# A Spatial Approach to the Hedonic Pricing of Apartment Attributes

- The Case of Vladivostok -

# 헤도닉 가격모형을 이용한 아파트 특성에 대한 공간적 접근

- 블라디보스톡의 경우 -

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## 국문초록

**1. 내 용**

**(1) 연구목적**

본 연구의 목적은 러시아 블라디보스톡의 지리적인 위치의 효과를 고려한 아파트의 상대적인 특성을 탐색하기 위함이다. 첫째로, 아파트의 가격은 이웃 아파트의 평균 가격에 영향을 받는 다는 것이고, 둘째로, 아파트 지역이나 혹은 가장 가까운 철도역까지의 거리와 같은 질적인 특성을 나타내는 관찰할 수 없는 공간적인 특성을 분리하였다는 것이다.

**(2) 연구방법**

모델은 아파트의 다면적 특성에 대한 헤도닉 가격모형을 설정하였다. 헤도닉 가격설정 모형에 공간가중구성(spatial weight matrix)을 포함함에 의하여 이웃 아파트의 평균 가격의 영향을 모델에 설정하였다. 또한 공간가중구성(spatial weight matrix)의 함수로 관찰 할 수 없는 이질성(heterogeneity)을 고려하여 관찰 할 수 없는 공간효과를 모델 설정하였다. 샘플의 크기는 블라디보스톡의 729개 아파트를 실증분석하였고, 모델의 추정방법은 R을 활용 하였다.

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**(3) 연구결과**

연구 분석 결과 샘플에서 통계적으로 매우 유의한 공간 이질성 효과의 존재가 증명되었으며, 이는 분석에서 공간회귀방법(spatial regression methods)의 적용을 보장하는 것이었다. 연구결과는 3개의 가장 근접한 이웃을 고려한 방법이나, 혹은 지리적인 거리나 개인적인 특성의 효과의 크기나 공간모델의 선택에 근거한 방법은 동일하다는 관점에서, 공간가중구성(spatial weights matrix)을 선택함으로써 견고(robust)한 연구결과를 나타내었다.

## 2. 결과

실증분석의 결과는 아파트 위치의 관측 되지 않는 특징들이 차지하는 역할이 아파트의 평균 가격이나 질적인 특성의 영향과 비교하여 상대적으로 큰 것으로 나타났다. 아파트의 지역은 아파트 가격을 결정하는데 결정적인 역할을 하는 반면, 주방 크기의 추가적인 확장이 거실 크기의 확장보다 50%이상의 효과를 나타내었다.



## 3. 핵심어

• 헤도닉가격 함수, 다중 질적 속성, 공간이질성, 공간회귀, 공간가중


## ABSTRACT


In this study we look at the effects spatial heterogeneity produces on the apartment price variation in Vladivostok, an important city in the Russian Far East. Along with the traditional apartment attributes such as living area, we also consider the kitchen area, which appears to be more important in Russia. We report estimates based on six specifications of the spatial lag and error models, and the spatial weights based on the geographical distance or the k nearest neighbors. Our estimates imply that our data sample is most adequately described by the spatial error model, suggesting that any apartment's price is largely a function of the unobserved characteristics of the neighboring apartments rather than its own attributes. However, our results leave open a possibility of the Vladivostok apartments' prices being a function of geographical location alone.



**KEY WORDS : Spatial Heterogeneity, Spatial Lag, Spatial Error, Spatial Weight, Hedonic Price**

# I. Introduction

This study is estimating hedonic price functions for the apartments market in Vladivostok with specific focus on the spatial heterogeneity. While there is little doubt that location is of primary importance to the housing market anywhere, in many instances the discussion is focused on the valuation of quality attributes of the housing units such as the quality of high school education[1], air pollution[2)3)] or the airport noise[4]. In a more original line of research, apartment and residential land prices were related to the buyers' characteristics[5] and macroeconomic variables[6]. Yet, ignoring the spatial effects present in the data such as the average price of the neighboring apartments or the unobserved location-related characteristics may result in biased and inconsistent estimates of the quality attributes' shadow prices[7].

