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Estimating price gradient in Bratislava with different distance measurements

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Purpose: This article analyses the price gradient of apartments in the city of Bratislava with different measurements of travel time and distance to the city centre.

Design/methodology/approach: The price gradient is analysed by means of a hedonic price model. To overcome the problem with spatial autocorrelation in the data the authors apply a spatial error model.

Findings: The paper provides empirical insights into the size of the price gradient in the city of Bratislava. In addition, it suggests that even in the case of a city with complicated urban structure, Euclidean distance is the best proxy for distance to the city centre and it is not necessary to use a more demanding distance calculation in hedonic price models.

Originality/value: Price gradients are usually analysed in western European or American cities whose urban structure differ from the cities in Central and Eastern Europe. This article is the first in which the price gradient is estimated with different measurements of time and distance to the city centre using a spatial econometric model.

Keywords: Hedonic model, Price gradient, Distance measurement, Spatial error model, Bratislava, Slovakia

Paper type: Research paper

1. Introduction

The decline in real estate prices and rents with rising distance from the centre is a typical feature of cities. The distance between the dwelling and the city centre is one of the key factors of the attractiveness of individual localities in the city and consequently determines the price of real estates in the city. In addition, higher prices induce more intensive land use, which results in higher density, higher buildings and a smaller size of apartments in the centre of the city. Empirical research has confirmed the existence of a negative price gradient in various cities in the world, particularly in Western Europe and the United States. However, the research on price gradients in cities in Central and Eastern Europe is very limited. As Bertaud (2006) noticed, given their common past in the system of planned economy, these cities have several differences. One of the typical features is that sites with a higher population density are not locations, which are more attractive (such as a centre) but those that were built later (Bertaud, 2006). Without the functioning real-estate market before 1989 there were no mechanisms that would increase the intensity of land use in the city centre (Bertaud and Renaurd, 1997). The economic changes in Central and Eastern Europe after 1989 brought private ownership of real estate and market prices. As a result, real estate prices should reflect the attractiveness of individual sites and a negative price gradient should emerge.

This article will analyse the price gradient in Bratislava, the capital of the Slovak Republic. Bratislava is a typical monocentric city with a concentration of employment in the city centre and a radial arrangement of transportation. The city centre became an attractive location especially due to a massive ggrowth in employment in market services and public investment in the revitalization of public spaces. Residential construction was rather limited and located mainly out of the centre. There was also rather intensive suburbanization of smaller settlements around Bratislava (Ondoš *et al.*, 2017). Bratislava is not located on a featureless plane. The Carpathian Mountains and the Danube River represent natural barriers that influence transportation to the city centre. As a result, the distance and travelling time to city centre with different transportation modes vary significantly. In this article, we will compare the results of the price gradient analysis based on different ways of measuring distance and time to the city centre. The influence of different distance measurement in hedonic models has been already examined in the case of the economic valuation of open space. Sander *et al.* (2010) showed that the use of network distance compared to Euclidean distance lead to higher values of open space.

2. Theoretical background - monocentric city

The theoretical concept of the price gradient research is the monocentric model of the city of Alonso / Muth / Mills (Alonso 1964; Mills 1967; Muth 1969). The model explains the difference in land prices based on the distance of the land from the *central business district* (CBD). The model assumes that transport is perfectly available from every point in the city, with transport costs being proportional to the distance from the centre. In addition, it assumes rational individuals with perfect information. The households divide their income into the costs of commuting to work, housing and other goods. In equilibrium conditions, households are indifferent between sites and have the same level of utility. Households are willing to pay higher house prices near the centre than in remote locations so we should observe the negative relation between a distance from the centre and housing prices.

Empirical research points to some problematic areas. Among the most important are the number of employment centres in the city and the differences in transport accessibility in individual parts of the city. Modern cities may have more than one employment centre, with an important part of jobs being located in secondary centres, including suburban parts of cities (Heikkila *et al.*, 1989; Sivitanidou, 1996). Second, the transport system is more complicated than assumed by the model. As noted by Iacono and Levinson (2017), the concept of a monocentric city did not presuppose the existence of different modes of transportation in the city and the differences in transport availability in individual parts of the city. Anas and Muth (1979) worked on a theoretical model that includes the impact of two different modes of transport on the urban structure. As a result, different urban forms can be derived from different modes of transport. Therefore, the original model of the urban structure is, according to Anas and Muth (1979), a specific case with the only transportation mode. With increasing distance from the centre the traffic density increases and therefore the transport time increases due to traffic congestion (Solow, 1972). The estimation of price gradients should, therefore, take into account not only distance but also time.

2.1 Review of the empirical research

Several authors have estimated the gradient of house prices, rent or land values, and in most cases they confirmed the existence of a negative price gradient. It is not surprising that the authors use different methods of measuring the distance of the city centre such as Euclidean distance (Heikilla *et al*., 1989, Colwell and Munneke 2009, Herath and Maier 2013), transport time (Osland *et al*. 2007) or combination of several measurements (Rodriguéz *et al*. 1995; Sodberg and Janssen 2001.

The most common way to measure distance is Euclidean (as-the-crow-flies) distance. This distance represents the shortest distance between two points in the space, the length of the line. However, this measurement is considered to be a basic geographic error in real estate analysis (Thrall, 1998). It is suggested to measure the network distance, which more faithfully represents the way people move in the city. The network is defined by a set of links and nodes that have different attributes, maximum speed, type of traffic, directionality, and so on. Cities may have a complicated geographic structure with different natural barriers (e.g. rivers, forests), so the difference between the Euclidean distance and the network distance can be significantly different. In addition to the physical distance, transport time is also used. Individuals try to minimize opportunity costs of time spent in transportation, so they choose travel mode, which is a combination of the shortest time and the cheapest price.

