ACTA Acta Sci. Pol., Administratio Locorum 22(3) 2023, 321–334.
https://czasopisma.uwm.edu.pl/index.php/aspal plISSN 1644-0749 eISSN 2450-0771 DOI: 10.31648/aspal.8421

ORIGINAL PAPER
Received: 18.11.2022 Accepted: 15.06.2023

SPATIO-TEMPORAL MODELLING OF HOUSING SATISFACTION INDICATORS BASED ON STATISTICAL DATA – EVIDENCE FROM POLAND

Radosław Cellmer✉

ORCID: 0000-0002-1096-8352
University of Warmia and Mazury in Olsztyn
Oczapowskiego Street, 2, 10-719 Olsztyn, **Poland**
radoslaw.cellmer@uwm.edu.pl

ABSTRACT

Motives: The research problem addressed in the paper is the identification of sources of the spatial differentiation of housing satisfaction under the influence of external factors (economic, demographic and social).
Aim: The main research objective was to identify the determinants and spatial differentiation of housing satisfaction in Poland. Both classical panel models and spatial panel models were used for the analyses.
Results: The results of the study confirmed the hypothesis that the inclusion of spatial dependencies significantly improved the quality of the panel model. The developed models supported the determination of statistical relationships between economic, demographic and social factors, the number of dwellings per 1000 inhabitants, and the average floor space per person. In addition, the spatial distribution of individual effects in spatial panel models revealed variation in housing satisfaction that resulted from different levels of socio-economic development.

Keywords: housing needs, spatial dependencies, spatial panel model, spatio-temporal analysis

INTRODUCTION

Housing needs have a universal dimension and affect all citizens throughout their lives, and meeting this need is a fundamental and significant consumption challenge (Myers et al., 2002). The needs of households in this regard are unlimited and change as their wealth increases, which makes them difficult to measure. They are a determinant of the social function, the essential element of satisfying human needs, and the economic function as the fundamental object of investment. Housing is generally the most costly of all goods acquired over a lifetime, and many citizens cannot afford to acquire their dwellings for their entire lives. The housing situation of citizens affects, among other things, the professional activity, qualifications and spatial mobility of workers. Improved housing conditions mean a reduction in health care expenditures, facilitate economic development and ensure labour mobility, and above all, mobilise households to accumulate funds and save for housing purposes (Tibaijuka, 2013). Therefore, diagnosing actual housing needs and individual

✉radoslaw.cellmer@uwm.edu.pl

households' reported housing demand is a crucial challenge of state housing policy.

The motive of undertaking the indicated topic of work is the premises of Poland's long-term unsatisfied housing needs among economically different groups of the population. Since housing is at the forefront of the essential goods of individual consumption and social needs and its satisfaction, directly affecting the human environment, it is a critical element of scientific research.

The main research objective was to determine the determinants and the spatial differentiation of indicators that indicate the level of satisfaction of housing needs in Poland. Both classical panel models and spatial panel models were used for the analyses.

There is consensus among many economic and sociological theories about the extraordinary importance of the housing market in individual, social, and state life (Nurzafira et al., 2019). Housing conditions are particularly influential in shaping the material and social environment in which a person lives and develops. Housing not only satisfies basic human housing needs but acts as an essential determinant of a family's quality of life (Kam et al., 2018). Dynamic change in lifestyles of developing societies causes changes in consumer needs towards convenience, higher quality of goods and services, and individualisation, which translates into an increase in housing needs in quantitative and qualitative terms (Myers et al., 2002). However, housing quality indicators are difficult to measure and compare across time and space.

Housing need is defined as the aggregate of households unable to access market provided housing or requiring some form of housing assistance in the private rental market to avoid a position of rental stress (Rowley et al., 2017). Measuring the extent to which housing needs are met is quite complicated because it involves a subjective assessment of a particular place, time, and evaluation purpose (Nurzafira et al., 2019). Satisfaction of these needs can be described as housing satisfaction, defined as a feeling of satisfaction with one's housing conditions (Mohit et al., 2014). Housing satisfaction can also be defined as an indicator of the assessment of residential property owners' overall quality of life and can mean fulfilling an individual's housing expectations (Tan, 2016). Furthermore, housing satisfaction describes residents' quality of life in a particular residential environment and acts as a trigger influencing residential mobility (Amerigo & Aragones, 1997).

In Poland, there were only 390 dwellings per 1,000 inhabitants in 2019, which increased 11.1% (349.6 dwellings) compared to 2010. More than half of EU member states had more than 500 dwellings per 1,000 inhabitants in 2019. This ratio was highest in countries where the economy is based on tourism and holiday homes distort the statistics, thus not reflecting actual social housing needs.

Several factors influence the level of housing needs (housing satisfaction), including socio-demographic factors and the physical characteristics of housing (Nurzafira et al., 2019). Age, income level, education and employment are crucial (Max, 1999; Vera-Toscano & Ateca-Amestoy, 2008). The physical characteristics of the dwellings are primarily their size, the number of bedrooms, age of the building and overall quality (Roslan et al., 2020). However, a clear distinction must be made between housing needs and housing preferences (King, 2006). Other authors also point out this distinction (Kim & Kim, 2017; Mohit et al., 2014; Roslan et al., 2020; Vera-Toscano & Ateca-Amestoy, 2008), indicating factors influencing needs, preferences and housing satisfaction. Housing needs are also often identified with potential demand; hence econometric demand models are used for research (Bajari et al., 2010; Bayer et al., 2016; Xiong et al., 2020). Problems of modelling housing needs understood as potential demand are also discussed, among others, by Bramley et al. (2010), indicating broad possibilities of using simulation and forecasting models.

In past research, factors shaping the level of housing need satisfaction have generally been treated as non-spatial or discrete in space (Bajari et al., 2010; Wang et al., 2014). The groups mentioned above of determinants have the most significant influence on the existing demand for housing and can also be quantified in spatial terms. Spatial diversification of particular indicators and different intensity

✉radoslaw.cellmer@uwm.edu.pl

and directions of social processes (e.g. migrations) determine different shapes of demand, both potential and effective, for dwellings in various country places. These factors are continuous, exhibit spatial autocorrelation, and show dynamics of change in space. Lack of assumptions about their spatial heterogeneity and variability in time may be a significant barrier to understanding the processes occurring in the real estate market and their importance for local and regional development (Jayaraman et al., 2013; Jones & Leishman, 2006). The scientific problem, in this case, is the identification of the sources of spatial differentiation of indicators of satisfaction of housing needs under the influence of exogenous conditions (economic, demographic, social, etc.). On the other hand, the main aim of the research is to determine the spatial differentiation of the satisfaction of housing needs in the form of a diagnostic model which can support the state housing policy. The main focus was on presenting the possibility of applying spatial panel models to identify areas with different degrees of housing needs fulfilment in Poland.

