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Spatial Dependence in Apartment Offering Prices in Hamburg

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Spatial Dependence in Apartment Offering Prices in Hamburg, Germany *

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Abstract

This paper applies spatial econometric techniques to a hedonic apartment price model employing maximum-likelihood techniques. Accounting for spatial dependence of apartment offering prices in Hamburg, Germany, the empirical analysis uses a semi-logarithmic price equation based on 4,029 offered apartments between 2008 and 2010. Starting with the traditional hedonic OLS-regression, we assess presence of spatial dependence using Lagrange Multiplier test statistics for error and lag dependence. These tests leads us to the spatial Durbin model and a spatial weight matrix based on the 15 nearest neighbors. Estimation results show that apartment prices exhibit a positive relationship with neighboring apartments. In addition to a high spatial autoregressive parameter, the estimated indirect effects (following the methodology of [LeSage and Pace \[2009\]](#)) show significant results. Consequently, a change in a single explanatory variable in a particular apartment not only affects the apartment price itself but also the price of neighboring apartments. Following the estimation results, spatial dependence is present, least- square estimates are biased and spatial hedonic models do explain more of the price variation with significant indirect effects in the spatial Durbin model.

JEL Codes: C23, R23, R31

Keywords: Spatial dependence; hedonic price equation; spatial Durbin model; indirect effects

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1 Introduction

Explaining house prices is not trivial. First of all, there is the heterogeneity problem. Instructive results can only be achieved if prices refer to houses of comparable quality. Given the nature of houses, this precondition is typically not fulfilled. Houses differ in size, location, design, age, and other characteristics. Therefore, the question of whether a price change is actually a price change or rather a compensation for a change in quality is ambiguous. Secondly, only a small fraction of the housing stock is transacted every year. The heterogeneity of real estates would not be an obstacle if individual properties were sold regularly and in short time intervals. In that case, the probability for price measurements to be distorted by property attributes and modernization work is small. However, real estate properties come onto the market irregularly and at large time intervals, thus making heterogeneity an important issue. In order to assure the homogeneity of real estate needed to construct sound house price indexes, the hedonic method explains the price of a house in terms of its price-determining attributes. Moreover, real estate prices are known to be influenced by prices of recent real estate sales nearby. In other words, apartment prices are often spatially autocorrelated with distance. Apartments located nearby each other tend to have similar prices (cf. Tobler's first law of geography, [Tobler \[1970\]](#)). This correlation weakens with distance. But nevertheless, one must allow for possible spatial dependencies between such prices. Reasons why dwelling prices depend, among others, upon location are ([Fahrländer \[2007\]](#); [Militino, Ugarte and Garcia-Reinaldos \[2004\]](#); [Basu and Thibodeau \[1998\]](#); [Kain and Quigley \[1970\]](#)):

1. Houses in the same neighborhood have similar structural characteristics, such as building material, total living area, age of construction, garage, and storage rooms.
2. Households in the same neighborhood share common social services, such as schools, health centres, libraries or malls.
3. Households in the same neighborhood share the same distance to administrative and commercial agglomerations.

Disregarding relevant spatial effects usually leads to spatial autocorrelation or spatial dependence. On the one hand, neglecting relevant location characteristics usually lead to spatial autocorrelation between the error terms in the Ordinary-Least-Square (OLS) regression. This

entails unbiased but inefficient parameter estimates due to biased variance estimators for the OLS results.

On the other hand, spatial dependence can occur due to the existence of spatial spillover effects. These spatial spillovers are modeled by a spatial multiplier which determines by the coefficient of a weighted transformation of spatially lagged prices. If spatial dependence is present between the observations, the spatial multiplier measures the benefits, where the direct effect of an improvement is magnified by the spillovers effect among neighboring properties. The neighbors house price affect the utility of my house because of unobserved aspects of the real estate market or of my neighbors behavior ([Small and Steimetz \[2012\]](#)). Ignoring spatial dependence in the dependent variable or in the explanatory variables, when present, leads to biased coefficient estimates.

The importance of spatial effects and, in particular, of spatial dependence for the efficiency and consistency of hedonic model estimates has only very recently started to receive some attention. The neglect of spatial considerations in econometric models not only affects the magnitudes of the estimates and their significance but may also lead to serious errors in the interpretation of standard regression diagnostics such as for heteroscedasticity. Comparing the baseline model with a model which explicitly corrects for spatial endogeneity gives us insights into spatial dynamics over time.