Rodriguez *et al.* (1995) were the first who used GIS to compare the distance to the CBD through the Euclidean distance and network distance. Both approaches confirmed the existence of a negative price gradient in Baton Rouge, Louisiana metropolitan area (USA). Their results suggested that the calculation of network distance slightly improved the quality of the model. However, they pointed to the need for further analyses in region with larger difference between the network distance and the Euclidean distance. Sodberg and Janssen (2001) used the Euclidean distance and network (*walking*) distance to estimate the price gradient in Stockholm (Sweden). Both methods demonstrated the existence of a price gradient and the differences between them were very small. Osland *et al.* (2007) analysed the region around the city of Stavanger (Norway) with a spatial econometric model. They tested several functional forms and conclude that exponential function specification of the travelling time results in more reliable housing price gradients than a power function specification. Colwell and Munneke (2009) also confirmed that the price of vacant land decreases with the distance to the CBD in Chicago (USA). Magnitude of the effect varied up to three times in different direction from the CBD. They suggest that it is the result of differences in traffic infrastructure in individual corridors. The recent research in Vienna by Herath and Maier (2013) showed that one percent increase in distance from the CBD reduces its price by 0.06 percent in general hedonic model and 0.10 in spatial error model.

There are several studies from the post-socialist countries in Central and Eastern Europe. The study of apartment prices in Moscow showed that although the price gradient was relatively flat at the beginning of the economic transformation (Bertaud and Renaurd, 1997). In later years the gradient increased which is likely a result of an increase in transport costs and the growth of opportunistic costs due to income growth (Bertaud and Renaurd, 1997). The study of Krakow (Poland) (Dale-Johnson and Brzeski, 2001) and Prague (Czech Republic) (Melichar and Kaprová 2013) also confirmed the existence of a price gradient.

3. Study area, data and methods

Bratislava is the capital of Slovakia and with the population of 450,000 inhabitants, it is also the largest city in Slovakia. It is situated in the south-western part of Slovakia near the borders with Hungary and Austria. Bratislava is a monocentric city with a concentration of service jobs in the central parts of the city. The share of employment in manufacturing industry in Bratislava is only about 10 percent. Industrial areas are situated mainly on the outskirts of the city. Approximately 25 percent of inhabitants in Bratislava live in the largest Slovak settlement - Petržalka. The city of Bratislava consists of 17 previously independent municipalities. Most peripheral municipalities still have rural character with family houses (Jarovce, Rusovce, Čuňovo, Záhorská Bystrica, Devín, Vajnory).

Bratislava is located in the foothills of the Little Carpathian Mountains, which extends to the city centre. The Danube River crosses the city and forms a riverbed in the south. To the west and north of the city centre are large forest areas. The network of streets in Bratislava does not form a regular rectangular system, as it is in the case of American cities, but transport links copy natural barriers or overcome them in some locations (bridges, tunnels). Public transport is mainly provided by a radial system of tram and bus transport, supplemented by trolleybus services in the central part of the city. Partial ring road allows faster connection to the city centre with its peripheral parts.

Figure 1. about here

For calculation of distance from the apartment to the CBD, we chose the building of historic theatre in Staré Mesto district, which is easily accessible by all types of public and private transportation.

Since there are no official statistical data on real estate prices in Bratislava, we use data on bid prices for apartment advertisements posted on the reality.sme.sk website. Manual data entry took place from June to October 2016. Each offer from 2,507 has been manually inspected and geocoded. Deleted offers (1,173 in total) were mostly multiple offers of the same apartment or those where a key information was missing. After the data-cleaning step, we ended up with 1,334 observations in 14 city districts in Bratislava.

The dependent variable is the price of the apartment (in log). The structural characteristics of apartment include area, number of rooms, location in the apartment house, state of reconstruction and additional equipment (design, parking place, etc.). The characteristics of the apartment house include age, number of floors and the type of construction. Local characteristics in the model are represented by dummy variables for individual city districts. The districts differ significantly in their image, environmental characteristics, density of housing and size and quality of public goods they provide (kindergartens, elementary schools, public greenery, quality of public spaces, etc.).

Table 1. about here

The main independent variable is the distance and travelling time to the city centre. Traditionally, the distance to the city centre was measured with Euclidean distance. Emergence of new online technologies allows measuring the distance and time of transport by different types of travel modes at significantly lower costs. The specific aim of this article is to examine how distance is measured may influence model results. We use four different ways of measuring distance to the centre as well as four different ways of measuring the time to the centre. The reference distance is the Euclidean, which we calculated in the QGIS software. For calculating other distance and time we used *gmapsdistance* package in the R program (Melo *et al.*, 2018). It calculates the distance and time of transport between two points using the Google Maps API. The software allows four types of transportation - *bicycling, walking, transit* and *driving*. Since it does not offer bicycle routing calculation in Bratislava, we only use 3 types of transport. It should be noted that *transit* mode is a combination of public transport and walking to and from the stop. Google Maps API always calculates the fastest route. We set the time of departure for Monday 8.00am on 12.3.2018, which is a normal working day. The time to the centre on Euclidean distance was calculated using average speed 4.86 km per hour, which is average walking speed as calculated by Google Maps. All distances and transport times are in log forms.

