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Hedonic price model for Warsaw housing market

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Abstract

A hedonic price model has been constructed for Warsaw housing market using 2006 asking price data. Model parameters reveal a substantial influence of proximity to the metro station on flat prices. If there is a metro station within 1 km distance to a flat its price increases by 15% according to the estimated basic hedonic model. Also green areas have a positive impact on flat prices while industrial areas affect negatively flat prices. To account for spatial autocorrelation two types of spatial hedonic model were constructed: spatial autoregression model and spatial error model. Both proved that there is a significant spatial autocorrelation present in the basic hedonic model.

JEL codes: C21, Q51, R21
Keywords: hedonic price analysis, spatial model, housing, location

Introduction

The aim of this paper is to estimate the impact of various location factors on the price of a flat in Warsaw. The analysis is focused on such factors as: proximity to metro station, green areas, industrial areas etc. In the analysis a hedonic price model is used. It is the approach widely recognized in real estate for quite a long time. The idea of a hedonic model is to perceive a certain product as a bunch of characteristics, where each of them gives a distinct utility to a buyer and therefore has its own price. For example: we can perceive a flat as a bunch of certain characteristics – access to metro, parks, city centre, age of the building etc. Therefore we can treat the price of a product (flat in this case) as a sum of "implicit prices" of those characteristics.

Hedonic model should answer the question: what would be the value of a flat if we add a certain amount of some of its characteristics. For example if we assume that a good access to the city centre has an impact on a flat price, then a model should answer the question, how the value of the flat will change if a metro station was built nearby.

Hedonic price model is a tool to assess effectiveness and costs of public projects e.g. construction of metro line, sports stadium, removing or developing green areas etc. There were few public goods, which were analysed this way: climate, air pollution, social infrastructure or noise level. In this case hedonic price model is better then surveys among citizens, as it reflects real decisions of buyers and not hypothetical decisions. Brookshire (1982) estimated willingness of Los Angeles citizens to pay for a better air quality using hedonic price model. In 2002 in one of the Spanish cities Castellon hedonic model was used to estimate the value of urban green areas in order to include them into financial analysis of urban planning (Morancho, 2003). Another interesting example is the analysis of the impact of newly constructed sports stadium on the value of neighbouring flats (Tu, 2005). Impact of the planned airport development and inherent rise in noise level on prices of neighbouring houses was evaluated with the help of hedonic model in Amsterdam. The estimates show that a noise above 65dB causes price of a house drop by 12% (Theebe, 2004). McMillen (2003) estimated the impact of state expenditures on industrial areas revitalization using hedonic model.

The idea and assumptions of a hedonic model

Sherwin Rosen was the one who contributed mostly to the popularity of a hedonic model (Brasington, 2005). He solved the problem of estimating demand-supply function of goods, for which there was no visible market. He suggested an estimation procedure with the use of hedonic theory. This theory claims that a price for a good is actually a sum of prices for its characteristics. Each of these characteristics has its own implicit price (Brasington, 2005). In other words, the transaction, which we can observe, is in fact a bunch of several smaller hidden transactions.

Many relationships and dependencies in the economy resemble hedonic model. So far it has been widely used in the analysis of such products as: computers, cars or houses. It is assumed that each product is made of the same „ingredients", only in different proportions. When a client buys a product, they don't buy one item, they buy a bunch of characteristics put into this product. For a computer these characteristics are for example: size of the memory, speed of the processor, size of the disk etc., for a flat these characteristics are – area, age, location. Hedonic theory assumes that these characteristics are what buyers really want. They give a utility to a buyer. Therefore a buyer chooses among alternative bunches of certain characteristics. Hedonic function, in order to reveal prices of these characteristics, analyses relationship between the total price of a certain bunch of characteristics and the amount of these characteristics in a given product. Coefficients of explanatory variables show the unit price for a given ingredient (characteristic), the so-called implicit price. The level of the price depends on demand and supply. It reflects a degree of desirableness for a certain characteristic.