The aim of the current paper is to estimate an appropriate spatial econometric model for apartment offering prices, based on data for the city of Hamburg, Germany. We are one of the first applying the spatial econometric methodology to data on the German apartment market. Thereby, we obtain ordinary least squares estimates for the hedonic model and assess the presence of spatial dependence using Lagrange Multiplier test statistics for error and lag dependence ([Anselin \[1988\]](#)), as well as their robust forms ([Anselin et al. \[1996\]](#)). The results consistently show very strong evidence of spatial dependency and positive residual spatial autocorrelation, with an edge in favor of the spatial Durbin model. Second, we are one of the first focusing on the interpretation of direct and indirect effects of the spatial Durbin model. Direct effects measure the impact of changing an explanatory variable on the offering price of the apartment itself. Indirect effects measure the impact of changing an exogenous variable in a particular apartment on the offering price of neighboring apartments. A comparison to the

OLS regression results reveals the extent to which the coefficients and the direct and indirect effects estimates are over- or underestimated in the OLS model.

The outline of this paper is as follows: Section 2 gives an overview on hedonic house price models and analysis taking into account spatial structure into house price equations. Section 3 describes the theoretical framework of the OLS and spatial econometric model. Furthermore, it gives a detailed specification for spatial effects. Section 4 describes the data and gives a short overview of the housing market in Hamburg. Section 5 presents the estimation results which is followed by the conclusion in Section 6.

2 Principles of Hedonic House Price Modelling

Apartment prices are characterized by facility, quality and location. According to the theory that goods are attributed by their utility ([Gorman \[1956\]](#) and [Lancaster \[1966\]](#)) the hedonic price model is a quality adjusted market price model ([Rosen \[1974\]](#)). Real estate properties incorporate a bundle of characteristics so that the implicit price of the different attributes can be measured and reveal the marginal willingness to pay of consumers ([Can \[1992\]](#)).

[Straszheim \[1975\]](#) argue that one fundamental characteristic of urban housing markets is the variation in housing characteristics and prices by location. Many paper incorporate location into their house price modelling; surveys can be found, among others, in [Basu and Thibodeau \[1998\]](#), [Bitter, Mulligan and Dallerba \[2007\]](#) and [Palmquist and Smith \[2002\]](#).

One of the pioneers incorporating neighborhood effects in hedonic price models are [Kain and Quigley \[1970\]](#), [Dubin \[1988\]](#) and [Can \[1990\]](#) applying very different approaches. [Kain and Quigley \[1970\]](#) using a quantitative approach to estimate the market value of specific bundles of residential services consumed by urban households. They found that the residential service has about as much effect as the house characteristics itself. Using a geo-statistical approach (krigging) [Dubin \[1988\]](#) simultaneously estimate the parameters of the correlation function and regression coefficients of a linear hedonic price model under a maximum likelihood procedure. [Can \[1990\]](#) introduce spatially weighted dependent variables into the hedonic housing price equation. Due to the use of both spatial spillovers and spatial parametric drifts the variations are better explained and allow for the quantification of neighborhood effects.

In recent house price modelling geo-referenced data are used and the potential bias and

loss of efficiency that can result when spatial autocorrelation or spatial heterogeneity are ignored in the estimation process are taken into account. Thereby, the methods how to model spatial dependence are broadly spread. One way is to apply spatial statistics approaches like in [Dubin \[1992\]](#), [Valente et al. \[2005\]](#), [Neill, Hassenzahl and Assane \[2007\]](#) or [Páez, Long and Farber \[2008\]](#). This field is applied on geostatistical data using methods such as variograms and autocorrelation, spatial regressions and space-time models. Moreover, [Valente et al. \[2005\]](#) modelling a conceptual rent at every location in the market and explicitly specify spatial association between pairs of location as a function of distance between them. [Neill, Hassenzahl and Assane \[2007\]](#) circumvents the limitation of maximum likelihood estimation to small data sets by bootstrapping from a Monte Carlo Simulation that accounts for spatially dependent data.

Another way is to estimate, spatial hedonic models. These models incorporate the spatial dependence in cross-sectional data into model specifications and become common place in empirical housing and real estate studies, leading to so called spatial hedonic models such as in [Can \[1992\]](#), [Anselin and Le Gallo \[2006\]](#) or [Kim, Phipps and Anselin \[2003\]](#). These models are based on a predetermined spatial weight matrix. [Kim, Phipps and Anselin \[2003\]](#) measure the benefits of air quality improvement using spatial data. The authors identify the spatial Lag model using a continuity spatial weight matrix. Applying a semi-logarithmic specification, [Kim, Phipps and Anselin \[2003\]](#) show, that different kinds of air pollution have different effects on house prices.

The dependence on the spatial weight matrix in spatial econometric techniques leads researchers to compare their spatial econometric results with those obtained using spatial statistics. [Tsutsumi and Seya \[2009\]](#), for example, discuss several spatial hedonic approaches and show the limitations of spatial econometric techniques. Thereby, their focus on the spatial weight matrix and the fact that the matrix must be predetermined and is dependent on pre-conditions, which are not occur in spatial statistic models.