In this study we focus on the two broadly defined spatial effects, namely, the spatial lag and spatial correlation[8]. Spatial lag models capture the peer effects common for a specific neighborhood and quantified by an average price of apartments therein. Using the analogy with the time series analysis, including the spatial lag variable is similar to detrending the time series data[9]. Spatial correlation models, on the other hand, capture the unobserved effects that are shared by the neighboring units that cannot be modeled directly such as common perceptions about the neighborhood's attractiveness in general.

It is worthwhile noticing that location effects on the housing prices have not been entirely ignored in the received literature. For instance, [10] and [11]discuss, among other issues, the effect of the geographical region on the Korean apartment prices. However, location- related variables are treated as just

1) Sedgley, N.H., Williams, N.A., and Derrick, F.W., "The effect of educational test scores on house prices in a model with spatial dependence", *Journal of Housing Economics*, 2008,17,2, pp.191-200.

2) Kim, Ch.W., et al., "Measuring the Benefits of Air Quality Improvement: A Spatial Hedonic Approach", *Journal of Environmental Economics and Management*,2003,45, pp.24-39

3) Habb, T.C., McConnell, K.E., "Valuing environmental and natural resources: the econometrics of non-market valuation". Edward Elgar, Cheltenham, UK,2002, pp.115-150.

4) Cohen, J.P., and Coughlin, C.C. , "Spatial hedonic models of airport noise, proximity and housing prices", *Federal Reserve Bank of St. Louis working paper,* 2007, no 2006-026C, pp.2-7.

5) Yang, Young Jun and Yim, Sang Hyuk , "Effect That Characteristics of Buyers Haver on Land Price On the Trade Case in Seogwipo, Jeju Special Self-Governing Province", *Korea Real Estate Academy Review,* 2014, vol.58, pp.72-85.

6) Chun, Hae Jung., "Asset Pricing Theory based on the Study on the Determinants of Housing Prices by VECM", *Korea Real Estate Academy Review*, 2013, vol.52. pp.241-255.

7) Dubin, R.A., "Spatial autocorrelation and neighborhood quality", *Regional Science and Urban Economics,* 1992, 22, pp.432-452

8) Anselin, L. "Spatial Econometrics: Methods and Models", Kluwer Academic Publishers, Dordrecht, Netherlands, 1998, pp.217-248.

9) Anselin, L., "Spatial Regression", mimeo, Department of Geography, University of Illinois.2007, pp.7-10.

10) Lee, Jin Sung and Lee, Chang Hyun , "Analysis on the Determinants of Korea Housing Price Index in Unstable Housing Market by Volatility of the Housing Price", *Korea Real Estate Academy Review*,2014,vol.59, pp.203-216.

11) Lee, Jin Sung and Kim, Hyun Suk, "Study on Influential Factors toward Housing Price Volatility by Region", *Korea Real Estate Academy Review,* 2013, vol.55, pp.266-278.

another set of apartment attributes without taking account of the issues of spatial lag and spatial correlation discussed above.

Historically Russians considered the kitchen room to be more of a family convention center rather than a mere cooking place. However, the kitchen area is rarely included in the list of apartment attributes in similar studies. For instance, in a recent paper by [12] the kitchen area is just aggregated into a composite variable. We include kitchen area as a separate apartment attribute and find its effect to be relatively large and significant.

Our empirical estimates imply it is the unobserved characteristics of the neighboring apartments that are mostly explaining the variation in apartments' prices, with the measurable apartment attributes playing an auxiliary role.

This paper is organized as follows. Section 2 presents and summarizes the data. Section 3 briefly describes the theoretical background. Empirical findings are listed and discussed in Section 4. Section 5 concludes.

## Ⅱ. Data

The data at our disposal comes from realty.yandex.ru, Russia's major Internet portal, that provides data for the Russian secondary market apartments.

We started with a Vladivostok sample of more than two thousand observations whose size was reduced to 729 as a result of excluding the obvious outliers and observations with missing attributes. Table 1 below summarizes the apartments' quality attributes in our sample. The choice of our apartments' quality attributes is rather standard, as evidenced, among other studies, in [13] and [14].