4. Hedonic model

The models of repeated sales and the hedonic pricing models are most frequently used in the empirical research to analyse the price gradient (see Yiu and Tam, 2004 for a review). In this study, we analyse the price gradient utilizing the hedonic model of apartment prices. The hedonic model can by written as:

$$LnP_i = \beta_0 + \beta_1\, Apartment_i + \beta_2 House_i + \beta_3 Local_i + \beta_4 LnDistanceCBD_i + \varepsilon_i$$

Alternatively, if we use travelling time instead of distance from the city centre, the model specification is:

$$LnP_i = \beta_0 + \beta_1\, Apartment_i + \beta_2 House_i + \beta_3 Local_i + \beta_4 LnTimeCBD_i + \varepsilon_i$$

LnP_i stands for the apartment price (in natural logarithm), $Apartment_i$ represents the vector of apartment characteristics, $House_i$ is the vector of apartment house characteristics, $Local_i$ is the vector of local characteristics, $LnDistanceCBD_i$ is the distance from the apartment to the city centre (logarithm) and $LnTimeCBD_i$ is the travel time from the apartment to the city centre (logarithm). Finally, ε_i is the random error. Since we use spatial data, from the viewpoint of spatial econometrics, the spatially close observations may be correlated. In that case, the observations are not independent and the variables' values may be influenced by the values of neighbouring observations. This may lead to violations of the traditional assumption of independent and identically distributed errors. The price dependence of spatially close properties may be a consequence of several economic processes. On the one hand, it may be the result of information effect. If sellers are not sure about the value of the property, they may set the price based on the prices of similar properties located nearby. Another possible reason may be omission of a spatially concentrated variable from the model specification. The extant studies utilize spatial econometric models to mitigate the consequences of spatial autocorrelation or to identify the omitted explanatory variables (Osland, 2010). The most frequently used procedure to identify the form of spatial autocorrelation is the one suggested by Anselin et al. (1996). The presence of spatial autocorrelation is tested using the Moran's I. If the spatial correlation is detected, Lagrange multiplier test is employed to decide between the spatial error model and spatial lag model. The spatial error model is used if the residuals are spatially correlated. Alternatively, the spatial lag model is used if spatial correlation of dependent variable is detected.

The spatial analysis requires the definition of the neighbourhood matrix. There is no clear-cut advice as to how the matrix should be constructed. The neighbourhood can be defined based on the distance between observations or based on k nearest neighbours. In the first method, to assure that each observation has at least one neighbour a threshold distance needs to be determined. The neighbourhood matrix is symmetric in that if A is the neighbour of B then B is the neighbour of A. The threshold distance was 1.57 km in our case which is a rather large distance if we consider the city size (the diameter is about 20 km). The alternative neighbourhood matrix definition is based on k nearest neighbours. Such neighbourhood matrix is not symmetric since if A is the neighbour of B then B does not have to be the neighbour of A. In our paper, we used five nearest neighbours method for the neighbourhood matrix construction. The most frequently used weights in spatial econometrics are row-standardized weights and we used them here, too. We are not aware of theoretical justification of the number of nearest neighbours and weights definition. However, the results are usually not sensitive to a specific selection of spatial weights matrix (LeSage, 2014).

5. Empirical model

Preliminary tests of spatial autocorrelation using Moran's I were conducted to determine the specification of spatial model. They confirmed the presence of spatial autocorrelation with the test statistics ranging from 0.3094 to 0.3357. Following specification search strategy of Anselin et al. (1996) and Florax et al. (2003) we identified spatial error model as the relevant model for all our models.

The final specifications of the hedonic models are as follows:

$$LnP_i = \beta_0 + \beta_1 \, Apartment_i + \beta_2 House_i + \beta_3 LnDistanceCBD_i + \varepsilon_i$$

(1)

$$\varepsilon_i = \lambda W\varepsilon + \mu_i$$

$$LnP_i = \beta_0 + \beta_1 \, Apartment_i + \beta_2 House_i + \beta_3 LnTimeCBD_i + \varepsilon_i$$

(2)

$$\varepsilon_i = \lambda W\varepsilon + \mu_i$$

$$LnP_i = \beta_0 + \beta_1 \, Apartment_i + \beta_2 House_i + \beta_3 Local_i + \beta_4 LnDistanceCBD_i + \varepsilon_i$$

(3)

$$\varepsilon_i = \lambda W\varepsilon + \mu_i$$

$$LnP_i = \beta_0 + \beta_1 \, Apartment_i + \beta_2 House_i + \beta_3 Local_i + \beta_4 LnTimeCBD_i + \varepsilon_i$$

(4)

$$\varepsilon_i = \lambda W\varepsilon + \mu_i$$

In the above equations W stands for the spatial matrix of weights and λ is a parameter of spatial autocorrelation to be estimated. The price gradient is represented by the variable $LnDistanceCBD$ (logarithm of distance from the city centre – used in specifications (1) and (3)) or the variable $LnTimeCBD$ (logarithm of travelling time to the city centre – used in specifications (2) and (4)). In the specifications (1) and (2) we explore the impact of distance or travelling time, respectively, without the dummy variables for city districts. The differences between the various locations are partially captured with the spatially correlated errors and the term $\lambda W\varepsilon$. In the specifications (3) a (4) we explore the impact of distance or travelling time, respectively, and the impact of other local characteristics, using the dummy variables for the city districts. The main objective of this paper is not to inspect the impact of individual features of neighbourhood on the property prices and that is why we use the indicators of the city districts as aggregated variables representing their quality. As we mentioned earlier, we compute the distance to the centre, or travelling time to the centre, using four different measures – Euclidean distance, driving distance, walking distance and the transit distance. That is why each model specification from (1) to (4) has four modifications (A) to (D).