Hedonic model doesn't have a specified functional form by definition. It depends on assumptions arbitrarily chosen by a researcher (Cassel, 1985). A classic hedonic model has a functional form:

$$P_i = X_i'\beta + \varepsilon_i, \qquad (1)$$
$$i = 1, 2, ..., N$$

where P_i is the product price (e.g. a house), X_i is an array of characteristics values explaining the price, β is an array of parameters to be estimated (parameters indicating willingness to pay for an additional unit of a particular characteristic), ε is a residual. Though there are many examples in the literature of linear hedonic models, there is a belief that hedonic model is nonlinear. (Ekeland, 2002; Kauko, 2003). Quite often a semi-log or log-log form is used as the nonlinear representative. General functional form of such a model is as follows:

$$lnP_i = \alpha + \sum_{k=1}^{K} p_{ki} lnx_{ki} + \sum_{m=1}^{M} p_{mi} x_{mi} + \sum_{l=1}^{L} p_{li} d_{li} + \varepsilon, \qquad (2)$$

where

lnP_i – log of price of product i (flat, computer, employee's pay etc.),

lnx_{ki} – logs of explanatory variables,

x_{mi} – explanatory variables without any transformations,

d_{li} – dummy variables,

p_{ki} – implicit prices for characteristics, in the form of an elasticity,

p_{mi} – parameters, which after multiplying by 100% indicate how much in percentage points the price of a product will rise if we increase the amount of the characteristic by one unit,

p_{li} – parameters, which after multiplying by 100% indicate, how much in percentage points the price of a product will increase if a certain characteristic is present.

More or less typical characteristics included as explanatory variables in hedonic models used for housing analysis are shown in Table 1 and Table 2. The list is based on articles describing hedonic analysis of regions in the United States, Asia and several countries in Europe.

Table 1. Characteristics used as explanatory variables in hedonic models for housing markets (variables characterising a flat/house)

Variables characterising a flat/house
Age of the building
Area
Area of the lot
Number of bathrooms
Number of rooms
Is there a fireplace
Is there a pool
Is there a garage
Heating (gas, oil, other)
Is there an air conditioning
What are the construction materials
Is there a lift
Area of a balcony
Tiled roof

Table 2. Characteristics used as explanatory variables in hedonic models for housing markets (variables characterising location)

Variables characterising location
Quality of a school in the region (ranking place)
Expenditures per pupil in the region
Crime level
Budget expenditures on safety
Percentage of white neighbours
Are incomes of neighbours low/average/high
Air pollution (NO_2, SO_2)
Proximity to the city centre (km/time)
Proximity to the beach
Proximity to the industrial area
Proximity to the nearest highway
Proximity to the airport
Proximity to school (time/km)
Proximity to the nearest hospital
Proximity to the nearest park or swimming pool (time/km)
Area of the nearest green area
Real estate tax rate in the region
Climate mildness (estimated in points taking into account temperature amplitude etc.)
Ocean view
Park or garden view

If a hedonic model is built on spatial data (which is usually the case of housing market), it should account for spatial autocorrelation. One of possible ways is to add a spatial lag of a dependent variable. Such a model has a functional form:

$$P = \rho WP + X\beta + \varepsilon, \qquad (3)$$

Where $P_{n\times n}$ is an array of flat prices, $W_{n\times n}$ is a weight matrix which together with P array forms a WP array of weighted prices of neighbouring houses, $X_{n\times(k+1)}$ is a matrix of explanatory variables, $\beta_{(k+1)\times 1}$ is the vector of coefficients by explanatory variables, ρ is a spatial lag parameter. Parameter of spatial autoregression ρ measures degree of spatial dependency between neighbouring observations. The above model is called SAR – spatial autoregressive lag model. Such a model accounts for the impact of prices of neighbouring houses on the price of analysed house.

