Article

Modelling Housing Rents Using Spatial Autoregressive Geographically Weighted Regression: A Case Study in Cracow, Poland

Mateusz Tomal [iD]

Department of Real Estate and Investment Economics, Cracow University of Economics, Rakowicka 27, 31-510 Cracow, Poland; tomalm@uek.krakow.pl

check for updates

Abstract: The proportion of tenants will undoubtedly rise in Poland, where at present, the ownership housing model is very dominant. As a result, the rental housing market in Poland is currently under-researched in comparison with owner-occupancy. In order to narrow this research gap, this study attempts to identify the determinants affecting rental prices in Cracow. The latter were obtained from the internet platform otodom.pl using the web scraping technique. To identify rent determinants, ordinary least squares (OLS) regression and spatial econometric methods were used. In particular, traditional spatial autoregressive model (SAR) and spatial autoregressive geographically weighted regression (GWR-SAR) were employed, which made it possible to take into account the spatial heterogeneity of the parameters of determinants and the spatially changing spatial autocorrelation of housing rents. In-depth analysis of rent determinants using the GWR-SAR model exposed the complexity of the rental market in Cracow. Estimates of the above model revealed that many local markets can be identified in Cracow, with different factors shaping housing rents. However, one can identify some determinants that are ubiquitous for almost the entire city. This concerns mainly the variables describing the area of the flat and the age of the building. Moreover, the Monte Carlo test indicated that the spatial autoregressive parameter also changes significantly over space.

Keywords: housing market; rental price; housing rent; housing price; spatial hedonic model; spatial hedonic pricing model; spatial dependence; spatial heterogeneity; geographically weighted regression; GWR

1. Introduction

Currently, the rental housing market is increasingly researched. This is because of the fact that the rental market is developing dynamically, especially in urban areas. The reason for this includes, among other things, the rising prices of houses, which causes the housing affordability problem [1]. In addition, there is now an established preference among young people towards renting a flat [2], as this provides greater flexibility in moving houses. Moreover, the development of the rental market is determined by the growing popularity of the gig economy [3]. The latter is characterised by contract work and unpredictable income, which, in a large number of cases, makes it impossible to buy a flat.

In view of the above, it must be concluded that the residential rental market is a very important part of the housing market as a whole and an essential supplement to home-ownership. The importance of the rental housing market is also underlined by statistics showing that, worldwide, 1.2 billion people live in rented accommodation [4]. The number of tenants, however, varies widely across Europe; in particular, the highest percentage of households renting in market terms can be found in Switzerland and Germany (51.1% and 40.8%, respectively). Conversely, tenancy is least popular in Central and Eastern European (CEE) countries, where renters represent less than 10% of the population.

The relatively low interest in this form of residence in the above-mentioned countries also affects studies on the rental housing market, which are quite rare. The latter applies especially to micro-level research, that is, rent price modelling. On the macro level, however, an increasing number of analyses can be observed, the subject of which is the residential rental market in CEE countries. For example, Rubaszek et al. [5,6] showed that a developed rental market mitigates the fluctuations in the residential sector and contributes to macroeconomic stability.

The premises set out in the introduction, however, give reason to believe that, even in countries where home-ownership is dominant, the rental market will also develop dynamically. Therefore, research in emerging residential rental markets, and especially those where the determinants of rental prices are identified, is extremely important for policy-makers, as it provides valuable information about the housing market, which translates into better housing policy-making. The aim of this study was defined on this basis, and is to identify factors at the micro level significantly affecting housing rents in the city of Cracow. In order to carry out the survey, unique data on offer rental prices using web scraping technique were obtained from the internet platform otodom.pl.

To the best of the author's knowledge, this will be the first such investigation in Poland. Moreover, when analysing previous research on the detection of determinants of house or rental prices, it should be noted that authors put particular emphasis on the study of spatial dependence and spatial heterogeneity. There are very few empirical analyses, however, combining these two elements. Therefore, the geographically weighted regression (GWR) model with a spatially varying spatial autoregressive parameter will be used in this study to identify the determinants of rental prices. It should be noted that the above model has not yet been used to examine rental prices empirically.

Taking into account the outlined goal and research methodology, this article is intended to answer the following research questions:

1. What factors significantly affect housing rents in Cracow?
2. Is there spatial autocorrelation of rental prices?
3. Is there spatial heterogeneity in relation to independent variables or to the spatial autoregressive term?