METHODS

The study was conducted using panel data modelling, i.e., data resulting from combining multiple observations for individual units. Particular attention is paid to the spatial aspect in identifying the analysed phenomena. Hence, the main focus of the analyses was on the use of spatial panel models.

The importance of panel models in economic sciences is emphasised by Heng (2014) as well as Griliches and Intriligator (1984). In classical panel models, it is assumed that, in addition to the explanatory variables, unmeasured, time-constant, and object-specific factors, called group effects, and time-constant relative to object-specific factors, called time effects, can influence the evolution of the explanatory variable. The panel model in its general form can be represented as follows (Baltagi, 2021):

$$y_{it} = \beta_0 + \sum_{k=1}^{k} \beta_{kit} x_{kit} + \alpha_i + \upsilon_t + \varepsilon_{it} \qquad (1)$$

where y_{it} denotes the dependent variable, x_{kit} denotes the explanatory variable, β_0 is intercept, while β_{kit} is the structural parameter of the model (i denotes an object, t denotes time, while k denotes the number of the explanatory variable). In addition, αi denotes individual effects, ν_t denotes period effects, and ε_{it} denotes the random disturbance component.

Individual and periodic effects may be fixed effects, i.e., fixed over time or for a given individual, in which case they do not depend on random factors (FE – Fixed Effects Model). In Random Effect Models (RE), each individual is assigned a random variable, the realisation of which is responsible for the individual effect in a given period. As a result, individual effects are not treated as parameters. Under the assumption of factor constancy, the random component is assumed to capture all differences between objects and periods (oneway model). On the other hand, we obtain a twoway model if we assume that the intercept differs for different periods and objects.

Panel models with spatial autoregression of both the explanatory variable and the random component taking into account fixed effects (FE) and random effects (RE), were used in the study. The model with spatial autoregression of the explanatory variable, including fixed effects (SAR-FE – Spatial Autoregressive Fixed Effect Model), can be presented in the following simplified form:

$$y_{it} = \alpha_i + x_{it}^T \beta + \rho (Wy)_{it} + u_{it}, \quad u_{it} \sim N(0, \sigma_u^2) \qquad (2)$$

However, when taking into account random effects (SAR-FE – Spatial Autoregressive Random Effect Model), the form of the model will be as follows:

$$\begin{gathered} y_{it} = \alpha_0 + x_{it}^T \beta + \rho (Wy)_{it} + v_{it} \\ v_{it} = \alpha_i + u_{it} \end{gathered} \qquad (3)$$

where ρ denotes the spatial lag parameter, while $(Wy)_{it}$ denotes the corresponding observation of the spatial image of the explained variable at the i-th location, in period t.

✉radoslaw.cellmer@uwm.edu.pl

The fixed effects model accounting for the spatial autocorrelation of the random component (SE-FE – Spatial Error Fixed Effect Model) has the form:

$$y_{it} = \alpha_i + x_{it}^T\beta + u_{it}$$
$$u_{it} = \lambda(Wu)_{it} + \varepsilon_{it}, \quad \varepsilon_{\mathrm{it}} \sim N(0, \sigma_\varepsilon^2) \tag{4}$$

In contrast, the Spatial Error Random Effects Model (SE-RE) can be written as follows:

$$y_{it} = \alpha_0 + x_{it}^T\beta + v_{it}$$
$$v_{it} = \alpha_i + u_{it}$$
$$u_{it} = \lambda(Wu)_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \tag{5}$$

where λ denotes the spatial autocorrelation parameter of the random component.

To verify the existence of spatial interactions, a marginal Lagrange multiplier test (marginal LM test for spatial error correlation or random effects) was used (Baltagi et al., 2003), which also determined whether it was reasonable to introduce regional effects into the model. Locally robust LM tests for spatial lag correlation sub spatial error correlation were used to select an appropriate model form (Anselin et al., 1996; Elhorst et al., 2014). The type of spatial dependence (spatial lag or spatial error) was determined using this test. The Hausman test (Millo & Piras, 2012) was also used to confirm the results.

MATERIALS

The research was conducted on the territory of Poland. Data used for analysis refer to the period from 2011 to 2020 and come from the local data bank maintained by the Central Statistical Office (www.stat.gov.pl). According to the valid in Poland nomenclature of territorial units for statistical purposes developed based on the European Nomenclature of Territorial Units for Statistics (NUTS), as a statistical unit was adopted the poviat area (NUTS level 4). The number of dwellings per 1,000 people and the average usable floor space per person was selected from many housing needs satisfaction indicators. Each examined unit also collected data on the fundamental social and economic indicators. The selection of the adopted set of variables was guided primarily by the factual premises and the results of research conducted so far. Although the taken into account conditions are represented in national statistical data by a much larger number of indicators, limiting their number allows minimising the risk of collinearity (i.e. their correlation). The list of adopted indicators and their designations are presented in Table 1. In total, data were collected for all 380 poviats in Poland.

Table 1. Indicators used in the study and their symbols

Indicator (variable)	Symbol
Number of dwellings per 1,000 persons	Y_1
The average floor area of a dwelling per 1 person	Y_2
Marriages per 1,000 population	X_1
Population density (person/km^2)	X_2
Percentage of the working-age population in the total population	X_3
Population growth in %	X_4
Migration balance	X_5
Entities entered in the business register per 10,000 population	X_6
Revenue of municipal budgets per 1 inhabitant	X_7
Registered unemployment rate	X_8
The average monthly gross salary	X_9
The average price of 1m^2 of an apartment	X_{10}

Source: own preparation.

In Poland, the housing issue is one of the most pressing challenges facing the government and local governments. According to a report prepared by Habitat for Humanity Poland (www.habitat.pl/forum-mieszkaniowe-2020), the lack of housing and prospects for solving this problem is one of the three most critical problems for Polish families.

Figure 1 shows the number of dwellings per 1,000 population (variable Y_1) in 2021 in selected European countries.