W matrix contains weights between each pair of all observations in the sample. This is a $n \times n$ matrix $W = [w_{ij}]$. Weights w_{ij} shall represent some kind of measure of the geographical relationship between locations *i* and *j*. They may be constructed in various ways. Wilhelmsson (2002) presented several simple methods:

$w_{ij} = \frac{1}{dist_{ij}}$ or $w_{ij} = \frac{1}{(dist_{ij})^2}$ where $dist_{ji}$ is a distance between flat *j* and flat *I* (the greater the distance between the two flats, the weaker the relationship between them i.e. the smaller the weight)

$w_{ij} = \frac{1}{dist_{ij}}$ if $dist_{ij} \leq x$ weights are greater than 0 only for a subsample of flats that are not further than *x* meters from flat *i* (*x* arbitrarily chosen), 0 for all other flats

$w_{ij} = 1$ for the nearest neighbour, 0 for all other flats

$w_{ij} = \frac{1}{n}$ for the nearest *n* neighbours, 0 for all other flats

The last type of weight matrix was used by Peterson and Boyle (2002). In case of each house *i* all neighbours within 0.5km were given 1 and the rest were given 0. The weight matrix is standardized, so that the sum of weights in each row equals 1:

$w_{ij} = \frac{1}{n_i}$, where n_i = number of houses within 0.5 km from house *i*

Another type of model called SEM (Spatial error model) (Acharya, 2001) accounts for spatial autocorrelation of residuals, it has a functional form:

$$P = X\beta + \varepsilon, \qquad (5)$$

$$\varepsilon = \lambda W\varepsilon + u,$$

Where $P_{n\times n}$ is again an array of flat prices, $X_{n\times(k+1)}$ is a matrix of explanatory variables, $\beta_{(k+1)\times 1}$ is the vector of coefficients by explanatory variables, $W_{n\times n}$ is a weight matrix, ε is a residual of a hedonic model, $u \sim N(0,\sigma^2)$ and λ measures spatial interaction between residuals ε. In the second equation residual of a given observation is a function of residuals of all other observations.: $\varepsilon_i = f(\varepsilon_j, \ldots, \varepsilon_k)$.

Housing market in Warsaw

Warsaw has more than 1.7 million citizens and covers the area of 517 sq. kms. Vistula river divides city into two parts: quite active in terms of housing market Western part and much less active Eastern part. About 70%-80% of offers for sale on the housing market are in the Western part of the city. The city has one centre, which is Srodmiescie district (in the Western part). With the surrounding districts it accounts for more than a half of secondary housing market. Środmiescie and particularly the Old Town are the most expensive locations in the city. Public transport is well developed in Warsaw, however much better in the Western part. There is one metro (underground) line going in the direction North-South. It is a main mean of transport for many citizens of the capital, that's why in offers of flats for sale the proximity to the metro station is often underlined. Apart from public infrastructure an access to green areas is also important. There is a National Kampinos Park to the North of the City, Kabacki Forest in the Southern district Ursynow, Mazowiecki Park in Southern-Eastern part of the city and many public parks spread throughout the city. Many industrial areas are located close to the centre as well as in the suburbs and they obviously influence flat prices in a negative way. The quality of Warsaw housing stock is much diversified. Major part was constructed in 70s-80s with the use of concrete-block technology. Flats in these blocks are usually cheaper, as they require higher maintenance expenditures.

Up until 2004 Warsaw housing market was quite calm. Prices grew in a moderate pace. After joining European Union housing price growth accelerated. In 2006 (the database used in this paper comes from this period) the housing market was still in the phase of substantial price increases. On one hand this is a good time for doing analyses, as there are many offers-observations. On the other hand, analysis of 'unsettled' market is more difficult, as it can give less precise results. Buyers who are in a hurry may be less rational and be ready to pay more for a given flat then they would in more stable times.

Data

Data on housing prices come from an Internet website which allows to search homes for sale. These are offers of flats for sale in Warsaw in 2006. As offers do not reveal precise addresses but only street names, only flats located on short streets (up to 0.5 km long) were analysed. Altogether there were 2300 observations. Using coordinates of all city objects new variables were created containing distance between each flat and the nearest specified object (metro station, green area, industrial area etc.). List of variables is presented in Table 3.