3 Empirical Strategy

The theoretical discussion starts with a hedonic apartment price model defining the dependent variable as the apartment offering price while the independent variables are defined by

apartment attributes, neighborhood characteristics and time indicators. Using the Ordinary-Least-Squares (OLS) approach the model takes the following form:

$$P = \alpha \iota_n + \mathbf{X}\beta + \epsilon, \quad (1)$$

where P is the outcome variable indicating the log of apartment offering prices, ι_n is associated with the constant term parameter α to be estimated, β is a vector of unknown parameters associated with exogenous explanatory variables (apartment attributes), \mathbf{X} . The idiosyncratic error is ϵ .

If prices are spatially correlated, either in their levels or in the errors, OLS assumptions are typically not fulfilled and OLS regression can give spurious results and should be interpreted with caution ([Anselin and Le Gallo \[2006\]](#)). In particular, in real estate cross-section data sets inclusion of all neighbourhoods attributes is problematic and leads to autocorrelation in the error term (e.g. [Militino, Ugarte and Garcia-Reinaldos \[2004\]](#)) or omitted variable bias (e.g. [Wilhelmsson \[2002\]](#)). As a result parameter estimations are still unbiased but inefficient and the estimates of the variance of the estimates are biased. The application of the spatial econometric techniques can avoid these problems.

Theoretically, the spatial Durbin model is defined as:

$$P = [I - \rho \mathbf{W}]^{-1} \mathbf{X}\beta + [I - \rho \mathbf{W}]^{-1} \mathbf{W}\mathbf{X}\theta + [I - \rho \mathbf{W}]^{-1} \epsilon \quad (2)$$

where P , \mathbf{X} and β are defined as above and I being an identity matrix. Following [Wall \[2004\]](#) ρ is the spatial autoregressive parameter. In this way ρ reflects the strength of price dependencies. Furthermore, $\mathbf{W}P$ is the spatially lagged offering price accounting for various spatial dependencies with \mathbf{W} defined as spatial weight matrix. Just as β , θ is a vector of unknown parameters to be estimated.

The underlying spatial weight matrix \mathbf{W} is based on prior knowledge of spatial structure and is exogenously determined. The k -nearest neighbors (based on actual distances) weight

matrix in general form is defined as in [Baumont, Ertur and Gallo \[2004\]](#):

$$\begin{cases} w_{ij}(k) = 0 & \text{if } i = j, \forall k \\ w_{ij}(k) = 1 & \text{if } d_{ij} \leq d_i(k) \text{ and } w_{ij}(k) = \frac{w_{ij}}{\sum_j w_{ij}(k)} \\ w_{ij}(k) = 0 & \text{if } d_{ij} > d_i(k) \end{cases} \quad (3)$$

Given this structure all matrix elements which belong to the k nearest neighbors are one, and zero otherwise. Finally the spatial weight matrix is row normalized so that each row sums up to one ($W\iota = \iota$ with ι is the unit vector (cf. [Small and Steimetz \[2012\]](#))) and leads to asymmetry in the case of actual distances. Following the literature, there is an agreement that the predetermined spatial structure of the spatial weight matrix influences the regression results, especially the presence of the spatial structure in the model. In their paper “The biggest myth in spatial econometrics” [LeSage and Pace \[2010\]](#) find little theoretical basis of for that criticism if the estimates are based on the partial derivatives, i.e. the direct and indirect effects.

3.1 Direct effects, indirect effects and the spatial multiplier

In a simple hedonic OLS model, parameter interpretation is obvious since the parameters can be interpreted as the partial derivatives of the dependent variable with respect to the explanatory variable ([LeSage and Pace \[2009\]](#)) and indirect effects are set to zero by definition ([Seldadyo, Elhorst and De Haan \[2010\]](#)). Taking into account other regions dependent and explanatory variables, the model is enriched by an indirect effect that measures the impact on the price of a particular apartment from changing an exogenous variable in another apartment. Or the impact of changing an exogenous variable in a particular apartment on the price of all other apartments ([Seldadyo, Elhorst and De Haan \[2010\]](#)). These effects, direct and indirect, are calculated by the partial derivatives of the expected values with respect to the explanatory variables (x_{ik} with $i = 1 \dots N$ and k being the explanatory apartment characteristics). Regarding our model, the partial derivatives are given as

