrix might be indicative of model misspecification rather than typical flaws with the weighing scheme (LeSage & Pace, 2014).

As a final step of the specific-to-general approach, we consider the STARAR model which nests the STAR and SEM specifications through spatial dependence in both the dependent variable and the error terms as shown in (9). These outcomes are presented in the last two columns in Table 5 under the heading Model 9. The error term spatial parameter (λ) has a negative sign and does not reach the 5% significance level, indicating model over-specification issues. Overall, other parameter estimates seem consistent across the STAR and STARAR models albeit showing a slight decline in magnitude in the latter due to the slight impact of lambda (λ) and increased values of rho (ρ) and psi (ψ). To understand which model best describes the data we employ a formal likelihood ratio (LR) test using the Log-likelihood values of the restricted (STAR) and unrestricted (STARAR) models. This test is based on the formula -2*(L_like$_{\text{restricted}}$ – L_like$_{\text{unrestricted}}$) and its statistic has a χ^2 distribution with *df* = number of restrictions, in this case 1: the parameter λ (Elhorst, 2014). The outcomes indicate that we cannot formally reject the STAR model in favour of the STARAR model (LR test value of 2.99 while the critical value for .05 significance level with 1 degree of freedom is 3.84).[12]

Having specified the model that best describes the data we turn our attention to the exact effect estimates of the explanatory variables. As indicated in the previous section, these cannot be represented by the point estimates of the $k \times 1$ vector of parameters $\boldsymbol{\beta}$ due to the presence of the spatial multiplier $(\mathbf{I}-\rho\mathbf{M})^{-1}$. We alternatively use the diagonal elements of $(\mathbf{I}-\rho\mathbf{M})^{-1}\beta_r$ for the direct effect estimates and the off-diagonal elements of $(\mathbf{I}-\rho\mathbf{M})^{-1}\beta_r$ for the indirect effect estimates (Elhorst, 2014; LeSage & Pace, 2009, 2014).[13] In regional studies, the indirect effect estimates are a major analysis concern, however in econometric studies of hedonic property prices the exact estimates of direct effects is the focus of analysis that (*ceteris paribus*) reflects the willingness to pay of buyers for each utility bearing attribute under consideration. In addition, the SAC and SAR type of models have been criticised for producing wrong indirect effect estimates (Elhorst, 2014). Consequently, we focus on the effect of the spatial multiplier on the point estimates of the STAR model by analysing the differences between the β parameter and direct effect estimates. By and large, these are very small throughout the parameter vector of the utility bearing explanatory variables. The last column in Table 6 shows this impact as the percentage of STAR model point estimates. It can be observed that these percentage values are lower than 2% except for the variables *Connect* (significant at 1%), *Receproom* (significant at 5%) and *height* appropriateness (not significant). A relatively higher percentage value is observed only in the latter (value above

Table 6. Effect estimates.

Variable	Direct		Indirect		Total		Beta (β)	*MY* effect |% of β|
Age	−0.1482	(−3.0187)	−0.1096	(−2.4821)	−0.2578	(−2.9121)	−0.1457	1.6851
Area	0.7810	(11.8482)	0.5784	(4.4431)	1.3594	(8.5932)	0.7735	0.9737
Garage	0.1866	(4.2387)	0.1394	(2.8598)	0.3260	(3.7591)	0.1840	1.4219
Bedrooms	0.0272	(1.3444)	0.0208	(1.2301)	0.0480	(1.3125)	0.0269	1.2987
Receproom	0.1599	(2.3938)	0.1193	(2.0161)	0.2792	(2.2927)	0.1566	2.0965
Floorno	0.0401	(2.7659)	0.0292	(2.5390)	0.0693	(2.8015)	0.0397	0.8308
Finishing	0.0460	(1.8145)	0.0334	(1.7093)	0.0795	(1.8154)	0.0451	1.9850
Identity	0.0633	(1.7733)	0.0455	(1.7222)	0.1089	(1.7966)	0.0625	1.3781
Materialqual	0.1811	(5.1906)	0.1316	(4.7000)	0.3127	(5.9349)	0.1794	0.9191
Fenestration	0.1041	(3.3122)	0.0767	(2.7380)	0.1808	(3.2245)	0.1041	0.0086
Massing	0.0864	(4.6856)	0.0643	(3.1380)	0.1507	(4.1908)	0.0856	0.9351
Height	0.0129	(0.6277)	0.0089	(0.5941)	0.0218	(0.6183)	0.0133	3.5138
Condition	0.0471	(1.4522)	0.0353	(1.3163)	0.0824	(1.4160)	0.0466	1.0688
Connect	0.0640	(3.3092)	0.0476	(2.5723)	0.1117	(3.1125)	0.0625	2.4425
BpR	0.0082	(4.9756)	0.0060	(3.7997)	0.0142	(4.9933)	0.0081	1.2658
Attindex	−0.0509	(−3.8918)	−0.0379	(−2.8455)	−0.0887	(−3.5901)	−0.0500	1.7822
Dgreen	−0.0888	(−5.1246)	−0.0659	(−3.3650)	−0.1546	(−4.6131)	−0.0876	1.3218
NearST	0.0319	(4.0912)	0.0239	(2.8178)	0.0558	(3.6480)	0.0313	1.9212
PWdist	0.0621	(6.7944)	0.0457	(4.3211)	0.1078	(6.5949)	0.0615	1.0183