The number of rooms in a typical apartment in our sample is two.

**〈Table 1〉 Descriptive statistics of the characteristics of Vladivostok apart ments**

| Variable Name | Mean | Minimum | Maximum |
|---|---|---|---|
| Price (Rubles) | 6,410,854 | 1,700,000 | 95,000,000 |
| Living area, sq.m. | 41.43 | 10 | 160 |
| Kitchen area, sq.m. | 8.31 | 3 | 35 |
| Floor | 5 | 1 | 23 |
| Total number of floors | 9 | 2 | 25 |
| Number of rooms | 2 | 1 | 5 |
| Distance to the nearest railway station, km | 1.56 | 0.2 | 6.4 |
| First/top floor apartment, % of observations | 36.6% | NA | NA |
| Separated toilet / bath tub, % of observations | 54.2% | NA | NA |
| Insulated veranda, % number of observations | 42.7% | NA | NA |

Note: total number of observation is 729, 1 ruble buys 15.93 Korean won as of January 31, 2015

12) Bhattacharjee, A., Castro, E., and Marques, J., "Spatial Interactions in Hedonic Pricing Models: The Urban Housing Market of Aveiro, Portugal". *Spatial Economic Analysis,* 2012, 7:1, pp.133-167.

13) Kim, Hee Jae and Jun, Myung Jin , "An Analysis on Effect of Amenity on the Apartment Rents in the Seoul Metropolitan Region", *Korea Real Estate Academy Review,* 2013,vol.53, pp.14-128.

14) Song, Myung-Gyu., "The Fluctuation of Housing Characteristics' Influence on Apartment Price according to the Passage of Time", *Korea Real Estate Academy Review,* 2014,vol.59, pp.124-138.

Apartments on the first or top floor of the building are typically experiencing problems with water supply and heating, which is why we included a dummy for the first or top floor. The total amount of stories and the actual floor is also included in the set of apartment attributes.

Distance to the nearest railway station is important since in the Vladivostok context, railway stations play a similar role to subway in Moscow and other large Russian cities. Finally, we included the dummies for the bath tub being located in a different room than the toilet (separate location generally perceived as being more preferable) and for the glass-insulated verandas.

The average price of a Vladivostok apartment is around 6.4 million rubles, which is equivalent to 106,000,000 Korean won at the current exchange rate (January 2015). Kitchen on average constitutes around one-fifth of the total living area with the latter averaging forty-one square meters. An average apartment is located in the fifth floor of a typical nine-floor building. A typical Vladivostok apartment has two rooms, and is located an average of 1.6 kilometers away from the nearest railway station. Around thirty-seven percent of our apartments are unfortunate to be located on the first or the top floor. Slightly more than one-half of the apartments are boasting separated toilet seat and the bath tub. Finally, around forty percent of apartments in our sample are enjoying an insulated veranda.

## Ⅲ. Theoretical Framework

The starting point of our analysis is the hedonic price function of a multi-attribute apartment formulated in a seminal paper by [15]. The price of a house in the hedonic price function framework is a function of its quality characteristics as well as of those of the neighborhood: $P = f(Xs, Xn) + \varepsilon$, where Xs is the vector of the apartment's characteristics such as the living area or the number of rooms, and Xn is the vector of characteristics of the neighborhood. All in all, we employ nine characteristics.

Consumers maximize their utility that is a function of the apartment composite good $X=(Xs, Xn)$ subject to the constraint $I = C+P(X)$ where I is income, C is a nu meraire commodity and $P(X)$ is the price of apartment $X=(Xs, Xn)$. The s shadow price of the apartment's attributes can be then shown to be equal to the ratio of the marginal utility of the apartment at tributes to that of the numeraire good: $\frac{\partial p}{\partial z} = \frac{\partial U/\partial z}{\partial U/\partial p}$. We can then estimate those shadow prices by specifying an empirical form of the hedonic price function.