Table 3. List of variables

Year	Year of construction
X	X coordinate of a flat
Y	Y coordinate of a flat
P_sqm	Price per square meter in PLN
Green	Distance to the nearest green area: park, forest, garden (in meters)
Metro	Distance to the nearest metro station (in meters)
Centre	Distance to the city centre – the Old Town (in meters)
Airport	Distance to the Chopin Airport (in meters)
Industr	Distance to the nearest industrial area (in meters)
Palace	Distance to the nearest palace (in meters)

Green areas

Green areas are inevitably an advantage of a location and increase the price of a flat. A view on a garden with a lake may increase price by 30% (Luttik, 2000). Forests and parks guarantee cleaner air, partial isolation from car noise and are a place for pastimes. A binary variable was included in the model *Green1km* taking value 1, if the nearest green area is within 1 km distance from a flat and 0, if there are no green areas within 1 km distance.

Industrial areas

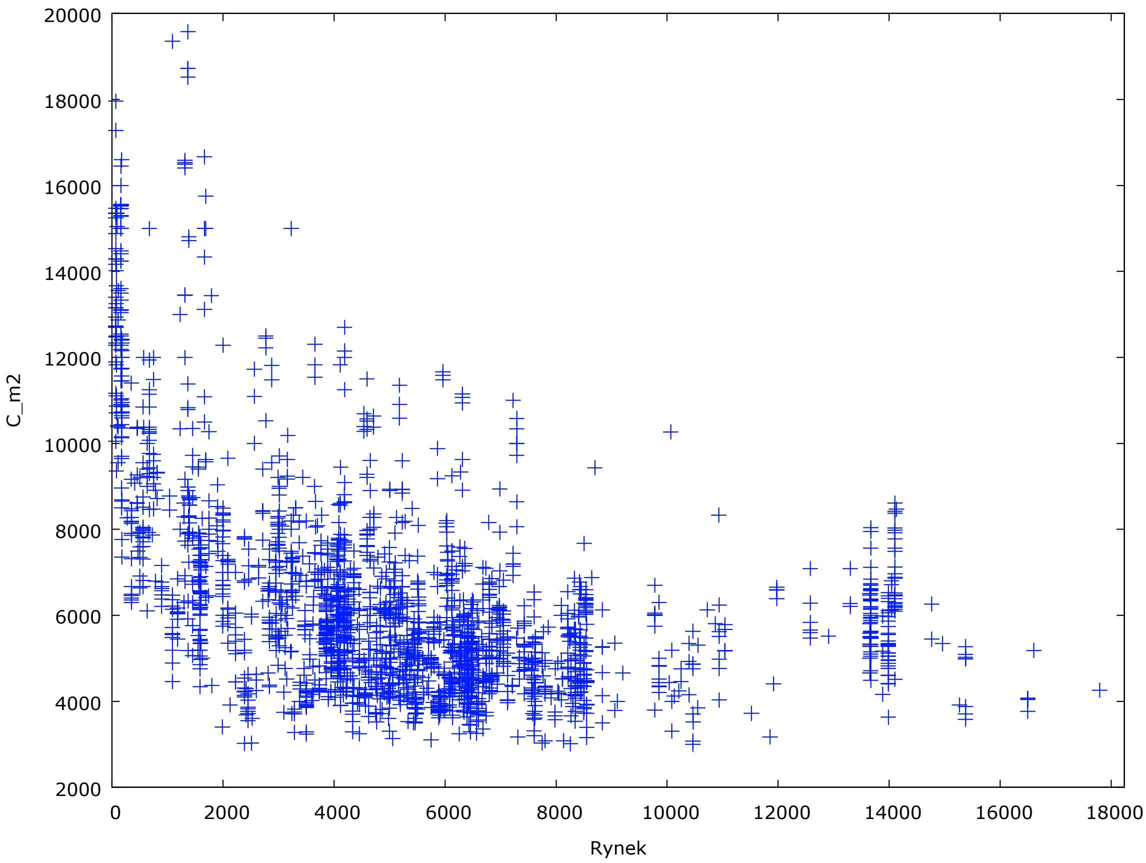
Industrial areas negatively influence flat prices as they cause air pollution but also don’t create a very pleasant view. According to a research carried out in the United States in Ohio in 2001, increasing distance of a house from the nearest industrial plant by 10%

increases house price by 3% (Brasington, 2005). There are many industrial areas in Warsaw, therefore it is worth estimating their impact on flat prices. A dummy variable was included in the model *Industr1km* = 1, when a flat is within 1km distance from an industrial area.