These are estimates of the Deloitte consulting firm (www.deloitte.com), as Eurostat does not publish such statistics for the whole EU. However, they can be found, among others, in reports by Deloitte, which

✉radoslaw.cellmer@uwm.edu.pl

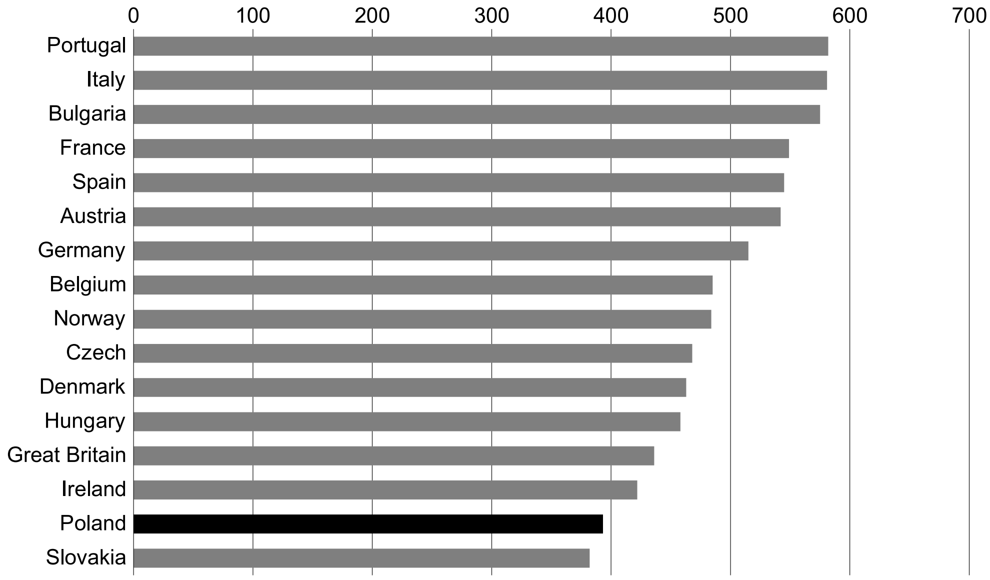

Fig. 1. Number of dwellings per 1,000 population
Source: own preparation based on www.GetHome.pl and www.deloitte.com.

uses data on the number of inhabitants and the number of dwellings, which are published by statistical offices of individual countries. On average, in Europe, there are 435 apartments per 1,000 people. With 393 apartments, Poland is still far from the more affluent EU countries, such as Austria, France or Germany, and even from Central and Eastern Europe, such as Hungary or the Czech Republic.

Moreover, the indicator does not always reflect the actual level of satisfaction with housing needs. For example, Portugal, Italy and Bulgaria boast the highest apartments per 1,000 inhabitants. However, these are countries where a large part of the resources are holiday apartments.

Regarding the average usable floor area of a dwelling per person (variable Y_2), according to Eurostat data, in Poland, it amounted to slightly more than 29 m^2, while a statistical inhabitant of Europe has a floor area of approx. 40 m^2. About 40 m^2 per person is in France, Spain, Latvia, Finland or Italy. The largest area is in Denmark, over 60 m^2 per person. Figure 2 shows the variation of the explanatory variables Y_1 and Y_2 in the cross-sectional and time series for all 380 poviats in Poland.

Information provided by the Ministry of Development (www.gov.pl/web/rozwoj-technologia) shows that the housing deficit at the end of 2019 was 641,000 units. However, based on CSO data, it can be concluded that the housing situation is consistently improving. At the beginning of the analysis period, there were just over 330 dwellings per 1,000 inhabitants, while in 2020, there were 30 more dwellings. However, it is worth noting that this relationship looked much better in the five major cities: 539.9 in Warsaw, 500.7 in Wrocław and the least – 478.9 in Gdańsk. This may be due to the different social models that describe demographics in cities (especially the largest ones) and rural areas. In cities, the ample supply of developer apartments and higher wages make it easier for even young families to get their property. In villages, in many regions of our country, we can still see multi-generational houses inhabited by grandparents, parents and their children.

The situation is also improving in terms of space per person. While in 2011 there were slightly more than 25 meters per person, today it is nearly 4 m^2 more. Based on the growing trends, it can be easily estimated that Poland will reach the current European average only in about 20 years.