The rest of the article is organised as follows. Section 2 presents an overview of research to date on the determinants of both house and rental prices, taking into account particular analyses using spatial econometrics. Section 3 describes the study area, the spatial differentiation of rents, and the research methodology used in this article. Section 4, in turn, discusses the results of estimations of econometric models. The final section deals with research conclusions, the main limitations, and directions of future analyses.

2. Literature Review on House and Rental Price Determinants

The literature on the determinants of both house and rental prices is quite extensive. In particular, it is possible to identify works that examine economic, demographic, and environmental determinants of housing demand and supply, which in turn define real estate market prices [7,8]. In this case, average prices among cities, municipalities, districts, or other larger areas are usually modelled, and their determinants are called macro or meso factors. It should be stressed, however, that there are far fewer studies of this type compared with research in which the variables are micro in nature, that is, prices or rents for individual properties. As far as the identification of micro determinants of house and rental prices is concerned, the largest number of scientific articles by far has been based on the so-called hedonic price model, which, econometrically speaking, adopts the form of multiple regression and mainly takes into account the physical characteristics of the property and its location.

It should be noted, however, that in the past few years, house and rental price modelling by means of spatial econometrics has been leading the way in research. In particular, many articles in this area concern the identification of factors shaping housing prices in China [9–15], USA [16–19],

United Kingdom [20–25], Canada [26], Malaysia [27], Republic of Korea [28], Austria [29–31], Norway [32,33], and Poland [34–39].

Far fewer analyses have been devoted to the determinants of housing rents. One such study was conducted by Li et al. [40], who modelled rental housing listings in Shanghai. The authors divided the variables that potentially affected rental price differentiation into three groups, that is, variables characterising the property itself, its immediate neighbourhood, and the regional environment. The results showed that the rental housing market in Shanghai is shaped mainly by economic factors (labour market and wage levels), as well as factors characterising the availability of public service amenities and public transport facilities. These conclusions were largely confirmed by Hu et al. [1], who analysed housing rental prices in Shenzhen using machine-learning algorithms. Another study of housing rents in China was conducted by Zhang et al. [41], identifying that factors, such as commercial centres, primary and middle schools, campuses, subways, expressways, and railways, were key in shaping the residential rental market. A survey of rent determinants was also carried out by Cui et al. [42]. Examining the rental housing market in Beijing, the authors found that the crucial factor for rent level is the proximity of a residential property to an employment centre and public transport. The identification of rent determinants was also performed by Leung and Yiu [43]. Researchers modelled the rental housing market in Hong Kong and found that both structural and environmental factors influence the rents in question.

Outside China, research on the housing rental market is very rare. One can mention, however, the work of Efthymiou and Antoniou [44], who examined both house prices and rents in Athens. They focused on the analysis of transport infrastructure factors and concluded that, in general, metro, tram, and bus stations positively influence prices and rents. By contrast, road infrastructure that produces negative effects (e.g., noise) reduces house and rental prices. It is also worth noting the study by Crespo and Gret-Regamey [45], according to which rents in Zurich are determined by a number of variables concerning both property characteristics and location. In turn, McCord et al. [46] found that the residential rental market is affected by socio-political conflicts, and ethnic and religious territorial segregations. In the context of the research on rent determinants, it is also worth mentioning the analyses carried out by Suárez-Vega et al., who modelled rental prices in tourist destinations, that is, Gran Canaria (Spain) [47,48], La Palma (Spain) [49], and Penghu (Taiwan) [49].

It should be noted that there are also studies in which the authors have compared the factors shaping rental and house prices. In particular, the works by Cui et al. [42], Hanink et al. [50], and Efthymiou and Antoniou [44] should be cited here.

A detailed analysis of the approaches to modelling house and rental prices in the literature shows that authors have taken into account the possibility of spatial autocorrelation of the dependent variable and/or the spatially varying parameters of independent variables, which is a response to the locality [51] and heterogeneity of the real estate market [52]. In particular, apart from the standard ordinary least squares (OLS) method, house and rent analyses were performed mainly using the following: (i) spatial autoregressive model (SAR), which accounts for spatial dependence; (ii) spatial quantile regression (SQR), allowing for spatial dependence and heterogeneity over price segments; (iii) geographically weighted regression (GWR), which takes into consideration spatial heterogeneity; (iv) geographically and temporally weighted regression (GTWR), accounting for local effects in time and space; (v) semi-parametric (mixed) geographically weighted regression (S-GWR/MGWR), which enables to model simultaneously both spatially varying and constant over space regression coefficients; (vi) multi-scale geographically weighted regression (MGWR), accounting for different bandwidths for each independent variable; and (vii) GWR modelling with spatial autoregressive parameter (GWR-SAR/GWRL). The latter version of the GWR framework is a desirable option for modelling the housing market because it takes into account both spatial effects [21] (spatial dependence and spatial heterogeneity).