Distance to the city centre

This is a typical and the most often used characteristic of a flat location. City centre is a work destination for a great part of city dwellers. Many people want to live close to the city centre in order to minimize costs of travel. Distance may be measured in many ways: distance in kilometres, logarithm of distance, time needed to cover the distance. According to Richardson (1974) choice of any of these methods does not make a substantial difference. Logarithm of distance to the centre was included into the model *l_centre*. It is justified by the fact that with greater distance from the centre its impact weakens. It can be seen on a Graph 1, which shows relationship between price and distance to the city centre – the Old Town (Rynek).

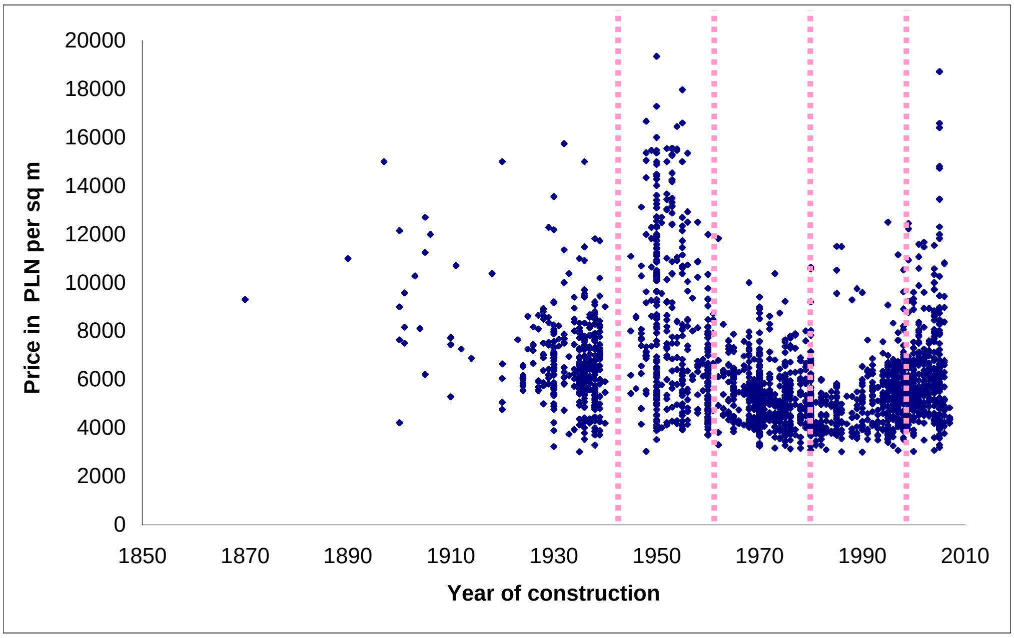
Graph 1. Price per sqm (C_m2) vs. distance to the city centre (Rynek)



Technology/Year of construction

In case of Warsaw both variables are connected. Choosing a particular construction period, with great probability we can define a particular construction technology. It concerns especially the most well known in Warsaw and generally in Poland prefabricated concrete-block technology. Due to this technology a fast construction of a great number of flats was enabled in 60s-80s. Flats in these blocks are cheaper as they require among others higher expenditures on heating and have worse noise isolation. The most desirable is traditional construction technology i.e. with use of bricks. This technology has been widely used since late 90s. Also in the period following the World War II bricks were the main construction material. Nowadays these can be renovated blocks of flats belonging even to the luxury segment, but as well flats in a very poor condition. Graph 2 showing relationship between year of construction and a price suggests which time periods to choose in order to create dummy variables. Quite low value is assigned to flats built in 80s. High prices are asked for those built since late 90s and in 50s.