✉radoslaw.cellmer@uwm.edu.pl

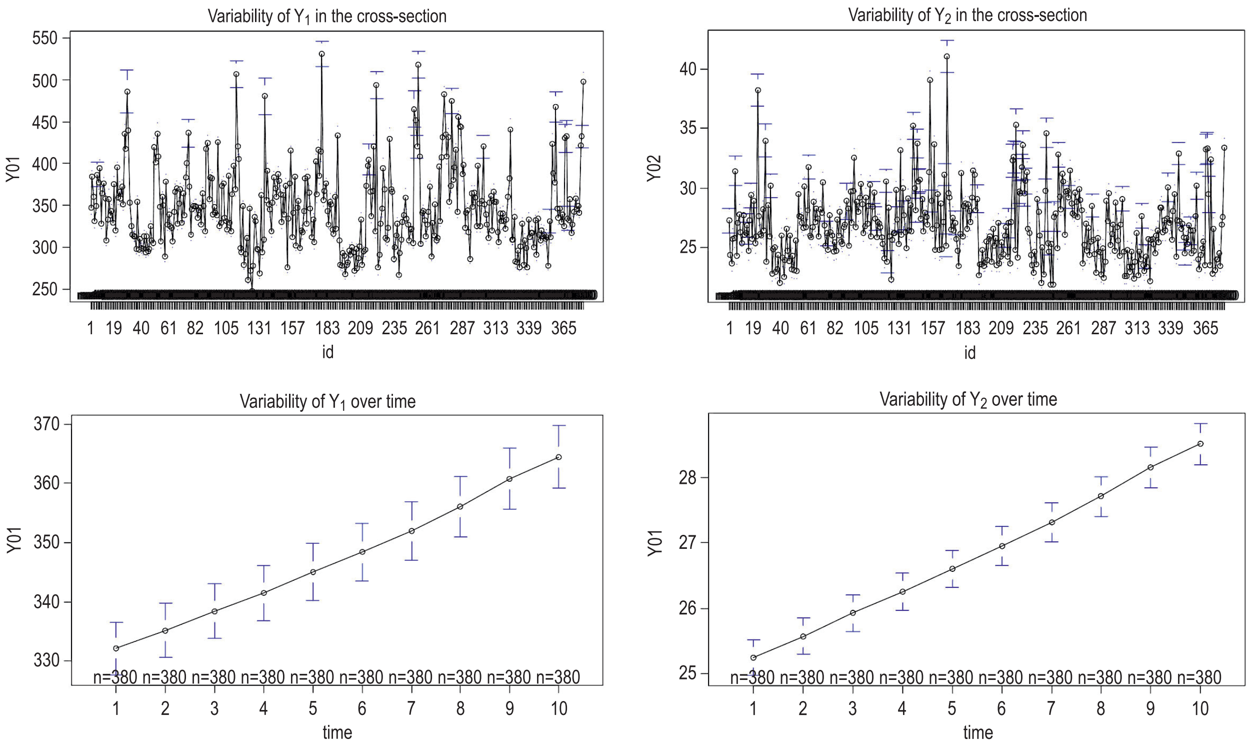

Fig. 2. Variability of Y_1 and Y_2 in the cross-section and over time
Source: own preparation.

RESULTS AND DISCUSSION

The number of dwellings per 1,000 people (Y_1) and the usable floor space per person (Y_2) were used as dependent variables. The explanatory variables are presented in Table 1. The developed models are primarily diagnostic; hence, the fundamental assumption for interpreting the results was that the modelled relationships and dependencies are not causal. In any case, the subject of analysis was not causality but only statistical relationships between analysed variables.

Pooled models

In the first step of the analyses, a pooled model was developed separately for the explanatory variables Y_1 and Y_2, and then tests were conducted to determine the significance of individual and time effects. These tests formed the basis for deciding on the form of the panel model. The panel model was then built and interpreted. In the next step, tests were performed to determine the significance of spatial relationships. Based on these tests, a spatial panel model was built, and the interpretation of time effects and the spatial distribution of individual effects was made. The results of the pooled estimation are presented in Table 2. For clarity, the model in which the dependent variable was the number of dwellings per 1,000 people was named as model Y_1, while the model in which the dependent variable was the floor area of the dwelling per person was named as model Y_2.

The general model is only a prelude to further analysis. Regressions are performed on all available observations as cross-sectional data in the pooled model. It assumes no individual effects and no changes of the analysed phenomenon over time. The parameters of the pooled model were determined using the ordinary least squares (OLS) method. The results show that parameters for all analysed variables are statistically significant at a significance level less than 0.05. In the model in which the

✉radoslaw.cellmer@uwm.edu.pl

Table 2. Pooled model. OLS estimation results

Model Y_1				Model Y_2			
Variable	Estimate	Std. error	p-value	Variable	Estimate	Std. error	p-value
Intercept	321.560	20.480	< 0.001	Intercept	32.888	1.795	< 0.001
X_1	7.262	0.773	< 0.001	X_1	0.705	0.067	< 0.001
X_2	0.032	0.001	< 0.001	X_2	-0.001	0.00005	< 0.001
X_3	-2.094	0.304	< 0.001	X_3	-0.166	0.026	< 0.001
X_4	-9.216	0.199	< 0.001	X_4	-0.509	0.017	< 0.001
X_5	0.891	0.127	< 0.001	X_5	0.393	0.011	< 0.001
X_6	0.634	0.020	< 0.001	X_6	0.013	0.001	< 0.001
X_7	-0.002	0.001	< 0.001	X_7	0.0001	0.00005	0.005
X_8	0.641	0.081	< 0.001	X_8	-0.129	0.007	< 0.001
X_9	0.008	0.001	< 0.001	X_9	-0.0002	0.00007	0.002
X_{10}	0.004	0.001	< 0.001	X_{10}	0.0006	0.00004	< 0.001
R^2 = 0.797, logLik = -17163.5, AIC = 34351				R^2 = 0.598, logLik = -7913.01, AIC = 15848			

Source: own preparation.

dependent variable was Y_1, three explanatory variables turned out to be destimulants. Somewhat puzzling is the result that more prosperous regions (X_7) have fewer housing units per 1,000 people than poorer regions. In the second model, where the dependent variable was Y_2, it is worth noting that in regions with higher earnings (X_9), the m^2/person ratio is lower. However, the very specificity of OLS estimation from all data should be considered. In this case, we omit information about the sample structure; hence, one should have limited confidence in the results, as the estimators will be inefficient and biased in some situations (Baltagi, 2021).

Panel models

In order to determine the appropriate regression model to analyse the panel data, some statistical tests were conducted, including the Breuch-Pagan test and Hausman test. The results are presented in Table 3.

The first two tests, i.e. Breuch Pagan LM Test and the F test for individual effects test, clearly indicate that in both cases, the panel model with both random effects and fixed effects are more appropriate than the general (pooled) model. Hausman test determines whether we deal with random effects or fixed effects (Baltagi, 2021). In both cases, the chi-square value proved to be statistically significant, which means that the hypothesis of random effects occurrence was rejected. The Breuch-Pagan test for the significance of time effects was also conducted. In both models, the chi-square statistic was statistically significant, which means that the hypothesis of no significance of time effects should be rejected. As a result, it was determined that the appropriate models would be twoways models in which individual effects (fixed effects) and time effects are simultaneously present. Table 4 presents the modelling results for the explanatory variables Y_1 and Y_2, respectively. Only those parameters that were found to be statistically

Table 3. Testing results

Test	Model Y_1		Model Y_2	
Breuch Pagan LM Test	LM = 105.9	p < 0.001	LM = 112.8	p < 0.001
F test for individual effects test	F = 317.0	p < 0.001	F = 385.1	p < 0.001
Hausman test	chisq = 274.2	p < 0.001	chisq = 88.37	p < 0.001
time effects (Breusch-Pagan)	chisq = 3687.0	p < 0.001	chisq = 136.8	p < 0.001

Source: own preparation.