3. Methodology

3.1. Study Area

Cracow is a city located in Poland (Figure 1) and is the capitol of the Małopolska Province. As Głuszak and Marona emphasise [53], Cracow is an extremely important place for real estate market research. This is because of several reasons. First of all, it is the second largest city in Poland in terms of population. Moreover, the real estate market in Cracow is developing in a dynamic way. In particular, the average transaction price for residential units from 2006 to 2019 increased from 5193 PLN(the Polish Zloty)/m^2 to 7414 PLN/m^2 on the secondary market, and from 6816 PLN/m^2 to 8244 PLN/m^2 on the primary market [54] (as at 30 April 2020, 1 USD represents approximately 4.17 PLN). Similarly, the average monthly rental price increased from 31.8 PLN/m^2 to 42.7 PLN/m^2 from 2013 to 2019 [54]. The importance of the real estate market in Cracow is also confirmed by data on the annual number of new flats delivered for use, which is one of the highest in Poland. In 2018, this reached almost ten thousand new dwellings.
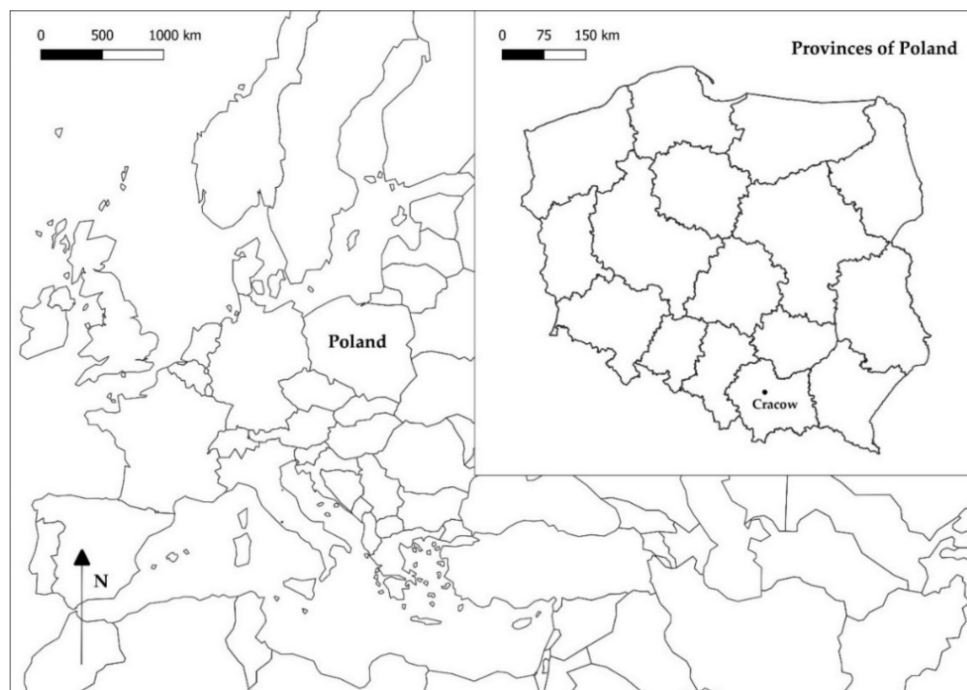
Figure 1. Study area.

It should also be noted that Cracow is a university town, with large numbers of students, both domestic and foreign, arriving each year. These users are a very strong determinant of prices in the rental market. Additionally, Cracow is also a very popular tourist destination. According to the Małopolska Tourist Organisation, in 2019, the city was visited by 14,050,000 tourists. Such increased tourist traffic is obviously not without significance for the functioning of the rental market. It can be expected that, especially within the city centre, there may be price bubbles caused by the so-called short-term renting. All of the above influence the price-to-rent ratio in Cracow, which has oscillated in recent years between 12 and 16 (Figure 2). This translates into much less interest among residents in long-term renting.