$$\begin{bmatrix} \frac{\partial E(P_1)}{\partial x_{1k}} & \frac{\partial E(P_1)}{\partial x_{2k}} & \cdots & \frac{\partial E(P_1)}{\partial x_{Nk}} \\ \frac{\partial E(P_2)}{\partial x_{1k}} & \frac{\partial E(P_2)}{\partial x_{2k}} & \cdots & \frac{\partial E(P_2)}{\partial x_{Nk}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial E(P_N)}{\partial x_{1k}} & \frac{\partial E(P_N)}{\partial x_{2k}} & \cdots & \frac{\partial E(P_N)}{\partial x_{Nk}} \end{bmatrix} = ((I_N - \rho \mathbf{W})^{-1}) \begin{bmatrix} \beta_k & w_{12}\theta_k & \cdots & w_{1N}\theta_k \\ w_{21}\theta_k & \beta_k & \cdots & w_{2N}\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\theta_k & w_{N2}\theta_k & \cdots & \beta_k \end{bmatrix} \quad (4)$$

with $[I_N - \rho \mathbf{W}]^{-1}$ being the “spatial multiplier matrix” (Anselin [2003])¹.

As can be seen from the “spatial multiplier” properties, a change in a single X variable can affect the equilibrium price in Equation (??), provided $\rho > 0$. Both, indirect and direct effects depend on the coefficient estimate of θ_k of the spatially lagged value of the explanatory variable. Moreover, indirect effects do not occur in a spatial Durbin model, if both $\rho = 0$ and $\theta_k = 0$. Provided that $\rho \neq 0$ and $\theta_k \neq 0$, indirect effects are different for different units in the sample since the non-diagonal elements of the matrix $((I_N - \rho \mathbf{W})^{-1})$ and the spatial weight matrix \mathbf{W} are different. The total impact of a change in one apartment characteristic on the apartment price at location i is the sum of direct impacts $\partial P_1 / \partial x_{ik}$ plus included impacts $\sum_{i=2}^N \partial P_1 / \partial x_{ik}$. In the spatial Durbin model no prior restrictions are imposed on the magnitude of both, direct and indirect effects and thus the ratio between the indirect effects and the direct effect may be different for different explanatory variables. This is since the coefficient estimate of θ_k of the spatially lagged value of that variable depends on both, the direct and indirect effect of a particular explanatory variable. This is an advantage compared to other spatial regression specifications (Elhorst [2010]; p. 22).

¹Row normalization of the spatial weight matrix implies $[I_N - \rho \mathbf{W}]^{-1} \iota = (1 - \rho)^{-1} \iota$. Postmultiplication by ι simplifies the spatial weight matrix to the scalar “spatial multiplier” $(1 - \rho)^{-1}$ (see Kim, Phipps and Anselin [2003] and Small and Steinmetz [2012]). The infinite series expansion of the spatial multiplier is $(I - \rho \mathbf{W})^{-1} = I + \rho \mathbf{W} + \rho^2 \mathbf{W}^2 + \rho^3 \mathbf{W}^3 + \dots$. The non diagonal elements of the identity matrix represents the direct effect of an change in X . The diagonal elements of are zero by assumption, this term represents the indirect effect of an change in X , while all further terms on the right hand side represent second- and higher-order direct and indirect effects Vega and Elhorst [2013].

4 Data Description

4.1 Study region

Located in the north and being one of three federal city states in Germany, Hamburg is with around 1.8 million inhabitants the second largest city and one of the most important economic zones (harbour) in Germany. Moreover, Hamburg has a highly competitive regional apartment market which is mainly influenced by topographic conditions and administrative borders. As can be seen from Figure 1 the apartment market in Hamburg is dichotomous– most obvious is the north-south divide. With the Elbe as a natural border, we observe, on the one hand, spatial structure of high apartment prices in the north of Hamburg, with the highest prices on the Elbe riverbank and around the Alsterseen (the Alsterseen are located in the middle of Hamburg). While on the other hand, the industrial zone of the harbor is located in the south and apartments on this side are much cheaper. Beside the north-south divide, in the north of the Elbe, we observe a slight west-east divide. While apartments surrounding the Alsterseen are most expensive, apartments become cheaper with increasing distance to the Alsterseen indicating spatial clustering in the apartment offering prices within the citycenter.