6. Results

The estimation results are presented in Table 2 to Table 5. Before coming to description and interpreting the results, let us briefly comment on the statistical verification of the models. Several diagnostic tests were conducted to check the usual assumptions of linear regression model. White's heteroscedasticity tests revealed that homoscedasticity assumption is violated. That is why we employed the robust estimators of standard errors. However, their use did not influence the outcomes of statistical significance of estimated coefficients in terms of the usual 5% level of significance. We calculated also variance inflation factors (VIF) since hedonic pricing models have often high degree of multicollinearity between the explanatory variables but none of our explanatory variable had higher VIF than seven. The Jarque-Bera test of normality was significant, i.e. the residuals were not normally distributed but this did not pose a substantial problem since our sample is sufficiently large (Allison, 1999, p. 130).

The reference model in the specification (1) is model 1A (Table 2) where the apartment location with respect to the city centre is measured using the Euclidean distance. The model explains about 85.35% of variation in dependent variable, i.e. the logarithms of apartment prices in Bratislava. All explanatory variables except one are statistically significant at the significance level of 5%. The explanatory variables representing apartment and house characteristics are statistically significant with expected sign. The apartments with greater area and those with more rooms are more expensive. All else equal, the increase in area by one square meter is associated with apartment price increase by one percent. When compared to one-room apartments (the reference category), the price of a two-room apartment is on average higher by 22 percent and the price of a three-room apartment by 39 percent[1]. The additional rooms increase the apartment price only slightly. Extra equipment or additional services increase the apartment price, too. The furnished apartments are more expensive by five percent. The additional services such as security service or pre-paid parking lot increase the apartment price by 13 percent. The flats that are not renovated are by six percent cheaper. The apartments in houses with more than five floors are not significantly different from those in smaller buildings. A specific type of apartments in post-socialist countries are the apartments houses built from large concrete panels. The apartments in this type of buildings are on average cheaper by six percent.

The variable of interest in the models is the distance to the city centre. In model 1A, the coefficient for the variable is negative and statistically significant. The results of model 1A confirm the existence of the negative price gradient in Bratislava. The increase in distance from the city centre by one percent is associated with price decrease by 0.19 percent. Finally, the estimated parameter lambda representing the degree of spatial correlation of random disturbances in the model is equal to 0.61 and is highly statistically significant.

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[1] If the dependent variable is in logarithms and *b* the estimated parameter of a dummy variable, all else equal, the dependent variable is on average higher by (exp(*b*) – 1)*100 percent for observations where the dummy variable is equal to one, compared to the observations where the dummy variable is equal to zero.

The change of manner how the distance is measured from Euclidean distance to driving distance led to deterioration of the indicators of model quality. While model 1A explained 85.35% of variation of dependent variable, the model 1B explains just 80.65%. Similarly, log-likelihood indicates the decrease in model fit. The estimated parameters of the explanatory variables related to the apartment or house feature did not change very much when compared to model 1A. However, the coefficient of the spatial correlation of random errors lambda change markedly – it increased from 0.61 in model 1A to 0.72 in model 1B. The magnitude of the distance coefficient, on the other hand, decreased substantially and was no longer statistically significant. The increase in the driving distance from the city centre by one percent is associated with price decrease by 0.04 percent. Our understanding of these changes is that the location of a property or the distance from the city centre is the important determinant of the apartment price. Since the way of measurement in model 1B (driving distance when using the quickest route) does not seem to be a reasonable proxy for the location or distance to the city centre, the coefficient of spatial correlation of random errors lambda took on this function partially and that is why it is higher in model 1B than in model 1A.

As far as models 1C and 1D are concerned, their proportion of explained variation is similar to model 1A – they explain 85.66% and 85.21% (pseudo-R^2), respectively, of variation in dependent variable. Model 1D is slightly worse than models 1A and 1C in terms of other goodness-of-fit statistics (log-likelihood), although it is much better than model 1B. The estimated coefficients for the explanatory variables related to the apartment and house characteristics differ only marginally from those for models 1A and 1B. The value of parameter of spatial autocorrelation lambda in the models 1C and 1D is similar to model 1A. Finally and most importantly, the coefficient for distance is statistically significant with values of -0.19 in model 1C and -0.18 in model 1D.

Table 2. about here

In models from the specification (2) we compare the impact of travelling time to the city centre on the apartment prices. The estimated parameters are presented in Table 3. Similar to the analysis using models from specification (1) we analyse the price gradient using four different ways of measurement of time. The estimated coefficients of structural features of apartment and house and also the spatial autocorrelation parameter in models 2A to 2D are similar to those in models 1A to 1D and therefore we will not comment on them. As far as the goodness-of-fit statistics are concerned, with exception of model 2A, they decreased somewhat when compared to models from specification (1). The most notable decrease is in model 2D. Model 2A using the travelling time based on Euclidean distance and model 2C (walking time) are again better than models 2B (driving time) and 2D (transit time using public transport). The estimated coefficients for our main variable of interest (travelling time to city centre) in models 2A and 2C are equal to those in model 1A and 1C (distance to the city centre) – in all cases it is -0.19 and it is statistically significant. The same coefficient decreased in absolute terms in model 2B to -0.02 comparing to model 1B (-0.04) and it remained statistically insignificant. The greatest change with respect to previous specification was in model 2D where the coefficient for travelling time using public transport increased in absolute value to -0.24.