Note: *t*-values are in parentheses. Beta (β) values are from Model 7. Spatial effect (***MY***) on point estimates = (Direct-Beta)/Beta*100.

3.5%) which leads us to conclude that the model performs well with regard to estimation consistency.

Regarding key explanatory variables, as expected, *Area* makes the highest contribution to house prices (highest *t*-value). Overall, parameter signs meet prior expectations with the exception of commercial activity interaction (*Attindex*) and distance to the nearest train station (*NearST*) variables. One possible explanation might relate to the dis-amenity effect of being too close to the railway and also being close to the train station: 3.2% decrease in value for every 100 m proximity. As it can be observed, users value proximity to the green area (also city centre in our case: 8.9% increase in value for every 100 m decrease in distance) while preferring to be located farther away from the peace wall (6.2% increase in house value for every 100 m distance). Taller buildings also command higher prices (4% increase in price for 1 additional floor), a fact that can be associated with the view potential that the upper floors offer.

Findings related to interior subdivision are interesting as, all else being equal, users seem to value more a second reception room in their apartment (16% increase in price however, at 5% significance level), while similar results do not hold for number of bedrooms. This might be related to household composition in this area, the view potential of the extra reception room or its different purpose as a dining room. The latter explanation has particular importance in housing design as it might indicate that users do not particularly favour the 'modern open plan kitchen designs' and that a separate dining room might be more valuable than an extra bedroom in this market segment. Additionally, in line with expectations, presence of a garage seems to be highly valued in dense city centres as apartments with a garage seem to command an 18.7% price premium. This relatively high premium might be attributed to a combination of local idiosyncrasies namely scarcity of parking in the city centre and the fact that Belfast is considered to be the most motorised city in the UK. This finding needs to be treated cautiously also because properties with a garage comprise 7.3% of the data-set (Table 1).

In analysing the exterior quality variables a general pattern relates to the fact that from the seven variables employed those that reached statistical significance represent features of greater visual contrast and ease of identification, implying easier quantification. These variables are namely material quality, fenestration and massing while building height appropriateness (which we also consider to be easily quantifiable) might not be highly significant due to the earlier reported preference for tall(er) buildings. Conversely, concepts such as building identity, exterior finishing and overall condition appropriateness to the surroundings might be less clearly perceived by buyers, although in this study they were employed based on the existing body of knowledge and rated by experts. Compared to the OLS estimates (Model 1) there is a drop in the number of significant exterior quality variables (from five to three) in the STAR model (Model 7). This provides further supporting evidence regarding the estimation problems associated with OLS models in the presence of spatially autocorrelated disturbances (Table 3). Regarding impact on apartment prices, moving up one quintile in ratings for material quality, fenestration and massing appropriateness to the surroundings commanded 18, 10.4 and 8.6% premiums, respectively. Particularly the high premium in material quality appropriateness should be treated carefully as it might relate to an overall building quality appreciation of the experts (considering also the fact that there were no buildings rated in the top quintile (Table 1).