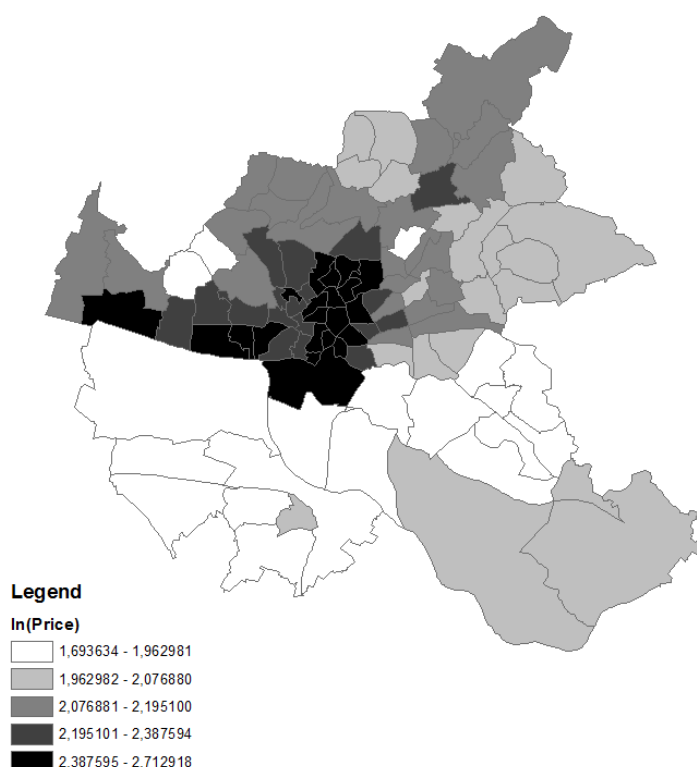
4.2 Data

The empirical analysis is based on cross sectional apartment offerings in Hamburg, Germany. The dataset, provided by vdpResearch², contains 4,029 observations over the period from 2008 to 2010. The dataset is adjusted for doublings and incomplete informations are removed. All offering prices are measured in euro per square meter of living space. Our analysis concentrate on offering prices within the city of Hamburg.

All variables included in the hedonic regression equation are given in Table 1. In addition, Table 1 shows the expected signs of the estimated regression equation and fundamental

²The vdpResearch is a 100% daughter company of the Association of German Pfandbrief Banks (Verband deutscher Pfandbriefbanken). The aim is acquisition, analysis, and forecast of real estate market developments, especially in Germany. Therefore, the Association initiates different property databases about transacted and offered real estates.

FIGURE 1
APARTMENT PRICES



Source: Authors' calculations based on *vdvResearch*.

descriptive statistics. Thereby, the explanatory variables are separated into three sub-classes: basic attributes, equipment characteristics, and quality variables. Characteristics such as 'First Occupancy' and 'Premium' may play an important role determining the apartment price, since Hamburg has a very low investment in new houses during the last years. Therefore, apartments characterized by high quality are expected to lead to very high apartment prices within the city (see [Gutachterausschuss für Grundstückswerte in Hamburg \[2010\]](#) and [Gutachterausschuss für Grundstückswerte in Hamburg \[2011\]](#)).

5 Estimation Results

The estimation results³ are presented in Table 2. Column (1) shows the results of a very simple hedonic OLS model, whereas column (2) presents the benchmark model, an OLS estimation

³All parameters are estimated in MatLab by procedures downloaded from www.spatial-econometrics.com presented by [LeSage and Pace \[2009\]](#) and procedures written by Paul Elhorst, presented in [Elhorst \[2012\]](#) and on the homepage <http://www.regroningen.nl/elhorst/software.shtml>.

TABLE 1
SUMMARY STATISTICS

Variable	Exp. Sign	Mean	Std. Dev.	Max.	Min.
Variable to be Explained					
ln(Price)		2392	1051	11250	352
Basic attributes					
Number of Rooms	+	2.9	1.3	18	1
Total Living Area	+	87	56	2094	20
Age	-	38	36	3433	0
Age squared	+	2754	4733		
Rented	-	0.33			
Equipment Characteristics					
Elevator	+	0.16			
Balcony	+	0.73			
Fitted Kitchen	+				
Garage	+	0.52			
Fireplace	+	0.03			
Terrace	+	0.62			
Winter Garden	+	0.02			
Central Heating	+	0.60			
Quality Variables					
Attic Flat	+	0.17			
First Occupancy	+	0.20			
Premium	+	0.19			
Newly Built	+	0.16			
Smooth	+	0.24			
Refurbished	+	0.11			

NOTES.—The number of observations is 4029. The standard deviation and minimum and maximum values of binary indicators are not presented.

SOURCE.—Authors' calculations based on *vdpResearch*.

controlling for apartment characteristics and location (zip-codes) but without spatially lagged variables. The results for the spatial Durbin model specification are listed in columns (3) and (4) with the corresponding direct, indirect and total effects in columns (5) to (7).

The main focus is on the spatial econometrics aspects so there are no detailed analysis of the functional OLS form. Following standard econometric theory, typical goodness-of-fit criteria are used to guide the choice of the best specification. For spatial econometric models the use of the standard R^2 is uninformative and should be interpreted with caution (see [Anselin \[1988\]](#); Chapter 14). Therefore, the maximized log-likelihood value is used as goodness-of-fit

criteria for models estimated by maximum likelihood. As the functions are estimated in semi-logarithmic form, the coefficients of the continuous variables reflect the percentage change on the variable being explained⁴.