Table 3. about here

In the models from specification (1) and (2) we did not include other variables representing the quality of the neighbourhood where an apartment is located. This is where the models from specification (3) and (4) differ from the previous ones – now the indicators of city districts are included (the reference category is Old Town – Staré Mesto). The estimation results for these models are shown in Table 4 and Table 5. Since the estimated parameters for apartment and house characteristics did not change when compared to specification (1) and (2), for the sake of brevity we do not show them here, however, they are available from authors upon request.

The inclusion of the city district indicators increased the quality of the models represented by goodness-of-fit statistics. Looking at the estimated parameters, as expected, when compared to Old Town (Staré Mesto), the apartments located in other districts are cheaper. However, the price difference is statistically significant only for four of them. The apartments located therein are cheaper from 15 percent (Petržalka) to 30 percent (Vrakuňa)[2]. The main variable under analysis (distance to the city centre) is highly statistically significant with p-value below one percent. The increase in the distance by one percent is associated with decrease in price 0.13 percent on average. This confirms the existence of the negative price gradient in Bratislava.

Table 4. about here

Looking at other models, model 3A (Euclidean distance) and model 3C (walking distance) are nearly identical – in both of them the estimated parameters for distance are higher and the parameters for city districts are lower comparing to models 3B and 3D. The goodness-of-fit measures for the former models (3A and 3C) are again slightly better when compared to the latter ones, although the difference of model B (using driving distance/time) from other models is much smaller than it was in specifications (1) and (2). Also the parameter of spatial correlation of random errors is similar to other models. However, the estimated coefficients for city districts indicators are much higher in model 3B than in other models. The parameter for distance to the city centre (driving distance) is again smaller than in other models and it is below the level of statistical significance. We conjecture that the above results for model 3B – similar goodness-of-fit, lower coefficient for distance measure, higher coefficients for city district indicators – are caused by the fact that in this case the indicators of city districts represent the quality of neighbourhood but also the distance. We observe the similar effect in model 3D, albeit it is not as strong as model 3B. As far as the estimation results for models from specification (4) are concerned (they are presented in Table 5), the figures and the implications are nearly identical to those from specification (3) and that is why we do not comment on them in greater detail.

In regard to price gradient and the best way how to measure it, the model specifications (3) and (4) give very similar results as the specification (1) and (2) – the price gradient is best represented by the Euclidean distance or by the walking distance. If the distance or travelling time to the city centre is expressed by driving distance (time) or public transport distance (time), the variation in apartment prices is explained relatively worse. If we want to answer the question of whether the distance or time is a better proxy of price gradient, it seems that overall the distance is a better measure than time for driving or public transport travelling, whereas it is very similar for Euclidean and walking distance (since time is calculated as a mathematical product of distance). All in all, we may say that the high-level result of the models is the finding that the price gradient for the apartment prices in

[2] See footnote 1 on how to translate the estimated coefficients for the dummy variables in models with dependent variable in logarithms so that percentage difference is obtained.

Bratislava is best represented by the simplest way – the Euclidean distance. When we consider the existence of the natural barriers in Bratislava – the Danube river and Small Carpathians (Malé Karpaty), it is somewhat surprising finding.

Table 5. about here

7. Discussion and conclusions

This paper contributes to the research on the spatial structure of real estate prices in the city. One of the main factors that influence prices is the distance from the city centre. Real estate prices in Bratislava reflect the mechanism typical of cities in developed countries, i.e. a decline of prices while moving from the centre, towards more peripheral parts. Increasing the distance from the city centre by 1% decreases the price of the apartment by 0.18 to 0.19% and this value ranges from 0.19 to 0.24% in case of the travel time. After inclusion of city district dummies into models the coefficients expressing the price gradient were smaller. One-percent increase in distance or time from the centre is associated with lower apartment prices by 0.11% to 0.14%. The inclusion of district dummies also resulted in fall of the coefficient of spatially correlated error (lambda) but this coefficient remains relatively high. Comparisons with other similar studies indicate that, that the size of the gradient in Bratislava is slightly steeper. For example the increase in distance from the CBD by 1% is associated with a decrease in the price of the apartment by 0.10% in Vienna (Herath and Maier, 2013) or from 0.03% to 0.11% in Stockholm (Sodberg and Jansen, 2001). A steeper gradient may result from differences in traffic infrastructure, e.g. the absence of a metro in Bratislava. Investments in the transport infrastructure, which lead to a reduction in the time of transport to the centre, should be capitalized through real estate prices. This is particularly the case in a short period of time, because in the longer term, the change in transport availability is also reflected in land use change (Higgins, Kanaroglou 2016). The steeper price gradient in Bratislava therefore may indicate the importance of investment in public transportation in Bratislava.