The spatial lag model accounts for the effects of the prices of neighboring apartments by specifically adding the spatially lagged variable to the

15) Rosen, S., "Hedonic Prices and Implicit Markets : Product Differentiation in Pure Competition", *Journal of Political Economy*,1974, vol.92, pp.38-41.

specification equation: P=f(Xs, Xn, WP), where W is the spatial weights matrix:

$$P_i = \rho W P_i + X_i \beta + \epsilon_i \qquad (1)$$

where $\epsilon_i$ are e.g. iid normal, and $X_i = (X_s^i, X_n^i)$ is a vector of apartment- and neighborhood-specific characteristics for apartment i.

The spatial weights matrix W identifies neighbors. For example, w 2,5 = 1 means that the second apartment is neighbors with the fifth apartment. If the rows of W are standardized in the sense that the sum of elements in each row is equal to one, the spatially lagged variable WP can be interpreted as the average price of the neighboring apartments. This approach appears to be used most frequently (see e.g. [16]). Another approach is to postulate that each apartment in the sample has a specific number of its closest neighbors, which will result in a different W. Our results are robust across the choice of the spatial weights matrices qualitatively, but not quantitatively.

In case spatial dependence is modeled by spatial correlation, the set of independent variables remains the same, but the error process is described differently:

$$P_i = X^i \beta + \epsilon_i \qquad (2)$$
$$\epsilon_i = \lambda W \epsilon_i + u_i$$

where $u_i$ is identically and normally distributed. The model in (2) is often called spatial simultaneous autoregressive error model, reflecting the fact that neghboring apartments may share unobservable characteristics.

# Ⅳ. Empirical Results

## 1. Hedonic price function specification and preliminary OLS results

We first need to identify the appropriate functional form for the hedonic equation. Unfortunately, economic theory provides us with little guidance to this issue, see e.g. [17].

We choose between logged and not logged independent variables by running the regression collinearity diagnostic procedure developed in [18] based on the computation of conditioning numbers for the matrix of independent variables. Since the matrix of logged independent variables produces an unacceptably large conditioning number of 38.18, we are left with the semi-log and linear-linear specifications. Since the OLS estimates of the former produce a much higher value of R-squared (67.26%) compared

16) Cressie, N.A.C., *Statistics for Spatial Data*, John Wiley and Sons, New York.1993, pp.45-170.

17) Halvorsen, R., and Pollakowski, H.O., "Choice of functional form for hedonic price equations", *Journal of Urban Economics*,1981,10, pp.37-49

18) Belsley, D., Kuh, E., and Welsch, R., *Regression Diagnostics*, Wiley, New York,1980, pp.28-59.

〈Table 2〉 OLS Estimates of the Hedonic Price Equation Dependent variable: (log) apartment price, million rubles

| | Coefficient | Percentage Increase in Price to a Unit Change |
|---|---|---|
| Living area, sq m | 0.002***<br>(0.000) | 0.15% |
| Kitchen area, sq m | 0.003***<br>(0.000) | 0.31% |
| Number of rooms | 0.002<br>(0.694) | 0.21% |
| Floor | 0.003***<br>(0.002) | 0.32% |
| Total floors | -0.002**<br>(0.045) | -0.19% |
| First/top floor dummy | -0.003<br>(0.601) | NA |
| Separated bathroom and toilet dummy | 0.018**<br>(0.026) | NA |
| Distance from the railway station, km | -0.005*<br>(0.060) | NA |
| Insulated veranda dummy | -0.007<br>(0.340) | NA |
| Constant | 2.142**<br>(0.016) | NA |
| R-squared | 67.26% | NA |
| Adjusted R-squared | 64.02% | NA |

Note: p-values are in parentheses. *** stands for a 1% significance level, ** for 5%, and * for 10%.

to the latter (32.34%), we choose the semi-log specification. Table 2 below presents OLS estimates of the semi-log specification. It is easy to see that in case of a semi-log specification, the estimated coefficients are approximately equal to the percentage increase in the value of the dependent variable in case of a unit increase in the value of an independent variable, reported in the third column.