Moreover, Cracow is an interesting place to study the determinants of residential rents because of the fact that its real estate market has been assessed as the smartest of all provincial cities in Poland [2]. This should be understood as the presence in a given city of modern online housing platforms or the so-called "automatic" residential rental market.
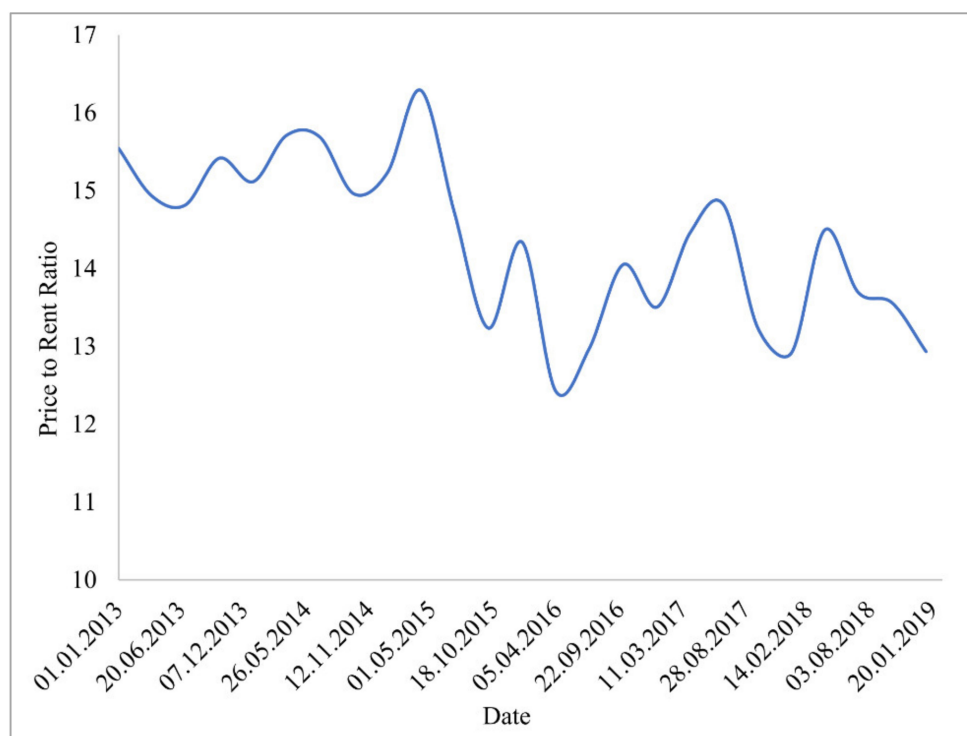
Figure 2. Price-to-rent ratio in Cracow. Source: Own study based on data from National Bank of Poland.

3.2. Data Collection and Processing

The dependent variable in this study is monthly housing rent (PLN/m^2). However, obtaining data on this subject is very challenging because in Poland lacks both official and private databases on transactional rental prices. This is because of the fact that, unlike real estate purchase transactions, lease agreements are drawn up directly by the parties involved and, in the vast majority of cases, do not have to be officially reported anywhere. Therefore, the analysis of determinant rental prices will be based on offer prices from the most popular portal in Poland containing long-term rental announcements, that is, the internet platform otodom.pl. It should be noted that the use of offer rents in this study will allow reliable conclusions to be drawn. This is because of the fact that, according to data from the National Bank of Poland [54], approximately from 2018, transaction and offer prices in the residential rental market in Cracow were even identical.

In order to obtain the data, the web scraping technique was used. On 14 February 2020, data on 4185 monthly housing rents in Cracow were collected. It should be noted, however, that very often in Poland, the same flat is posted on an internet platform by both the landlord and the real estate agency cooperating with him. Sometimes, the owner of a flat may collaborate with several agencies at the same time. This leads to the repetition of a large percentage of the data obtained. Therefore, preliminary data processing was carried out and the detected duplicates were removed. Moreover, outlier observations and those for which the exact location of the flat was not given, that is, the geographical coordinates (latitude and longitude), were also eliminated. At the end of this process, 2336 unique observations were collected.