Urban density is an aspect of design quality particularly valued by the end-users of this residential sub-sector. A one decile increase in the Building to plot Ratio (e.g. from BpR = 0.4 to BpR = 0.5) of the urban block where the property is situated commands approximately an 8.2% price premium. This suggests that inner-city apartment owners value vitality of the urban fabric which is generally associated with higher urban densities. Connectivity of the urban fabric also seems to be valued with properties located in more connected neighbourhood units commanding price premiums. Based on the definition of the spinal grid (Taaffe et al., 1996) this indicates preference for neighbourhood units of simple geometric shapes and a minimum number of dead ends. As a final analysis we consider the attraction index which captures interaction of retail activity foci and distance to the transacted property. Our initial tests point towards the relevance of only one activity focus attraction index out of the three originally constructed. We interpret this as a distance relationship where properties located further away from the shopping node command higher prices (all else being equal, 5% premium for every 100 m increase in distance). This clearly shows the competition for space between different land uses in city centre localities that results in most newly built apartments locating in the edge of the old city centre with the core predominantly identified with commercial real estate. Both urban scale and exterior design quality variable outcomes represent a typical empirical work in a single urban context. Consequently, similar studies in other cities might contribute to better generalisability and/or improve assessment of different design considerations.

6. Conclusions

The purpose of this paper is to estimate the impact of design quality on real estate value through empirical investigation of city centre-based apartments in a UK provincial city. Planning policies that focus on increasing density in central urban areas have shaped the relatively new apartment market while quantitative empirical evidence on potential impact is still embryonic. This paper estimates the value of different aspects of design quality in apartment units in Belfast City Centre by applying and extending the hedonic model to include building and urban level quality variables. Additionally, a concerted method for appropriately modelling spatiotemporal real estate data aims to remove bias in effects estimation for statistical inference. This is crucial in providing practitioners and policy-makers involved in shaping the built environment with the evidence required for decision-making on development, investment, financial and design criteria.

Empirical findings indicate that from the seven building quality features initially investigated, the ones mostly valued by end users are those that are easily perceived visually. These concern the appropriateness to the surroundings of a building's material quality, fenestration and massing. The other features namely finishing, identity, overall condition and height appropriateness were found to be statistically non-significant. The first three are considered to be relatively difficult for end-users to distinguish and visually assess when purchasing a home while the last is explained by more idiosyncratic factors. At the urban scale, the quality aspects valued by the users are built fabric density which is generally associated with vitality and increased urban fabric connectivity of simple patterns that do not include dead ends. These findings relate to the urban core of Belfast and considering the highly context-based nature of design, application to other cities necessitates research being undertaken in comparable urban contexts. From a modelling perspective, this paper has demonstrated the significance of the multidirectional spatial parameter restricted to the same time period and the dynamic spatiotemporal parameter that controls for transactions occurring only earlier in time. This indicates the importance of accounting for these factors in hedonic models.

The outcomes of this study have a high scaling-up potential through similar empirical work in other cities resulting in significant impact on the property development and investment process. Developers and investors can potentially benefit from the individual pricing of different aspects of quality design in shaping their investment priorities by taking into account the associated initial costs. Inner-city apartments are considered a crucial component in the successful delivery and long-term sustainability of urban regeneration. The current pressure for new housing development has significantly shifted the focus to the quantity of the new stock needed. A clear risk associated with direct action required to meet increasing demand for housing at affordable prices could result in a potential drop in design quality standards of the new proposed multi-family housing developments. In this context, this study is of relevance to stakeholders in providing evidence on the real estate value of the different aspects of built environment quality. Building upon the outcomes of this paper further research directions should integrate the financial case of delivering a higher quality product relative to the costs of production and the ability to buy in the current housing market.

Notes

1. An initial set of 1133 residential transactions was obtained from the NIQHPI based on the postcode records on the original SPSS file. These entries were additionally verified for their typology (multi or single family units), construction period in the database and exact location in GIS. Based on software syntax a large number of entries in this extract fell outside our study area (e.g. 'postcode' entry 16 stands for both the postcode zone 16 and sub-zone 6 of postcode zone 1). Following this, the final set of 424 apartment transactions in Belfast City Centre (postcode areas BT1 and BT2) was obtained.