## 2. Discussion of the OLS estimation results

Both living and kitchen area command predictable positive and statistically significant coefficients. However, the effect of a marginal increase in the kitchen area far outweighs that of an increase in the living area, reflecting the important role kitchen has been traditionally playing in the Russian homes: an additional square meter in the kitchen raises the apartment price by almost 0.3%, while that in the living area only does that by 0.1% percent.

The higher the floor of the apartment, the more expensive it is valued by the market with each floor adding 0.32% to the price. The rest of the explanatory variables are mostly estimated with the expected signs, but come out statistically insignificant. Thus, the first-top floor dummy is expectedly negative, which reflects the preference of the Russian households to buy an apartment on either first or the top floor. The separated bathrooms and toilets dummy estimated to be positive, too, and being far away from the nearest railway station appears to be decreasing the apartment price. However, since the statistical significance of the abovementioned variables is below the ten-percent level, our preliminary conclusion is that there are only six apartment characteristics that matter in Vladivostok, namely, the living and kitchen area, the floor of the apartment, the number of floors, distance from the nearest railway station, and the presence of separated bathroom and toilet.

As is well known, the OLS estimates of the standard errors are inconsistent in the presence of spatial errors, while the model's coefficient estimates become biased in case of the spatial lag effects. For that reason we take these estimates only as preliminary evidence and proceed with the analysis of possible spatial effects in our sample.

## 3. Testing for hetero skedas ticity of the residuals

In case either type of the spatial dependency is present in the data, in general the OLS residuals are not going to be homoscedastic. Indeed, in case of the spatial lag model (1) heteroskedasticity will be caused by the omitted variable WPi, while incase of the spatial error model (2) the error variance is by definition a function of geographical location.

Both the [19] test for multiplicative heteroskedas ticity and Szroeter [20] test for homoskedasticity against the alter native that the residual variances are monotonically increasing in the independent variables strongly suggest the presence of serious mis specification

〈Table 3〉 Breusch-Pagan and Szroeter Tests for Heteroskedasticity in OLS Residuals

| Breusch-Pagan test | Chi2 | p-value |
|---|---|---|
| All nine right-hand side variables | 44.51 | 0.000 |
| Szroeter test | | |
| Living area, sq m | 32.54 | 0.000 |
| Kitchen area, sq m | 34.24 | 0.000 |
| Number of rooms | 1.38 | 0.240 |
| Floor | 0.34 | 0.561 |
| Total floors | 22.08 | 0.000 |
| First/top floor dummy | 8.81 | 0.003 |
| Separated bathroom and toilet dummy | 11.52 | 0.001 |
| Distance from the railway station, km | 6.93 | 0.009 |
| Insulated veranda dummy | 18.86 | 0.000 |

19) Breusch, T. S., and A. R. Pagan., "A simple test for heteroscedasticity and random coefficient variation". *Econometrica*,1979,47, pp.1287-1294.

20) Szroeter, J., "A Class of Parametric Tests for Heteroskedasticity in Linear Econometric Models", *Econometrica*,1978,46, pp.1311-1327.

problems. Table 3 below presents estimation diagnostics for these tests.

Now that hetero skedasticity in the residuals indicates the possible presence of spatial effects, we proceed with testing for whether a specific type of spatial dependency (lag or error) is present. In order to perform these tests, we need to construct the spatial weights matrix first.

## 4. Constructing the spatial weights matrix

Most generally, there are two broad approaches to defining the weights in the spatial weight matrix W, see [21]. The element wij of the spatial weights matrix W is equal to unity in case region i is contiguous, with region j. Contiguity may be defined in terms of the geographical distance or by postulating a fixed number of neighbors for each apartment.

When computing elements of the spatial weights matrix W according to the geographical distance, we define apartment j to be a neighbor to apartment i if the geographical distance between the two is below a threshold distance, i.e.the minimum distance for which there are no geographical "islands" in the sample.

In the "fixed number of neighbors" approach, we choose this number to be equal to the average number of nearest neighbors for apartments in our sample, namely, three. Table 4 below summarizes the characteristics of the two spatial matrices W computed according to the two methods.