The descriptive statistics showed in Section 4 suggest spatial structure in the apartment prices over postal codes, moreover, apartments in neighborhoods with good reputation, next to parks or water, have higher prices than apartments located in the south of Hamburg. To measure neighborhood characteristics, the OLS regression is enhanced by postal codes to control for neighborhood characteristics (column 2). Including the neighborhood increases the goodness-of-fit criteria dramatically: the hedonic post code model explains 60.87 percent ($R_{adj}^2 = 0.6005$) of the variation in apartment prices. The OLS estimation shows the expected sign for all significant apartment characteristics. Since prices may be spatially correlated, either in their levels or in their errors, the OLS regression can give spurious results.

Using the classical Lagrange multiplier test (proposed by [Anselin and Bera \[1998\]](#)), both, the hypothesis of no spatially lagged dependent variables and the hypothesis of no spatially autocorrelated error terms must be rejected at the one percent significance levels as well as their robust LM-test counterpart (proposed by [Anselin et al. \[1996\]](#)). In addition, the likelihood ratio test (LR-test) is used to test the hypothesis whether spatially lagged independent variables are jointly significant, both, the hypothesis $H_0 : \theta = 0$ (LR-spatial-lag = 235.21, $p = 0$) and the null hypothesis $\theta = -\rho\beta$ (LR-spatial-error = 126.14, $p=0$) result in a rejection. Therefore there are reasons to prefer the spatial Durbin model to the spatial lag and the spatial error model⁵. Beside these test results, [LeSage and Pace \[2009\]](#) (page 28) gives another intuition why the spatial Durbin model describes the data best under the following three circumstances⁶: (1) at least one potentially important variable is omitted from the model, (2) the omitted variable is correlated with one of the included explanatory variables, and (3) the disturbance process may spatially dependent.

⁴Following [Halvorsen and Palmquist \[1980\]](#), the percentage impact of dummy variables in a semi-logarithmic functional form and calculated by $(e^{\beta} - 1) * 100$, where β is the estimated coefficient.

⁵These results are based on a spatial weight matrix using 15 nearest neighbors (NN). Varying the nearest numbers of NN (from 10 to 30) similar results are found. All results are available upon request.

⁶This is not fulfilled for other spatial models like the spatial cross-regressive model (SLX), Spatial error model (SEM) or spatial Durbin error model (SDEM).

Due to feedback effects the estimated coefficient ρ cannot be interpreted as the effect of a change in Y on neighboring apartments. The same holds true for θ which does not constitute the effect of changing X on neighboring apartments and β which cannot be interpreted as the change in Y due to a change in the vector X . LeSage [2008] proposes to view the spatial model parameters as the stable equilibrium of an intertemporal and interspatial process. The model parameters do not include those effects and thus are not reflect the true influence. That is, why the interpretation of results concentrate on the direct and indirect effects calculated according to LeSage and Pace [2009] as well as LeSage and Pace [2010]⁷.

In the adopted OLS model, the direct effect of an explanatory variable is equal to the coefficient estimate of that variable while in the spatial Durbin model, the direct effect depends on the θ_k of the spatially lagged value of that variable. Comparing OLS parameter estimates and the direct effects estimated by the partial derivatives of the spatial Durbin model show clear differences between the coefficients. Since we identify spatial correlation between the apartment prices and spatial correlation between the error term which leads OLS to be biased. While both, the OLS as well as the direct effects in the spatial Durbin model show the expected sign for the coefficients, the OLS regression over- or underestimates every coefficient to various degrees. A comparison between the parameters estimates show, for example, that the direct effect of premium in the OLS model compared to the spatial Durbin model is overestimated by 50 percentages⁸.

Beyond the direct effects, the indirect effects in the spatial Durbin model also depend on the coefficient estimate θ_k of the spatially lagged value of that variable (non- diagonal elements of Equation 4). I.e. they give the impact on the price of a particular apartment from changing an exogenous variable in another apartment, or the impact of changing an exogenous variable

⁷The actual estimated spatial Durbin model differs from the one presented in Section 3. The general spatial Durbin model would lead to spatially lagged postal codes, too. Since the neighborhood already define spatial characteristics, the postal codes should not be spatially lagged again. Therefore, no spatially lagged parameters ($W \cdot X$) are calculated for post codes under the spatial Durbin model. The corresponding regression equation is then given by $P = \rho WP + \alpha \iota_n + X_1 \beta + X_2 \beta + WX_1 \theta + \epsilon$, where P , W , ρ , α , ι_n , θ and ϵ are defined as in Section 3 above. Further, X_1 is a matrix including all apartment characteristics, while X_2 includes the postal code areas.