2. Considering the small study area and the number of transactions per year, in order to preserve confidentiality of the privately sourced data from real estate experts operating in the area, quarterly-based information is not available in the NIQHPI data-set. Additionally, post-2008 data were not made available for the same confidentiality reasons due to the small volume of transactions during the market downturn.
3. In our study area and its immediate vicinity the only active green space corresponds to the garden of the City Hall, we use the distance of each building centroid in our data-set to the main entrance of this area to construct the variable *Dgreen*.
4. This requires that observation i happened before observation j which in our case is satisfied when $i > j$, since data is ordered temporally. For the case when $i = j$ i.e. the diagonal values, these are set to zero to avoid considering each observation as their own neighbour, hence the final lower triangular form.
5. More explicitly, for transactions happening in the same time period, one period earlier, two periods earlier the weights are 1; 0.25 & 0.111, respectively, for $v = 2$ and 1; 0.125 & 0.037, respectively, for $v = 3$. Additionally, following time on market evidence from the UK which indicates approximately 90% market clearance in half a year (see Pryce & Gibb, 2006 for an example in Strathclyde) we consider only faster decay rates than the one represented by $v = 2$ and not slower ones.
6. For example, a weight of 1 is assigned only to transactions happening in the same building and at the same time period. Additionally, for the $v = 2$ case, transactions in the same building but one time period apart are weighted by 0.25 whereas transactions in the same period but, say 1.5 km apart receive a weight of 0.223. This is crucial in selecting spatiotemporal nearest neighbours to appropriately consider the behaviour of buyers and real estate agents.
7. Note that, following this specification, δ is now of dimension $(t\text{-}2) \times 1$.
8. Preliminary assessment indicates that these exact cut-off distances are 1.920 and 1.206 km, respectively.
9. We additionally test for the 1 km cut-off (rather arbitrary and does not ensure that each observations has at least one neighbour) and, as expected, we find that LM tests point towards a SEM form; LM test no spatial lag: 0.3278 (0.567) and LM test no spatial error: 3572.2127 (0.000), indicating clear misspecification problems, in this case of the weighting scheme. This further supports our empirical and context-based approach on weight testing based on preliminary analysis of the spatial dependence structure in the data. These outcomes might also explain to some extent SEM indication in the LM tests of related (spatiotemporal) studies with over-connected weight matrices (without cut-off distance) (Thanos et al., 2012).
10. This test requires that all models are estimated with the Bayesian Markov Chain Monte Carlo (MCMC) method and their posterior probabilities compared. We use the matlab routine sar_g from the spatial econometrics toolbox available at the www.spatial-econometrics.com website (LeSage & Pace, 2009). We performed 2000 sample draws omitting the first 500 to estimate a model with homoscedastic disturbances, since this is an underlying assumption of the model in (Equation 8). These results are similar to the ML estimations and are available upon request.
11. In an initial test of 6 models with 5, 10 and 15 NN and 2 temporal weight decays ($v = 2$ & $v = 3$) posterior Bayesian probabilities clearly point towards the specification of 10NN with $v = 2$.
12. As an indicative double check we refer the reader to the LR test between STAR and SAR models (Model 7 and 3, respectively) for the spatiotemporal parameter (ψ). This value is 16.17 and with 1 degree of freedom indicates that the SAR model can be rejected even at the .001 level (test statistic: 10.83) in favour of the STAR specification.
13. Based on our N size and block diagonal specification of the weight matrix we use full computation of the log determinant ln $|\mathbf{I} - \rho\mathbf{M}|$ (reported in Table 6) and, following recent considerations on the routines in the www.spatial-econometrics.com website (Elhorst, 2014, p. 26), we additionally use the matlab routines made available by Paul Elhorst at the website www.regroningen.nl to check for consistency. The estimation results are consistent across the two routines and can be made available upon request.

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No potential conflict of interest was reported by the authors.

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Appendix 1. Scoring process for quality design variables