〈Table 4〉 Spatial Weight Matrices

| | Three nearest neighbors | Geographical distance threshold, d=100m |
|---|---|---|
| Total number of apartments | 729 | 729 |
| Number of non-zero links | 15784 | 73551 |
| Percentage non-zero weights | 2.97% | 13.84% |
| Average number of links | 3 | 14 |

## 5. Spatial error/spatial lag estimation results

Table 5 below presents the results of our estimates for the spatial lag (first two columns) and the spatial error (the top column) specifications using the spatial weights matrix W constructed according to the principle of three nearest neighbors. The two-stage estimation methodology deals with potential endogeneity of the spatially lagged variable WPi. The spatially lagged housing characteristics are used as instruments for the spatially lagged dependent variable.

We observe that the spatial effects are only present in model (2), the spatial error model. We deduce from the estimates in Table 5 that most of the observed variation in Vladivostok apartment prices is due to the correlation with the unobserved characteristics of neighboring apartments rather than the own apartment characteristics.

21) LeSage, J.P., and Pace, R.K. (Eds.), "Introduction to Spatial Econometrics", *Taylor and Francis*. 2009, pp.213-249.

〈Table 5〉 Spatial Models, Neighbors-Based Spatial Weights Matrix

| | Spatial Lag Model Maximum Likelihood Estimation | Two Stage Spatial Lag Estimation | Spatial Error Model |
|---|---|---|---|
| Living area, sq m | 0.002*** (0.000) | 0.001*** (0.000) | 0.002*** (0.000) |
| Kitchen area, sq m | 0.003*** (0.000) | 0.003*** (0.000) | 0.003*** (0.000) |
| Number of rooms | 0.002 (0.674) | 0.002 (0.733) | 0.002 (0.693) |
| Floor | 0.003*** (0.001) | 0.003*** (0.001) | 0.003*** (0.002) |
| Total floors | -0.002** (0.033) | -0.002** (0.036) | -0.002** (0.029) |
| First/top floor dummy | -0.003 (0.650) | -0.004 (0.573) | 0.0003 (0.963) |
| Separated bathroom and toilet dummy | 0.017** (0.019) | 0.019** (0.018) | 0.018** (0.014) |
| Distance from the railway station, km | -0.005** (0.045) | -0.005 (0.104) | -0.005** (0.026) |
| Insulated veranda dummy | -0.007 (0.317) | -0.008 (0.289) | -0.005 (0.473) |
| Constant | 2.162*** (0.000) | 1.846*** (0.000) | 2.136*** (0.000) |
| ρ or λ | -0.009 (0.908) | 0.133 (0.188) | -0.329** (0.045) |

Note: p-values are in parentheses. *** stands for a 1% significance level, ** for 5%, and * for 10%.

We also observe that the standard errors of the spatial error model in the third column of Table 5 are uniformly lower than those obtained in the OLS approach. Thus, the p-value for the 'total number of floors' coefficient is reduced by 36%, the one for 'separated bathroom and toiled' goes down by one-half, and that for the 'distance from the railway station' gets reduced by 60%. These findings are in line with econometric theory that predicts the OLS estimates to be inefficient compared to the spatial models in (1) and (2).

Table 6 presents a similar set of estimates for the case of the spatial weight matrix constructed on the basis of the geographical distance.

In case of the spatial weights matrix constructed on the basis of geographical distances, we infer that the most appropriate model is the spatial error model in (2). Similarly to the estimates in Table 5, there is not much difference with the OLS estimates in terms of the coefficients' magnitude and significance, but the p-values and, correspondingly, the standard errors are in general higher compared to their counterparts in Table 5 and more similar to the OLS ones. Thus, no new conclusions can be derived by using a distance-based spatial weights matrix except that the spatial error model (2) where the spatial weights matrix is based on the concept of k nearest neighbors, most adequately describes the data generating process corresponding to our sample.