⁸Similarly, the coefficient of balcony is overestimated by 39.05 percentage, terrace by 35.39 percentage, new built by 19.17 percentage, garage by 17.04 percentage, first occupancy by 15.41 percentage, fireplace is overestimated by 10.44 percentage, and refurbished by 7.39 percentage. The basic attributes number of rooms is overestimated by 13.22 percentage, total living area by 16.50 percentage, and age² by 8.69 percentage, while the coefficient of age is underestimated by 3.92 percentage.

in a particular apartment on the price of all other apartments. The indirect effects in the spatial Durbin model differ in significance, sign, and size of the coefficients compared to the calculated direct effects.

Some of the indirect effects, such as technical amenities (e.g. elevator and central heating), which do not affect the equipment of the apartment itself but influences the quality and amenity of the apartment and come with additional payments increasing the apartment price. Other indirect effects may not reflect the neighboring apartments itself but the composition of the neighborhood. Therefore, we can interpret the significant results for garden, quiet location, total living area and refurbished as indicators for higher quality neighborhood where we consequently see a price mark up. The indirect negative significant result for the quiet location characteristics can be interpreted as a kind of relative quietness. Moreover, quiet areas are most often located in suburbs. In summary, the significant indirect equipment variables and quality attributes have a relatively high and significant indirect effect on the apartment price. This is an important result, since the OLS regression does not capture these indirect effects and thus leads to erroneous conclusions. The sum of indirect and direct effects is the total effects.

Nevertheless, beside the direct and indirect effects, the spatial Durbin model shows a highly significant spatial autoregressive parameter ρ indicating strong spatial dependency between the apartment prices in Hamburg. ($\rho = 0.5639$, $t\text{-value} = 28.32$).

TABLE 2
APARTMENT OFFERING PRICES

	OLS		Spatial Durbin				
	(1)	(2) ZIP code	(3) X	(4) W*X	(5) Direct	(6) Indirect	(7) Total
No. of Rooms	0.007 (1.34)	0.014*** (3.24)	0.013*** (3.39)	-0.018 (-1.39)	0.012*** (3.27)	-0.024 (-0.92)	-0.012 (-0.43)
Total Living Area	0.001*** (8.94)	0.074*** (7.78)	0.058*** (6.98)	0.086 (-1.39)	0.063*** (7.44)	0.266*** (4.11)	0.329*** (4.91)
Age	-0.003*** (-8.97)	-0.005*** (-15.14)	-0.005*** (-19.11)	0.003*** (6.37)	-0.0051*** (-17.34)	0.001 (0.83)	-0.004*** (-2.57)
Age (squared)	0.000*** (10.80)	0.000*** (12.21)	0.023*** (14.65)	-0.013*** (-4.05)	0.023*** (12.38)	0.002 (0.165)	0.025*** (2.43)
Rented	0.012 (1.00)	-0.003 (-0.27)	-0.008 (-0.93)	0.005 (0.16)	-0.0076 (-0.87)	-0.001 (-0.009)	0.008 (-0.15)
Elevator	0.075*** (5.15)	0.017 (1.42)	0.005 (0.42)	0.043 (1.56)	0.0071** (0.64)	0.104** (2.16)	0.112** (2.25)
Balcony	0.048*** (3.83)	0.047*** (4.56)	0.031*** (3.41)	0.030 (1.03)	0.033*** (3.65)	0.110* (1.86)	0.144** (2.34)
Attic Flat	-0.008 (-0.58)	0.001 (0.06)	0.010 (1.07)	-0.032 (-0.95)	0.0087 (0.92)	-0.061 (-0.91)	-0.052 (-0.76)
Fitted Kitchen	-0.016 (-1.10)	0.007 (0.63)	0.016 (1.54)	0.0056 (0.14)	0.0161 (1.58)	0.031 (0.49)	0.047 (0.71)
First Occupancy	0.211*** (14.47)	0.137*** (11.31)	0.119*** (11.05)	-0.102*** (10.96)	0.119*** (-1.27)	-0.081 (0.58)	0.038 (0.58)
Garage	0.040*** (3.32)	0.047*** (4.61)	0.040*** (4.45)	-0.016 (-0.62)	0.040*** (4.39)	0.012 (0.25)	0.052 (1.07)
Garden	0.001 (0.10)	0.006 (0.67)	0.009 (1.13)	0.051 (1.79)	0.0119 (1.41)	0.127** (2.42)	0.139** (2.53)
Premium	0.180*** (12.96)	0.132*** (11.40)	0.086*** (8.13)	-0.007 (-0.26)	0.088*** (8.52)	0.092** (1.75)	0.180** (3.36)
Fire Place	0.069** (2.30)	0.070*** (2.83)	0.061*** (2.85)	-0.023 (-0.31)	0.063*** (2.91)	0.0339 (0.21)	0.096 (0.60)
New Built	0.162*** (10.05)	0.112*** (8.32)	0.094*** (7.73)	-0.007 (-0.22)	0.096*** (8.07)	0.104 (1.87)	0.201*** (3.48)
Quiet Location	-0.006 (-0.47)	0.001 (0.10)	0.016 (1.84)	-0.099*** (-4.05)	0.0114 (1.32)	-0.201*** (-4.16)	-0.189*** (-3.78)
Refurbished	0.095*** (5.50)	0.084*** (5.93)	0.073*** (5.88)	0.068 (1.63)	0.078*** (6.33)	0.247*** (2.92)	0.326*** (3.72)
Terrace	0.038*** (3.11)	0.031*** (3.04)	0.024*** (2.76)	-0.039 (-1.28)	0.0226*** (2.62)	-0.056 (-0.99)	-0.034 (-0.57)
Winter Garden	0.039 (1.00)	0.042 (1.33)	0.034 (1.22)	0.074 (0.84)	0.0397 (1.40)	0.2011 (0.22)	0.241 (1.37)
Central Heating	-0.048*** (-4.44)	-0.012 (-1.30)	-0.002 (-0.18)	0.030*** (2.89)	0.0019 (0.23)	0.133*** (3.50)	0.135*** (3.47)
ρ			0.564*** 28.32				
Constant	7.432*** (315.29)	7.428*** (346.21)					
Observations	4029	4029	4029				
R^2	0.385	0.606	0.643				
Log-likelihood			316.69				
Spatial Lag, OLS model	LM $_{\rho}$ LM $^r_{\rho}$	1096.15 154.84	Spatial Lag, LR $_{\theta=0}$	Spatial Durbin 235.21	p = 0		
Spatial Error, OLS model	LM $_{\lambda}$ LM $^r_{\lambda}$	1850.14 908.81	Spatial Error, LR $_{\theta+\rho\beta=0}$	Spatial Durbin 94.84	p = 0		