✉radoslaw.cellmer@uwm.edu.pl

Table 4. Results of panel modelling (within, twoways)

Panel model Y_1			
Variable	Estimate	Std. error	p-value
intercept	446.446	7.314	< 0.001
X01	1.113	0.197	< 0.001
–	–	–	–
X03	-2.284	0.097	< 0.001
–	–	–	–
X05	0.327	0.067	< 0.001
X06	0.309	0.024	< 0.001
X07	-0.0009	0.0002	< 0.001
X08	0.205	0.042	< 0.001
X09	0.001	0.0006	0.037
X10	0.002	0.0002	< 0.001
R^2 = 0.902, logLik = -10076.3, AIC = 20176.7			

Panel model Y_2			
Variable	Estimate	Std. error	p-value
intercept	22.231	0.403	< 0.001
–	–	–	–
X02	-0.001	0.00009	< 0.001
X03	0.021	0.006	< 0.001
–	–	–	–
X05	0.039	0.004	< 0.001
X06	0.032	0.001	< 0.001
X07	0.00004	0.00002	0.030
X08	0.027	0.003	< 0.001
–	–	–	–
X10	0.00009	0.00001	< 0.001
R^2 = 0.921, logLik = 301.765, AIC = 187.529			

Source: own preparation.

significant at a significance level of less than 0.05 were included in the models.

The quality of fit of these models can be indicated by the pseudo R^2, logLik and AIC information criterion indices. The coefficient of determination for the panel model Y_1 was 0.902, while the OLS model was 0.797. In the case of the Y_2 model, the coefficient of determination was as high as 0.921, which may indicate a very high model fit the data.

However, in this case, much more critical substantively, because of the estimation method, are the information criteria, in this case, AIC (Akaike criterion). This criterion also indicates that panel models have a much better fit to the data than OLS models. Unlike the OLS models, not all parameters proved to be statistically significant. In model Y_1, this applies to the parameters at variable X_2 (population density) and variable X_9 (average wage), while in model Y_2, the parameters at variable X_1 (number of marriages), X_4 (birth rate) and X_9 turned out to be statistically insignificant. Especially noteworthy are the parameters located at variables X_3 and X_8 in the Y_2 model. The pooled estimation result indicated that these variables are destimulants, while the panel model indicates stimulants. The slight variation between poviats in the percentage of the population in multiple

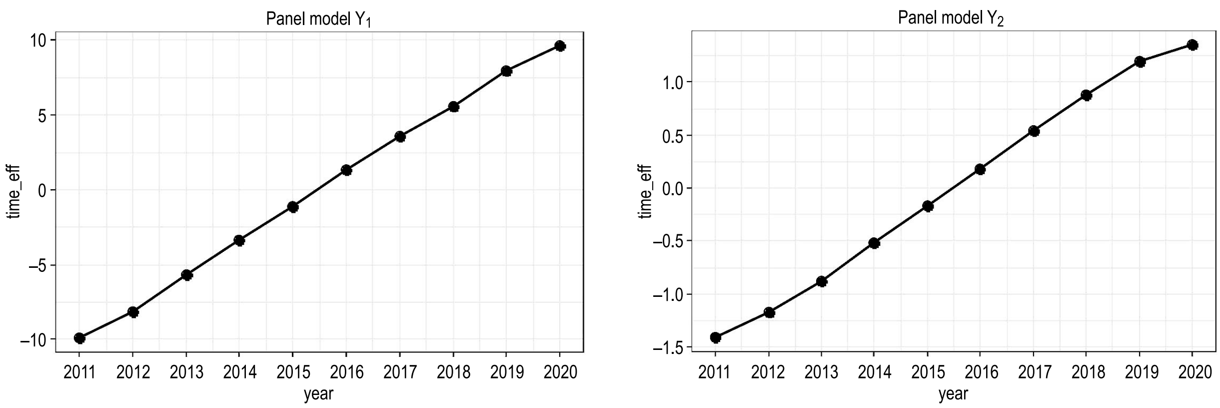

Fig. 3. Time effects in panel models
Source: own preparation.

radoslaw.cellmer@uwm.edu.pl

productive mobility in the total population means that this variable should not play a significant role. However, the unemployment rate should significantly impact housing need satisfaction. In this case, with increasing unemployment, one can observe a larger housing area per person. However, looking for a cause-and-effect dependence in this relationship could lead to unwarranted conclusions.

The time effects in both models show a clear increasing trend (Fig. 3) which confirms the long-term market observations based on statistical data.

Spatial panel models

In further research, it was assumed that an essential element of the processes occurring in the housing market is space, be it physical, economic, institutional-legal or social. As in many European countries, the country's territory is diversified economically, socially, and even culturally. Because of this, it can be expected that factors shaping the housing market vary in geographical space (Belke & Keil, 2018; Broitman & Koomen, 2015), which may result in temporal and spatial variation in the indicators indicating the level of satisfaction of housing needs. Spatial effects accounted for in real estate market models, especially on a regional basis, may include spatial autocorrelation accounted for in spatial panel models (Holly et al., 2010; Lee & Yu, 2010). During the construction of spatial models, the description of the spatial structure of data in a matrix of weights can be the subject of consideration. A weight matrix constructed based on the criterion of a common boundary (first-order neighbourhood) was adopted for the study.

In order to select an appropriate model form, some statistical tests were performed to determine the desirability of using spatial modelling and the choice between error and spatial lag models primarily (Millo & Piras, 2012). The results are presented in Table 5.

The LM test of the type of relationship (spatial error or spatial lag) in both models indicates the significance of both spatial error and spatial lag models. However, the choice of model form was determined by the lower significance level of the spatial error models. In the Hausman test, the null hypothesis is no individual effects. In both models, the significance level indicates that this hypothesis should be rejected, favouring the alternative hypothesis; hence the fixed effects estimator is the only consistent one. As a result, a spatial panel model with individual and time effects (twoways) was adopted for further analysis. The parameter estimation results of the models with explained variables Y_1 and Y_2 are presented in Table 6. As in the panel models, only those parameters that proved statistically significant at a significance level of less than 0.05 were included.

Both model Y_1 and model Y_2 showed a very high degree of fit to the data. This is evidenced, among other things, by the coefficients of determination, whose value in both models was 0.995. Also, the AIC information criteria indicate that the spatial panel models have a much better fit than the models without considering spatial dependencies. The values of the rho coefficients evidence the relatively high level of spatial autocorrelation of the residuals. For model Y_1, the coefficient was 0.346, while for model Y_2, the coefficient has reached a value equal to 0.310.

In the Y_1 model, only the parameter next to the X_2 variable (population density) was statistically insignificant at $p<0.05$, while the remaining parameters were statistically significant. The estimation results of the spatial panel model are similar to those of the classical panel model. It is worth emphasising that

Table 5. Testing for spatial dependence

Test	Model Y_1		Model Y_2	
LM test for spatial error dependence	LM = 1459	$p < 0.001$	LM = 951.1	$p < 0.001$
LM test for spatial lag dependence	LM = 551.4	$p < 0.001$	LM = 991.3	$p < 0.001$
Hausman test for spatial models	chisq = 3840	$p < 0.001$	chisq = 106.9	$p < 0.001$

Source: own preparation.