It is also worthwhile noticing that, while the spatial lag effects from model (1) do not appear to be adequately describing the data generating process for our sample no matter which spatial

〈Table 6〉 Spatial Models, Distance-Based Spatial Weights Matrix

| | Spatial Lag Model Maximum Likelihood Estimation | Two Stage Spatial Lag Estimation | Spatial Error Model |
|---|---|---|---|
| Living area, sq m | 0.002*** (0.000) | 0.002*** (0.000) | 0.001*** (0.000) |
| Kitchen area, sq m | 0.003*** (0.000) | 0.003*** (0.000) | 0.003*** (0.000) |
| Number of rooms | 0.003 (0.607) | 0.002 (0.694) | 0.003 (0.508) |
| Floor | 0.003*** (0.001) | 0.003*** (0.002) | 0.003*** (0.002) |
| Total floors | -0.002** (0.039) | -0.002** (0.044) | -0.002** (0.049) |
| First/top floor dummy | -0.003 (0.668) | -0.003 (0.663) | -0.001 (0.869) |
| Separated bathroom and toilet dummy | 0.016** (0.032) | 0.018** (0.029) | 0.016** (0.026) |
| Distance from the railway station, km | -0.006** (0.026) | -0.005* (0.067) | -0.005* (0.049) |
| Insulated veranda dummy | -0.008 (0.269) | -0.007 (0.341) | -0.005 (0.463) |
| Constant | 2.461*** (0.000) | 2.152*** (0.000) | 2.137*** (0.000) |
| ρ or λ | -0.144 (0.282) | -0.005 (0.977) | -0.429** (0.046) |

Note: p-values are in parentheses. ***, ** and * stand 1%, 5%, and 10% significance levels, respectively

weights matrix is used to define the apartments' proximity (i.e. k nearest neighbors versus the geographical distance one), the coefficient estimates are robust in terms of both their magnitude and p-values across all of the six specifications reported by Tables 5 and 6.

## V. Conclusion

In this paper we estimated hedonic price functions that take account of spatial dependence for a sample of Vladivostok apartments. While a variety of spatial models are available for estimation, our analysis implies that it is the spatial error model where proximity between apartments is defined in terms of the three nearest neighbors that most adequately corresponds behind the data generating process pertaining to our sample.

In choosing our hedonic price function specification, we took account of the cultural idiosyncrasies pertinent to Vladivostok and Russia in general. Thus, we included the kitchen room area since the kitchen has been traditionally viewed by most Russians as a convention place for the family, making it an important apartment quality attribute. One interesting finding was that a marginal increase in the kitchen room area affected the price approximately three times more strongly in terms of the percentage increase in the apartment price compared to a comparable increase in the living area.

Applying the log-linear specifi cation of the hedonic price function that we chose according to the correlation conditioning number tests as well as the goodness of fit, we estimated hedonic relationship according to the two alternative types of spatial weights matrices (distance-based and k-nearest neighbors). In line with the theoretical predictions, the magnitude and statistical significance of the estimated coefficients are very similar to their OLS counterparts, which stems from the fact that irrespectively of the spatial correlation of any kind the expectation of the dependent variable in a spatial model is exactly its OLS counterpart. However, we also find that the p-values and, correspondingly, standard errors significantly decrease in case of the spatial error model where the spatial weights are computed on the basis of the concept of three nearest neighbors. We also notice robustness of the estimated coefficients across all of the six specifications.

The fact that it is the spatial error model in (2) rather than the spatial lag model in (1) appears to be the preferred specification indicates to the fact that it is namely the unobserved attributes of the neighboring apartments that are most responsible for the variation in the apartments' prices in Vladivostok. Since the set of our attributes is rather comprehensive, it appears to be worthwhile inquiring into what other apartment characteristics can be driving variation in the apartments' price.

We can think of the amount of pollution due to industrial enterprises, the level of noise generated by the seaport (the Vladivostok sea port is the most important port for the whole of Russia's Far Eastern region) or the airport, or proximity to restricted areas (e. g. military bases), however, these attributes are not readily available. Another possibility is that the apartment prices are fluctuating around a certain 'Vladivostok mean' with the differences almost entirely driven by geographical location alone. We consider our paper to be one of the first steps that can be taken in the further study of the housing market in the Russian Far East.

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