NOTES.— Indicators for the observation year and zip-code are included. Standard errors are presented in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

SOURCE.—Authors' calculations based on *vdprResearch*

6 Conclusion

Hedonic apartment price regressions usually rely on individual characteristics which may exclude important spatially related neighborhood variables like accessibility, school quality, et cetera. Further, spatial dependencies are present in hedonic regressions since the offering price observed in one apartment depends on the values of neighboring offering prices. This analysis examines spatial autocorrelation and spatial dependence in hedonic apartment price equations using data of 4,029 apartment offering prices in Hamburg, Germany. Applying the semi-logarithmic approach the apartment offering prices are estimated under linear regression models and the spatial Durbin model.

Various applied tests compare different spatial models and OLS regression identify the spatial Durbin model describing the data best. The statistical results show that the offering prices are highly spatially dependent and spatially autocorrelated across apartments.

The current study improves past hedonic modeling efforts by directly incorporating spatial effects into the apartment hedonic price model. The spatial Durbin model measures both the direct and indirect effects of a change in one single explanatory variable of the base-apartment.– hence it deals with neighborhood effects. These neighborhood effects cannot be captured by non-spatial techniques. Further, the spatial Durbin model avoids the econometric problem of biased and inconsistent estimators when spatial dependence is present but ignored as well as the problem of inefficient parameter estimates due to biased variance estimators in the case of spatial autocorrelation. A comparison between the base- model and the spatial Durbin model shows that the OLS regression over- or underestimates the regression coefficients and thus leads to wrong interpretation.

According to [LeSage and Pace \[2009\]](#) three main points are found: First, we have similarities between the direct impact estimates and the response parameters – Response estimates and direct effects only differ in the second or third decimal place.

Second, there exist large discrepancies between the indirect impact coefficients and the spatially lagged coefficients in the spatial Durbin model. For instance, 0.1273 is, according to the

t-statistic, the significant indirect impact of garden. Contrary, the spatially lagged coefficient gives an insignificant value of 0.0513. Incorrectly viewing the spatial lagged coefficient as the indirect effect, a garden would have no significant impact on the apartment price whereas the correctly specified indirect effect shows a positive significant impact.

Third, total effects differ from the sum of the response parameter and the spatially lagged coefficient. Applying the garden example again, the total impact of a garden on the apartment price is significantly positive (0.1393); whereas the total impact suggested by summing up the response and spatially lagged coefficients would equal less than half this magnitude (0.0603). This difference will depend on the size of indirect impacts which cannot be correctly inferred from the spatial Durbin model coefficients.

Summing up, the incorporation of spatial structure characteristics improves the goodness of fit compared to the results following basic models where such location characteristics are not accounted for. Spatial structure is important in the construction of real estate price indexes. Unlike other real estate literature this analysis takes direct, indirect and total effects of the spatial Durbin model into account.

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