Graph 2. Relationship between year of construction and a price in PLN per sq m



Five periods were created (five dummy variables):

1. until 1939 (year1 = 1, reference group)
2. 1940 –1960 (year2 = 1)
3. 1961 –1979 (year3 = 1)
4. 1980 – 1995 (year4 = 1)
5. after 1995 (year5 = 1)

Metro

Impact of a new metro line in Toronto on house prices was analysed by Bajic (1983). Change in public transport access is treated as change in location attributes, which should be reflected in price increases of houses. A dummy variable was included in the model: *metro1km* =1, when a flat was located within 1km distance from the nearest metro station.

Airport

Research on the impact of noise near airports on housing prices was carried out since 70s. In Warsaw this is also a problem, as the biggest Polish airport, serving domestic as well as international air traffic, is located within city boundaries. Air traffic noise affects Southern-Western districts Ursus and Wlochy. According to a research carried out in Chicago in 1997 house value drops by 9% if it is close to the O'Hare airport and exposed to high level of noise (McMillen, 2004). In case of Chicago airport flats within 65dB izophone were analysed. In case of Warsaw airport this would require to analyse flats within 0.4 km distance from the airport. Unfortunately in the database the nearest to the airport flat is located 1km from its boundaries. Therefore a dummy variable was created where *Airport1.5km* = 1, when a flat is within 1.5 km distance from the airport.

Palace

Palaces increase prestige of the neighbourhood due to its architecture and history. There are 54 palaces located in Warsaw. A dummy variable was created *Pal1km*=1, if a flat is within 1km distance from the nearest palace.

Empirical results

In order to show the relationship between flat price and its characteristics described above a hedonic model was constructed:

$$lnP_i = \Sigma\, \alpha_k X_{ik} + \xi_i, \qquad (6)$$

Logarithm of a flat price per square meter is a dependent variable. Variables X_{ik} are flat characteristics and ξ_i is a residual. If X_{ik} is a dummy variable, then $100\alpha_k$ means, how much in percent would increase flat price, if X_{ik}: $0 \rightarrow 1$, i.e. a flat gains a certain characteristic, which it did not possess before e.g. a new metro station is built near the flat. Model is estimated with OLS. Estimates of the model coefficients are presented in Table 4.

Table 4. Hedonic price model for housing market in Warsaw (OLS regression)

Coefficients	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	9.87	0.05	181.58	< 2e-16	***
Year2	-0.07	0.02	-4.57	5.22e-06	***
Year3	-0.18	0.01	-12.27	< 2e-16	***
Year4	-0.19	0.02	-10.99	< 2e-16	***
Year5	0.00	0.01	-0.01	0.99458	
Pal1km	0.07	0.02	4.24	2.35e-05	***
Green1km	0.04	0.01	3.19	0.00145	**
Industr1km	-0.07	0.01	-6.80	1.35e-11	***
Metro1km	0.15	0.01	12.76	< 2e-16	***
l_centre	-0.14	0.01	-22.39	< 2e-16	***
Airport1.5km	0.28	0.22	1.31	0.19045	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2165 on 2289 degrees of freedom

Multiple R-Squared: 0.5615. Adjusted R-squared: 0.5596

F-statistic: 293.1 on 10 and 2289 DF. p-value: < 2.2e-16

All parameters are significant except for *Year5* and *Airport1.5km*. Coefficient by *Green1km* equals to 0.04, which means that if a flat is within 1km distance form the nearest green area its value increases by 4%. Tyrvainen and Miettinen obtained similar results for a city in Finland. They showed that increasing distance to the nearest green area by 1km led to a house market price decrease by 5.9% (Morancho. 2003). Estimate of the parameter by Me*tro1km* variable equals to 0.15 and indicates that if within 1km distance from the flat a new metro station is built, the price of a flat increases by 15%. If in the flat's neighbourhood (within 1km distance) an industrial plant is removed, the flat price increases by 7%. An increase in distance to the city centre by 1% causes price decrease by 0.14%. Parameters by dummy variables indicating year of construction tell, what is the difference between a flat constructed in a certain period and a flat constructed before 1940 (dummy variable *Year1* not included to the model, being the reference category). Estimate of a parameter by *Year2* variable equals –0.07 which means that a flat built in 40s-50s has an asking price 7% lower than a flat built before 1940, holding all other characteristics constant. Prices of new flats built after 1995 do not significantly differ from prices of flats built before 1940. If there is a palace near the flat (within 1km distance) its price increases by 7%.