In addition to the price gradient analysis, this article also brought new insights into the use of different types of distance and time measurements in hedonic models. Distance and travelling time to the city centre vary depending on how they are measured. However, even in the case of a city with complicated urban structure, it is not necessary to use more demanding calculations. The estimated price of apartments is not significantly different if the travelling time to the city centre is used instead of the distance. An interesting finding was that the quality of the Euclidean distance models is comparable to walking distance models and is significantly better when compared to distance and time measurements by car or public transport. We can think of a few explanations. The first is that Euclidean distance represents the mean distance to the city centre. Driving and transit time may change during the day, week and year because of changes in traffic. The second possible explanation is that the Euclidean distance may represent *perceived* distance instead of the physical distance. This means that the property owner perceives the city centre at a certain distance even though there are natural or artificial barriers that prolong travel to the centre. The hedonics price models are based on the assumption of perfect information about distance and time. However, these are usually not known when buying an apartment and individuals estimate price based on the aforementioned behavioral factors. However, this assumption requires deeper research.

The research results have several data limitations resulting from deficiencies in the data used. The main limitation is that we use bid prices that are not transaction prices. Using information on the time on the market may reduce the problem of with bid prices, but this information was not available to the authors. However, we believe that the difference between the actual price and the transaction price is not site-dependent and therefore has no significant impact on our main results.

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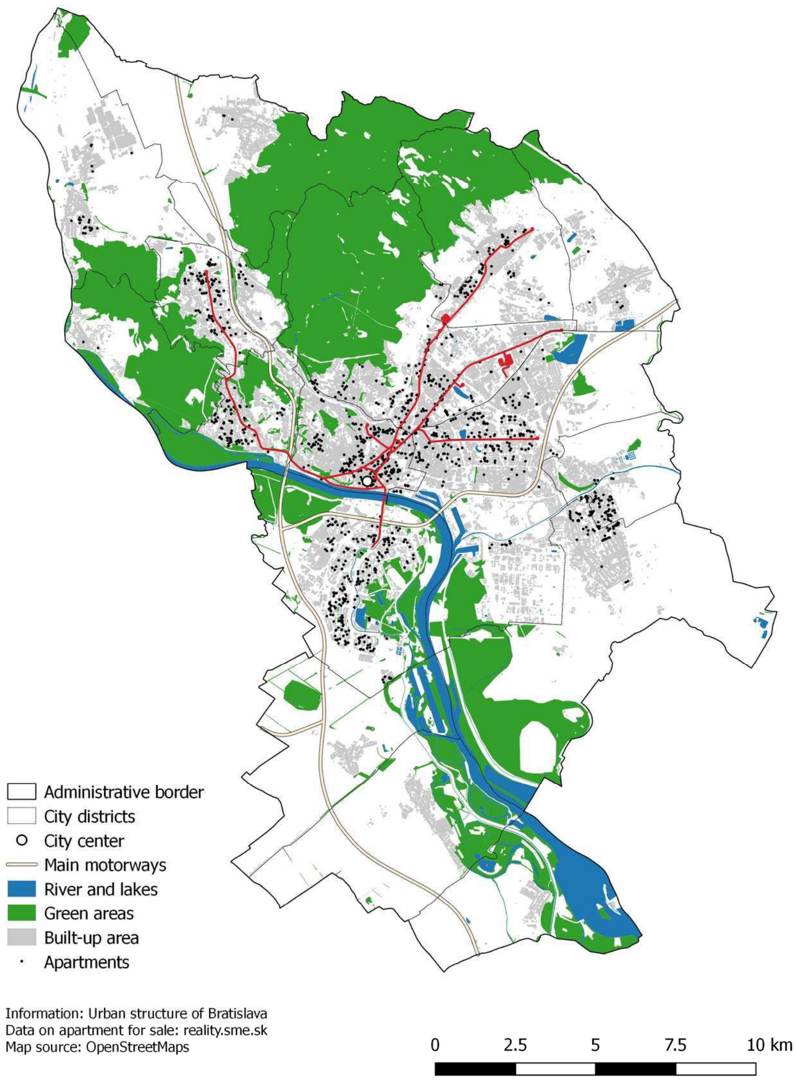

Figure 1. Study area

296x419mm (150 x 150 DPI)

Table 1. Descriptive statistics

Group	Variable	Description	Minimum	Maximum	Mean	Std. Deviation
	price	Total price of apartment	21,000	734,850	168,161	101,971
apartment	size	Size in m^2	15	329	78.75	41.37
	rooms	Number of rooms in apartment	1	6	2.66	1.02
	furnished	Apartment sold with furniture	0	1	0.19	0.39
	original condition	Apartment in original condition (no reconstruction)	0	1	0.13	0.332
	luxury	Additional services or equipment (e.g. parking place, security service)	0	1	0.18	0.39
	ground floor	Apartment located on the ground floor	0	1	0.06	0.24
house	panel	Panel construction of the apartment house	0	1	0.43	0.50
	new building	Newly built apartment house	0	1	0.31	0.46
	high house	Apartment located in house with more than 5 floors	0	1	0.49	0.5
distance	eucli_km	Euclidian distance to city centre (in kilometres)	0.045	13.577	4.288	2.675
	drive_km	Driving distance to the city centre (in kilometres)	0.000	22.625	6.875	4.315
	walk_km	Walking distance to the city centre (in kilometres)	0.051	15.808	4.972	3.015
	trans_km	Distance to the city centre with public transportation (in kilometres)	0.051	17.243	5.401	3.131
time	eucli_tm	Time to the city centre on euclidian route	0.5	167.6	53.8	35.2
	drive_tm	Driving time to the city centre (in minutes)	0.0	29.0	15.3	4.8
	walk_tm	Walking time to the city centre (in minutes)	0.6	195.5	61.4	37.1
	trans_tm	Time to the city centre by public transportation (in minutes)	0.6	71.8	24.8	9.6
local	Devín	Apartment located in city district Devín	0	1	0.00	0.04
	Devínska Nová Ves	Apartment located in city district Devínska Nová Ves	0	1	0.02	0.14
	Lamač	Apartment located in city district Lamač	0	1	0.01	0.10
	Záhorská Bystrica	Apartment located in city district Záhorská Bystrica	0	1	0.00	0.06
	Vajnory	Apartment located in city district Vajnory	0	1	0.00	0.07
	Podunajské Biskupice	Apartment located in city district Podunajské Biskupice	0	1	0.04	0.20
	Karlova Ves	Apartment located in city district Karlova Ves	0	1	0.07	0.25
	Dúbravka	Apartment located in city district Dúbravka	0	1	0.08	0.27
	Vrakuňa	Apartment located in city district Vrakuňa	0	1	0.05	0.23
	Rača	Apartment located in city district Rača	0	1	0.06	0.23
	Nové Mesto	Apartment located in city district Nové Mesto	0	1	0.15	0.35
	Petržalka	Apartment located in city district Petržalka	0	1	0.18	0.38