3.3. Spatial Distribution of Housing Rents

For the initial recognition of the data, information on latitude and longitude, and the spatial distribution of housing rents in Cracow, is presented in Figure 3. In particular, it can be noted that the vast majority of flats for rent are located at the city centre and along main roads. Conversely, to the east of the city, there are hardly any flats for rent, which is mainly because of the under-developed road network, as well as the presence of large areas with industrial functions, for example, the second largest

steelwork plant in Poland. When analysing rental prices, it should be noted that by far the highest level is present in the city centre, reaching as much as 136.36 PLN/m². Lower rents can be found in the northern parts of the city, where they oscillate between 20 and 40 PLN/m². In order to get a better understanding of the differentiation of rental prices, 3D IDW interpolation (Figure 4) was performed for the area marked in Figure 3. On the basis of Figure 4, it can be observed that, in some areas of the city centre, there are very large price bubbles. Taking into account the specificity of Cracow, these very high rental prices may occur for properties that have extraordinary features, such as attractive views on the Wisła River or the Wawel Royal Castle.
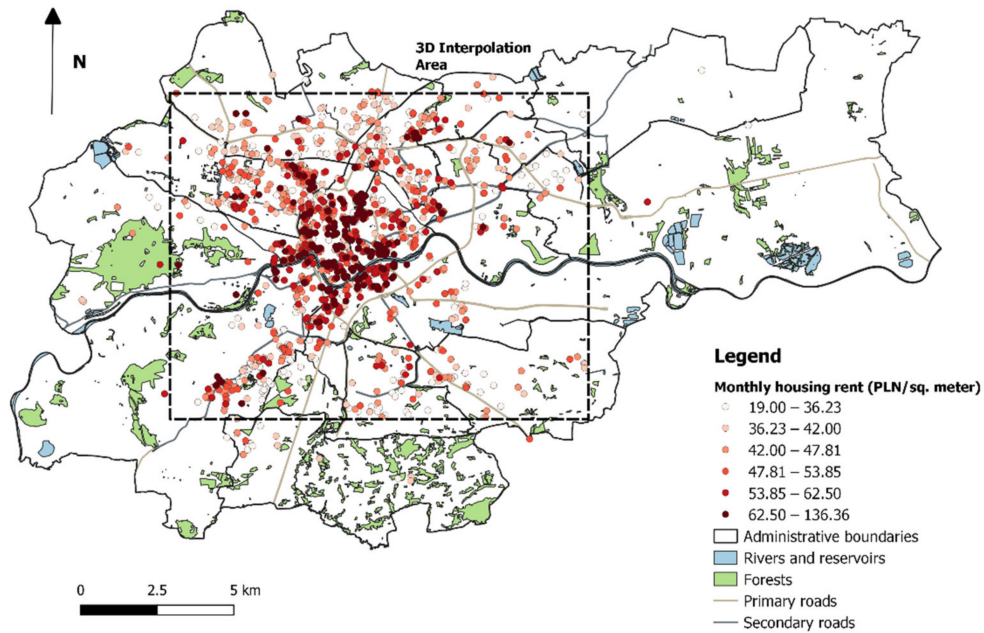

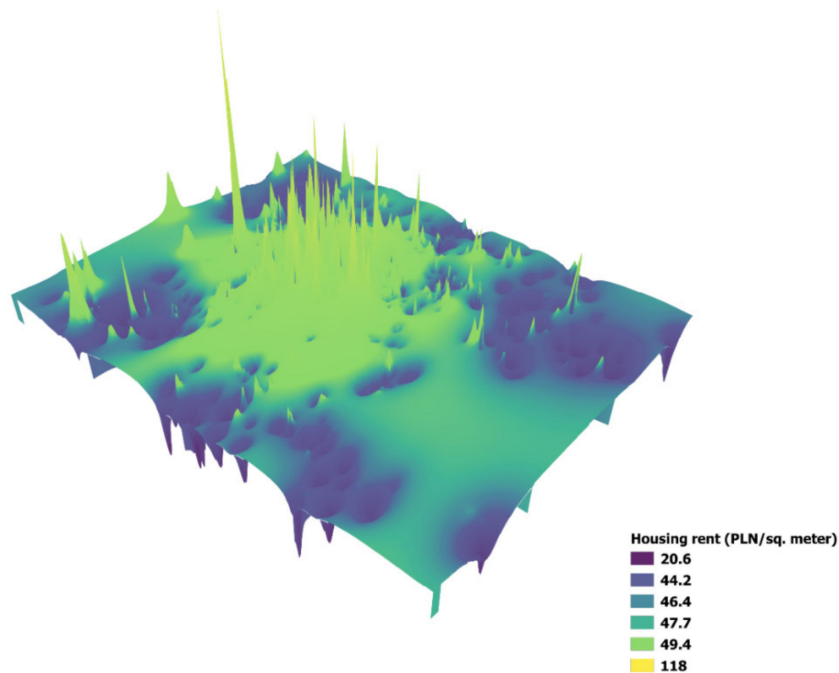**Figure 3.** Study area and spatial distribution of housing rents.