Spatial hedonic price model

Spatial autocorrelation is common in real estate price models. If it really exists and is not taken into account it causes bias in OLS parameter estimates. One of method to account for spatial autocorrelation is to create a spatial weight matrix $W_{n \times n}$. Its elements represent impact of neighbouring flats on a price of a given flat. (Wilhelmsson. 2002). In this paper a W matrix included in the model has a form:

$$w_{ij} \begin{cases} \frac{1}{10}, & \text{when a flat } j \text{ is one of 10 closest neighbours of flat } i \\ 0, & \text{when a flat } j \text{ does not belong to 10 closest neighbours of flat } i \end{cases}$$

Sum of weights w_{ij} in each row equals 1.

$$\sum_j w_{ij} = 1 \qquad (7)$$

Two types of spatial hedonic models were constructed: spatial autoregressive model - SAR (equation 4) and spatial error model - SEM (equation 5). Models are estimated with maximum likelihood method in R-project programme[1] with the use of *spdep* package. Estimates of model parameters are shown in Table 5.

Estimated value of ρ (see equation 4) equals to 0.71 and is statistically significant. So there is a strong dependency between prices of neighbouring flats. Estimated value of λ (see equation 5) is also statistically significant and equals to 0.74. Wilhelmsson (2002) constructing spatial hedonic model for Stockholm received even higher value of parameter $\rho=0.95$, however his weight matrix was built in a different way.

Conclusions

The aim of this paper was to measure the impact of certain location characteristics on housing prices with the use of spatial econometrics. A hedonic model was built for Warsaw housing market. The obtained results are similar to the ones reported in the literature. According to the estimated basic hedonic model green areas increase flat prices by 4% if they are within 1km distance. New metro station increases prices of flats located

[1] http://www.r-project.org

Table 5. Spatial hedonic price model for housing market in Warsaw

	SAR (spatial autocorrelation model)			SEM (spatial error model)		
	Estimate	asymptotic t value		Estimate	asymptotic t value	
(Intercept)	2.934	17.943	***	10.157	75.204	***
Year2	-0.042	-3.353	***	-0.069	-4.495	***
Year3	-0.076	-6.441	***	-0.114	-6.783	***
Year4	-0.065	-4.914	***	-0.07	-3.674	***
Year5	0.036	3.184	***	0.07	4.112	***
Pal1km	0.006	0.517		0.107	3.479	***
Green1km	0.006	0.723		0.02	0.917	
Industr1km	-0.028	-3.395	***	-0.04	-2.079	**
Metro1km	0.048	4.97	***	0.094	3.534	***
l_centre	-0.048	-8.882	***	-0.179	-11.409	***
Airport1500	0.206	1.231		0.261	1.58	
ρ	0.711	45.326	***	-	-	
λ	-	-		0.741	48.317	***

Lag model	Error model
Log likelihood: 780.2983 for lag model	Log likelihood: 805.6111 for error model
ML residual variance (sigma squared): 0.027919. (sigma: 0.16709)	ML residual variance (sigma squared): 0.027072. (sigma: 0.16454)
Number of observations: 2300	Number of observations: 2300
AIC: -1534.6	AIC: -1585.2.

within 1km distance by 15%. The industrial area decreases prices of flats within 1 km distance by 7%. However these are ‘implicit prices’ which do not account for spatial autocorrelation of flat prices. That is in the basic model we assume that a flat price depends only on its characteristics and is not influenced in any way by prices of neighbouring flats. In reality this is rarely true, therefore to improve model quality it is worth to account for spatial dependency between prices. Both hedonic models, which take into account spatial autocorrelation i.e. SAR (spatial autoregression model) and SEM (spatial error model) in fact proved to be better in explaining dependent variable in terms of AIC criterion. However, in this paper only one type of weight matrix *W* was used to build SEM and SAR models. It is worth to examine how model parameters change if another spatial dependency structure is assumed.

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