✉radoslaw.cellmer@uwm.edu.pl

Table 6. Results of spatial panel modelling (within, twoways)

Spatial panel model Y_1				Spatial panel model Y_2			
Variable	Estimate	Std. error	p-value	Variable	Estimate	Std. error	p-value
rho	0.346	0.021	< 0.001	rho	0.310	0.021	< 0.001
intercept	464.338	6.773	< 0.001	intercept	22.220	0.366	< 0.001
X1	1.223	0.180	< 0.001	–	–	–	–
–	–	–	–	X2	-0.001	0.00008	< 0.001
X3	-2.731	0.095	< 0.001	X3	0.023	0.006	< 0.001
X4	-0.279	0.087	0.001	–	–	–	–
X5	0.241	0.059	< 0.001	X5	0.036	0.004	< 0.001
X6	0.346	0.023	< 0.001	X6	0.033	0.001	< 0.001
X7	-0.0006	0.0002	0.015	X7	0.00004	0.00001	0.017
X8	0.281	0.043	< 0.001	X8	0.026	0.003	< 0.001
X9	0.002	0.0006	< 0.001	–	–	–	–
X10	0.002	0.0002	< 0.001	X10	0.00007	0.00001	< 0.001
R^2 = 0.995, logLik = -8229.07, AIC = 20008.2				R^2 = 0.995, logLik = 1848.54, AIC = -4714,3			

Source: own preparation.

most of the variables, as expected, are stimulants, which means that higher values of the variables are accompanied by higher values of the indicator of the number of housing units per 1,000 people. As in previous models, the variable denoting income of municipal budgets turned out to be a destimulant. However, this dependence should not be treated in the category of causality but only as a statistical relationship. Based on the relation between the parameter's value and its error (t-value), it may be concluded that the most significant for the formation of the number of dwellings per 1,000 people has the percentage of the mobile working population in the total population (X_3).

The Y_2 model also confirms the previous considerations, and the estimation results of the spatial panel model are similar to the estimation results without taking into account the spatial dependencies. The parameters next to X_1, X_4 and X_9 variables were not statistically significant. In this case, the variable X_6 (number of entities registered in the business register per 1,000 people) has the most significance for developing the floor space per capita. Population density (X_2) is slightly less important but also significant. This means housing needs fulfilment indicators to reach higher values in more urbanised areas.

The adopted form of models (models with fixed effects) means that each spatial unit is assigned an individual effect that indicates differences in the indicators of satisfying housing needs resulting from factors other than those taken into consideration as explanatory variables. These effects may result from, among other things, special conditions related to location and level of socio-economic development. The spatial distribution of individual effects in spatial panel models Y_1 and Y_2 and the spatial distribution of significance level (p-value) of individual effects are presented below (Fig. 4).

The distribution of individual effects of model Y_1 shows that clusters of individual negative effects occur mainly in the south-eastern and central-eastern parts of Poland. Positive individual effects do not form such clear clusters, but it is still possible to notice their grouping in Poland's central and eastern parts. The highest positive effects occur in poviats with the largest cities in Poland. The distribution of individual effects of the Y_2 model indicates that positive values are clustered along the belt from the southern to the central-eastern part of Poland. On the other hand, negative effects occur mainly in Poland's northern and south-eastern parts. In this case, the individual effect