	Ružinov	Apartment located in city district Ružinov	0	1	0.15	0.36
	Staré Mesto	Apartment located in city district Staré Mesto	0	1	0.19	0.40

Source: Own elaboration.

Table 2. Regression results of the Models 1A to 1D

	Model 1A Euclid	Model 1B Drive	Model 1C Walk	Model 1D Transit
constant	11.41*** (0.03)	11.26*** (0.03)	11.45*** (0.03)	11.45*** (0.03)
size	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
room 2	0.20*** (0.01)	0.20*** (0.02)	0.20*** (0.01)	0.20*** (0.02)
room 3	0.33*** (0.02)	0.33*** (0.02)	0.33*** (0.02)	0.33*** (0.02)
room 4	0.38*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.37*** (0.02)
room 5	0.35*** (0.04)	0.37*** (0.04)	0.35*** (0.04)	0.35*** (0.04)
room 6	0.41*** (0.08)	0.40*** (0.08)	0.42*** (0.08)	0.40*** (0.08)
furnished	0.05*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)
original condition	-0.06*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)
luxury	0.12*** (0.02)	0.12*** (0.02)	0.12*** (0.02)	0.12*** (0.02)
ground floor	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)
panel	-0.06*** (0.02)	-0.07*** (0.02)	-0.06*** (0.02)	-0.06*** (0.02)
new building	0.13*** (0.01)	0.11*** (0.01)	0.13*** (0.01)	0.13*** (0.01)
high house	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
eucli_km	-0.19*** (0.01)			
drive_km		-0.04*** (0.01)		
walk_km			-0.19*** (0.01)	
trans_km				-0.18*** (0.02)
lambda	0.61*** (0.02)	0.72*** (0.02)	0.60*** (0.03)	0.61*** (0.03)
Pseudo R2	0.8535	0.8065	0.8566	0.8521
Log likelihood	515.966	459.961	517.018	508.161
Number of observations	1,334	1,334	1,334	1,334

Notes*:* Statistically different from zero at * 5 percent ** 1 percent and *** 0.1 percent significance levels.
Standard errors are in parentheses.
Source: Own calculations.

Table 3. Regression results of the Models 2A to 2D

	Model 2A Euclid	Model 2B Drive	Model 2C Walk	Model 2D Transit
constatnt	11.87*** (0.05)	11.24*** (0.03)	11.93*** (0.06)	11.94*** (0.07)
size	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
room 2	0.20*** (0.01)	0.21*** (0.02)	0.20*** (0.01)	0.20*** (0.02)
room 3	0.33*** (0.02)	0.33*** (0.02)	0.33*** (0.02)	0.33*** (0.02)
room 4	0.37*** (0.02)	0.38*** (0.02)	0.38*** (0.02)	0.37*** (0.02)
room 5	0.35*** (0.04)	0.37*** (0.04)	0.35*** (0.04)	0.35*** (0.04)
room 6	0.41*** (0.08)	0.39*** (0.08)	0.42*** (0.08)	0.41*** (0.08)
furnished	0.05*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.04*** (0.01)
original condition	-0.06*** (0.01)	-0.07*** (0.01)	-0.06*** (0.01)	-0.07*** (0.01)
luxury	0.12*** (0.02)	0.12*** (0.02)	0.12*** (0.02)	0.12*** (0.02)
ground floor	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)	-0.09*** (0.02)
panel	-0.06*** (0.02)	-0.07*** (0.02)	-0.06*** (0.02)	-0.07*** (0.02)
new building	0.13*** (0.01)	0.11*** (0.01)	0.13*** (0.01)	0.12*** (0.01)
high house	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)
eucli_tm	-0.19*** (0.01)			
drive_tm		-0.02* (0.01)		
walk_tm			-0.19*** (0.01)	
trans_tm				-0.24*** (0.02)
lambda	0.61*** (0.02)	0.74*** (0.02)	0.60*** (0.02)	0.64*** (0.02)
Pseudo R2	0.8535	0.7916	0.8568	0.8436
Log likelihood	515.966	455.465	516.833	493.432
Number of observations	1,334	1,334	1,334	1,334

Notes*:* Statistically different from zero at * 5 percent ** 1 percent and *** 0.1 percent significance levels.
Standard errors are in parentheses.
Source: Own calculations.