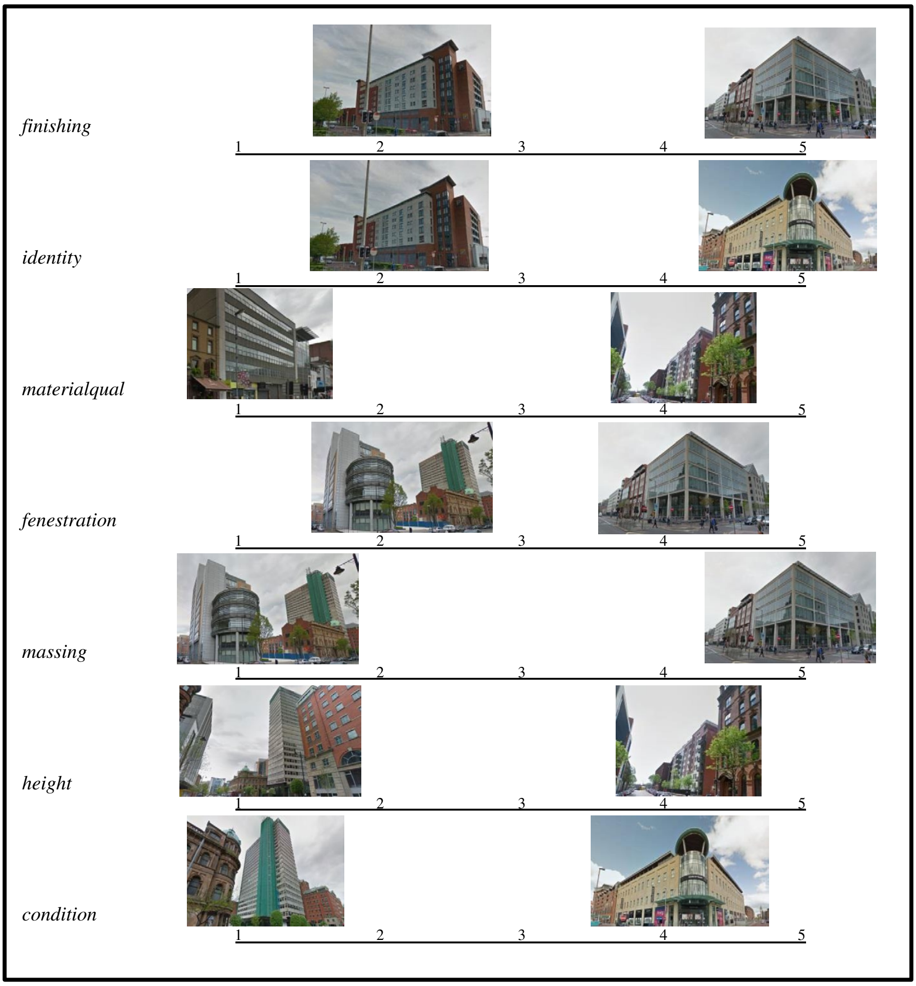

Figure A1. Visual representation of benchmarking.

This study is part of a larger project on the analysis of property performance in Belfast City Centre. Due to the large number of the buildings to be assessed (approximately 300) and the limited availability of the experts a score benchmarking process that included averaging expert scores was performed with a sample of approximately 10%. The expert opinion score sheet included visual information (photo/image) on building location (map), street/surrounding view and façade view and building name and address for subsequent coding purposes in the dataset. Regarding the scoring process, façade and street views were used to assess all attributes and location maps were additionally employed to in the assessment of identity and massing.

Regarding benchmarking per attribute this is visually shown with examples in Figure B-1. In the *finishing* (material choice) category the lowest scores were for modern red brick finishing that were 'inappropriately mimicking' the existing stock while the highest scores were for materials clearly indicating different era trends (e.g. among others, a combination of glass with other materials). *Identity* lowest quartile was mainly represented by building complexes associated with what was considered as 'non-appealing other land uses' (e.g. multi story car parking) whereas the highest quartile reflected clear city landmarks that could also be distinguished by their land use. Lowest scoring buildings in the *material quality* appropriateness category were those in need of refurbishment surrounded by newer or newly refurbished buildings and highest scoring buildings were generally represented by new buildings in newly redeveloped areas of the city centre. In other words, quality material (of e.g. plastering, marble, granite) surrounded by other buildings of the same quality material. *Fenestration* highest scores were awarded to floor levelling 'respecting the existing' and window repetition rhythms considering those of reference historic buildings and lowest scores for facades disregarding this. *Massing* considered both the building footprint and its volume and the ones that were clearly violating existing streetscapes and volumes scored the lowest with buildings of the infill type scoring on the highest quintile. *Height* appropriateness saw both relatively low and relatively high rise buildings scoring on the low end and same level or only one floor differences in height being awarded the highest scores. Overall *condition* reflected mainly façade maintenance levels and low scoring buildings showed clear need of façade refurbishment.

Appendix 2. Graphical explanation of the spinal connectivity pattern: γ = (#nodes-1)/ 3*(#nodes-2)

a) #nodes= 10; γ =0.3750 b) #nodes= 14; γ =0.3611

The graphical representation above indicates higher γ values of the connectivity index with 'simpler' urban block forms that do not include dead ends. This is particularly important in the urban fabric of Belfast where peace walls and the process of closing off streets has contributed to a fabric represented in *b*. Hence, our expected positive sign for the *Connect* variable in this specific urban context (preference for *a* despite the apparent lower number of nodes).