✉radoslaw.cellmer@uwm.edu.pl

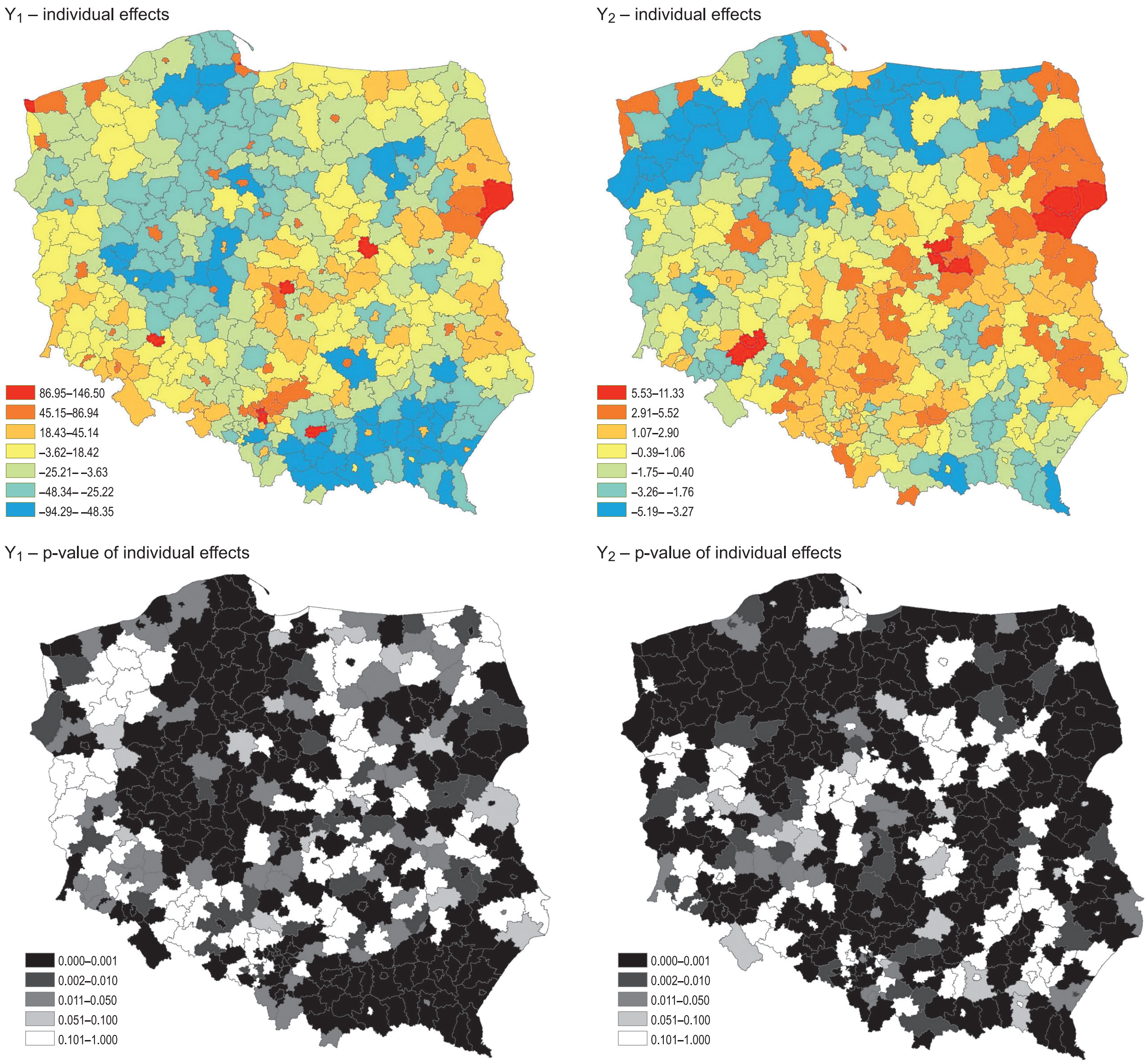

Fig. 4. Individual effects in a spatial panel model
Source: own preparation.

on the index of the functional floor area of a dwelling per person is not so strongly associated with urban centers, while the country's division into two parts is clear, which may result from differences in the socio-economic development the country.

Time effects for both Y_1 and Y_2 models show a clear upward trend (Fig. 5), similarly to panel models without spatial dependencies. At the same time, it signifies a clear improvement in the indicators characterising the satisfaction of housing needs. However, it is worth noting an inevitable deceleration of the trend in the last year of the analysis (i.e. 2020), which may be related to the economic slowdown caused by the pandemic situation.

✉radoslaw.cellmer@uwm.edu.pl

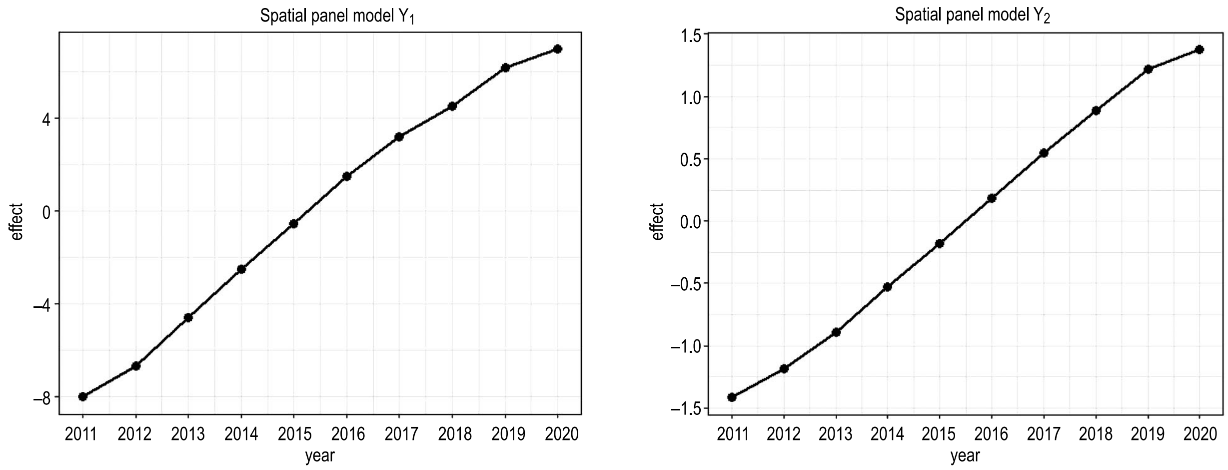

Fig. 5. Time effects in spatial panel models
Source: own preparation.

CONCLUSIONS

This study attempts to assess the relationship between socio-demographic and economic conditions and indicators of housing needs satisfaction in spatial terms. The research was conducted using panel models in classical and spatial terms. The great majority of variables accepted as determinants turned out to be statistically significant both in terms of influence on the number of apartments per 1,000 people and the usable floor space of an apartment per person, although the role of some factors such as unemployment is not as obvious as it might seem. Based on the research carried out, it was found that the determinants of indicators determining the level of satisfaction of housing needs are spatially diversified, resulting from divisions on the economic and cultural or historical grounds. As Poland, like most European countries, is not a homogenous country, the socio-economic analyses at the local level may differ significantly from those at the national level.

Spatial panel models fit the empirical data better than models estimated without considering spatial dependencies. This is evidenced by the value of the determination coefficients and the information criterion based on the reliability function (AIC).

The study results indicate that the problem of including space in socio-economic studies is extensive and not fully solved. At the same time, the use of spatial panel models can contribute to further analysis, in which a wide range of spatial relationships can be taken into account, which may concern not only physical space but also social, cultural and even legal space. This would enable a better understanding of the phenomena occurring in the real estate market at both global and local levels.

Author contributions: author has given approval to the final version of the article. Authors contributed to this work as follows: R.C. developed the concept and designed the study, R.C. collected the data, R.C. analysed and interpreted the data, R.C. prepared draft of article, R.C. revised the article critically for important intellectual content.

Funding: This research was not funded by external funds.

REFERENCES

Amerigo, M., & Aragones, J. I. (1997). A Theoretical and Methodological Approach to the Study of Residential Satisfaction. *Journal of Environmental Psychology*, *17*(1), 47–57. https://doi.org/10.1006/JEVP.1996.0038

Anselin, L., Bera, A. K., Florax, R., & Yoon, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, *26*(1), 77–104. https://doi.org/10.1016/0166-0462(95)02111-6

✉radoslaw.cellmer@uwm.edu.pl

Bajari, P., Chan, P., Krueger, D., & Miller, D. (2010). A Dynamic Model of Housing Demand. *NBER Working Paper Series*, *54*(April), 409–442. Retrieved from: http://www.nber.org/papers/w15955

Baltagi, B. (2021). *Econometric Analysis of Panel Data* (3rd ed.). Springer Nature.