Table 4. Regression results of the Models 3A to 3D

	Model 3A Euclid	Model 3B Drive	Model 3C Walk	Model 3D Transit
CONSTANT	11.43*** (0.03)	11.43*** (0.03)	11.46*** (0.03)	11.47*** (0.03)
Devín	0.00 (0.13)	-0.25 (0.13)	0.00 (0.13)	-0.07 (0.13)
Devinska Nová Ves	-0.05 (0.08)	-0.32*** (0.08)	-0.04 (0.08)	-0.12 (0.08)
Dúbravka	-0.09 (0.05)	-0.32*** (0.05)	-0.09 (0.05)	-0.16** (0.05)
Karlova ves	-0.08 (0.05)	-0.23*** (0.05)	-0.08 (0.05)	-0.13** (0.05)
Lamač	-0.05 (0.09)	-0.26** (0.09)	-0.05 (0.09)	-0.10 (0.09)
Nové Mesto	-0.05 (0.03)	-0.17*** (0.03)	-0.05* (0.03)	-0.09** (0.03)
Podunajské Biskupice	-0.27*** (0.06)	-0.49*** (0.05)	-0.27*** (0.06)	-0.33*** (0.06)
Petržalka	-0.16*** (0.04)	-0.28*** (0.03)	-0.15*** (0.04)	-0.18*** (0.04)
Rača	-0.10 (0.05)	-0.31*** (0.04)	-0.11* (0.05)	-0.16** (0.05)
Ružinov	-0.05 (0.04)	-0.18*** (0.03)	-0.05 (0.04)	-0.08* (0.03)
Vajnory	-0.30* (0.13)	-0.55*** (0.13)	-0.30* (0.13)	-0.37** (0.13)
Vrakuňa	-0.36*** (0.06)	-0.58*** (0.05)	-0.36*** (0.06)	-0.42*** (0.05)
Záhorská Bystrica	-0.13 (0.13)	-0.40*** (0.12)	-0.13 (0.13)	-0.20 (0.13)
eucli_km	-0.13*** (0.02)			
drive_km		-0.02 (0.01)		
walk_km			-0.14*** (0.02)	
trans_km				-0.11*** (0.02)
Apartment characteristics	YES	YES	YES	YES
House characteristics	YES	YES	YES	YES
lambda	0.53*** (0.03)	0.55*** (0.03)	0.52*** (0.03)	0.53*** (0.03)
Pseudo R2	0.8778	0.8703	0.8780	0.8761
Log likelihood	547.822	527.626	546.596	541.977
Number of observations	1,334	1,334	1,334	1,334

Notes*:* Statistically different from zero at * 5 percent ** 1 percent and *** 0.1 percent significance levels.
Standard errors are in parentheses.
Source: Own calculations.

Table 5. Regression results of the Models 4A to 4D

	Model 4A Euclid	Model 4B Drive	Model 4C Walk	Model 4D Transit
CONSTANT	11.77*** (0.06)	11.44*** (0.03)	11.79*** (0.06)	11.75*** (0.07)
Devín	0.00 (0.13)	-0.27* (0.13)	-0.01 (0.13)	-0.20 (0.13)
Devinska Nová Ves	-0.05 (0.08)	-0.35*** (0.07)	-0.05 (0.08)	-0.22** (0.08)
Dúbravka	-0.10 (0.05)	-0.34*** (0.04)	-0.10 (0.05)	-0.22*** (0.05)
Karlova ves	-0.08 (0.05)	-0.25*** (0.04)	-0.08 (0.05)	-0.17*** (0.05)
Lamač	-0.05 (0.09)	-0.29** (0.09)	-0.06 (0.09)	-0.16 (0.09)
Nové Mesto	-0.05 (0.03)	-0.17*** (0.03)	-0.05 (0.03)	-0.11*** (0.03)
Podunajské Biskupice	-0.27*** (0.06)	-0.51*** (0.05)	-0.27*** (0.06)	-0.37*** (0.05)
Petržalka	-0.16*** (0.04)	-0.29*** (0.03)	-0.15*** (0.04)	-0.24*** (0.03)
Rača	-0.10 (0.05)	-0.32*** (0.04)	-0.11* (0.05)	-0.21*** (0.05)
Ružinov	-0.05 (0.04)	-0.18*** (0.03)	-0.05 (0.04)	-0.10** (0.03)
Vajnory	-0.30* (0.13)	-0.56*** (0.14)	-0.30* (0.13)	-0.41** (0.13)
Vrakuňa	-0.36*** (0.06)	-0.59*** (0.05)	-0.36*** (0.06)	-0.46*** (0.05)
Záhorská Bystrica	-0.13 (0.13)	-0.42*** (0.12)	-0.13 (0.13)	-0.29* (0.12)
eucli_tm	-0.13*** (0.02)			
drive_tm		-0.01 (0.01)		
walk_tm			-0.13*** (0.02)	
trans_tm				-0.13*** (0.03)
Apartment characteristics	YES	YES	YES	YES
House characteristics	YES	YES	YES	YES
lambda	0.52*** (0.03)	0.56*** (0.03)	0.52*** (0.03)	0.54*** (0.03)
Pseudo R2	0.8778	0.8696	0.8780	0.8749
Log likelihood	547.821	526.794	546.353	538.884
Number of observations	1,334	1,334	1,334	1,334

Notes*:* Statistically different from zero at * 5 percent ** 1 percent and *** 0.1 percent significance levels.
Standard errors are in parentheses.
Source: Own calculations.