Baltagi, B., Song, S. H., Koh, W., Baltagi, B., Song, S. H., & Koh, W. (2003). Testing panel data regression models with spatial error correlation. *Journal of Econometrics*, *117*(1), 123–150. https://doi.org/10.1016/S0304-4076(03)00120-9

Bayer, P., McMillan, R., Murphy, A., & Timmins, C. (2016). A Dynamic Model of Demand for Houses and Neighborhoods. *Econometrica*, *84*(3), 893–942. https://doi.org/10.3982/ecta10170

Belke, A., & Keil, J. (2018). Fundamental Determinants of Real Estate Prices: A Panel Study of German Regions. *International Advances in Economic Research*, *24*(1), 25–45. https://doi.org/10.1007/S11294-018-9671-2

Bramley, G., Pawson, H., White, M., Watkins, D., & Pleasce, N. (2010). *Estimating housing need*. University of York. Retrieved from: https://eprints.whiterose.ac.uk/72850/

Broitman, D., & Koomen, E. (2015). Regional diversity in residential development: a decade of urban and peri-urban housing dynamics in The Netherlands. *Letters in Spatial and Resource Sciences*, *8*(3), 201–217. https://doi.org/10.1007/S12076-014-0134-Y

Elhorst, J., Scheuer, C., Boot, E., Carse, N., Clardy, A., Gallagher, J., Heck, S., Marron, S., Martinez-Alvarez, L., Masarykova, D., Mcmillan, P., Murphy, F., Steel, E., Ekdom, H. van, & Vecchione, H. (2014). *Spatial econometrics: from cross-sectional data to spatial panels*. https://doi.org/10.1007/978-3-642-40340-8

Griliches, Z., & Intriligator, M. D. (1984). *Handbook of Econometrics* (Vol. 2). Elsevier.

Heng, C. (2014). Analysis of panel data: Second Edition. In *International Journal of Forecasting* (Issue 1). Elsevier.

Holly, S., Pesaran, M. H., & Yamagata, T. (2010). A spatio-temporal model of house prices in the USA. *Journal of Econometrics*, *158*(1), 160–173. https://doi.org/10.1016/J.JECONOM.2010.03.040

Jayaraman, P., Lacombe, D. J., & Gebremedhin, T. (2013). A Spatial Analysis of the Role of Residential Real Estate Investment in the Economic Development of the Northeast Region of the United States. *Agricultural and Applied Economics Assaciation's AAEA & CAES Joint Annual Meeting, Washington, DC*. Conference paper. https://doi.org/10.22004/AG.ECON.150953

Jones, C., & Leishman, C. (2006). Spatial Dynamics of the Housing Market: An Interurban Perspective. *Urban Studies*, *43*(7), 1041–1059. https://doi.org/10.1080/00420980600711316

Kam, K. J., Lim, A. S. H., Al-Obaidi, K. M., & Lim, T. S. (2018). Evaluating Housing Needs and Preferences of Generation Y in Malaysia. *Planning Practice & Research*, *33*(2), 172–185. https://doi.org/10.1080/02697459.2018.1427413

Kim, J. S., & Kim, J. M. (2017). The Relation between Housing Needs and Housing Function according to the Maslow's Theory of Needs. *KIEAE Journal*, *17*(4), 13–19. https://doi.org/10.12813/kieae.2017.17.4.013

King, P. (2006). Housing, individuals and the state: The morality of government intervention. *Housing, Individuals and the State: The Morality of Government Intervention*, 1–151. https://doi.org/10.4324/9780203004746

Lee, L., & Yu, J. (2010). Some recent developments in spatial panel data models. *Regional Science and Urban Economics*, *40*(5), 255–271. https://doi.org/10.1016/J.REGSCIURBECO.2009.09.002

Max, L. (1999). Determinants of residential satisfaction: Ordered logit vs. regression models. *Growth and Change*, *30*(2), 264–287. https://doi.org/10.1111/0017-4815.00113

Millo, G., & Piras, G. (2012). Splm: Spatial panel data models in R. *Journal of Statistical Software*, *47*(1). https://doi.org/10.18637/jss.v047.i01

Mohit, M. A., Mahfoud, A., Al-Khanbashiraja, M., & Al-Khanbashi Raja, M. (2014). Residential Satisfaction – Concept Theories and Empirical Studies. *Planning Malaysia*, *III*(3), 47–66. https://doi.org/10.21837/PM.V12I3.131

Myers, D., Pitkin, J., & Park, J. (2002). Estimation of housing needs amid population growth and change. *Housing Policy Debate*, *13*(3), 567–596. https://doi.org/10.1080/10511482.2002.9521455

Nurzafira, Z. A., Mohamad, I. A., Noraliza, B., & Muhammad, N. A. (2019). Residential Satisfaction: Literature Review and A Conceptual Framework. *IOP Conference Series: Earth and Environmental Science*, *385*(1), 012040. https://doi.org/10.1088/1755-1315/385/1/012040

Roslan, S. N. M., Abd Azis, W. N. A. W., Kari, F., & Satar, N. M. (2020). Assessment of Housing Attributes Towards Neighbourhood Satisfaction in

✉radoslaw.cellmer@uwm.edu.pl

The Klang Valley. *International Journal of Property Sciences (E-ISSN: 2229-8568)*, *10*(1), 1–15. https://doi.org/10.22452/ijps.vol10no1.1

Rowley, S., Leishman, C., Baker, E., Bentley, R., & Lester, L. (2017). Modelling housing need in Australia to 2025. *AHURI Final Report*, *287*, 1–70. https://doi.org/10.18408/AHURI-8106901

Tan, T. H. (2016). Residential satisfaction in gated communities: Case study of Desa Park City, Kuala Lumpur, Malaysia. *Property Management*, *34*(2), 84–99. https://doi.org/10.1108/PM-02-2015-0009

Tibaijuka, A. K. (2013). *Building Prosperity: The Centrality of Housing in Economic Development*. Earthscan. https://doi.org/10.4324/9781849770040

Vera-Toscano, E., & Ateca-Amestoy, V. (2008). The relevance of social interactions on housing satisfaction. *Social Indicators Research*, *86*(2), 257–274. https://doi.org/10.1007/S11205-007-9107-5

Wang, Z., & Zhang, Q. (2014). Fundamental factors in the housing markets of China. *Journal of Housing Economics*, *25*, 53–61. https://doi.org/10.1016/J.JHE.2014.04.001

Xiong, X., Guo, H., & Hu, X. (2020). The housing demand analysis and prediction of the real estate based on the AWGM (1, N) model. *Grey Systems: Theory and Application*, *11*(2), 222–240. https://doi.org/10.1108/gs-09-2019-0035

✉radoslaw.cellmer@uwm.edu.pl