Figure 4. 3D IDW interpolation of housing rents for area marked in Figure 3.

3.4. Independent Variables

A description of variables used for modelling monthly housing rents is presented in Table 1. In particular, based on previous studies [1,13] and data availability, three groups of independent variables were defined: structural variables, locational variables, and neighbourhood variables. Unfortunately, in this study, it was not possible to take into account variables that characterise the economic aspect, for example, determinants such as wage levels. This type of data is not available at the micro level, either in terms of actual or offered wages.

Table 1. Independent variables.

Group	Category	Definition	Form	Abbrev.
Structure	Flat	Floor area (m^2)	Standard	FA
		Number of rooms	Standard	NR
		Floor level	Standard	FL
		Availability of additional space (garage, usable room, basement)	Standard	AA
	Building	Age of the building in years	Standard	AB
		Number of floors in the building	Standard	NF
		Availability of lift in the building	Standard	AL
		Type of building (block, tenement, apartment, house)—four dummy variables	Variables deleted because of high variance inflation factor (VIF) values	–
Location	Public transport	Distance to nearest bus stop, tram stop or train stop (m)	Standard	DPT
	Road accessibility	Distance to nearest primary or secondary road (m)	Standard	DR
	City centre	Distance to city centre (m)	Variable deleted because of high VIF value	–
Neighbour-hood	Publicfacilities	Distance to nearest local government building (m)	Standard	DG
	Job opportunities	Distance to nearest workcentre (m)	Logarithmic	DW
	Education facilities	Distance to nearest school (m)	Standard	DS
		Distance to nearest university (m)	Standard	DU
	Healthcare facilities	Distance to nearest pharmacy (m)	Logarithmic	DP
	Commercial facilities	Distance to nearest shoppingmall (m)	Standard	DSM
		Distance to nearestsupermarket (m)	Logarithmic	DSU
	Natural amenities	Distance to nearest park (m)	Logarithmic	DPA
		Distance to nearest river or reservoir (m)	Standard	DRR

Prior to establishing the final list of independent variables, they were subjected to preliminary analysis. In particular, the skewness of the variables was checked and the problem of multicollinearity was taken into account. Variables characterised by skewness above 3 were logarithmically transformed [55]. Then, using OLS regression, VIFs were calculated for the analysed variables. Determinants with a VIF value above 10 were removed from further analysis.

Looking at the final list of variables, the group of structural variables includes determinants that characterise the physical characteristics of both the flat itself and the building in which it is located. As far as locational variables are concerned, attention has been paid primarily to the distance from the nearest means of transport. In terms of neighbourhood variables, the focus was on education; healthcare; and natural, commercial, and public amenities, as well as job opportunities.

3.5. Econometrics Models

In this study, the starting point for identifying rent determinants is the traditional OLS regression, which can be expressed as follows:

$$y = X\beta + \varepsilon \tag{1}$$

where y denotes an $n \times 1$ vector of rental prices in the non-logarithmic form (skewness below 3), X is an $n \times k$ matrix of determinants, β is a $k \times 1$ vector of coefficients, and ε is an $n \times 1$ vector of error terms.

It should be noted, however, that ordinary least squares regression is far from sufficient to investigate the determinants of rental prices. First of all, housing rents can be spatially autocorrelated. This is directly because of the behaviour of the real estate market participants, who very often check prices or rents in the immediate vicinity before the flat is put on the market. Moreover, it is obvious that spatial autocorrelation results from the fact that the general location and properties of the

neighbourhood similarly influence real estate prices in given areas. These conclusions for the analysed data are confirmed by the value of Moran's *I* test, which is 0.37 and is statistically significant. The type of spatial model can be determined using *LM* tests [56], the results of which suggested the use of the spatial autoregressive model (SAR):

$$y = \rho W y + X \beta + \varepsilon \tag{2}$$

where ρ is the spatial autoregressive parameter, Wy denotes a spatially lagged dependent variable, and W is an $n \times n$ spatial weights matrix. In this study, a row-standardised binary k-nearest-neighbour matrix (with $k = 10$) was used to calculate Wy. There are many other proposals for defining the spatial weights matrix in the scientific literature; however, among others, a study on the determinants of house prices carried out by Basile et al. [57] indicated high robustness of the results to the choice of the weight matrix. Moreover, the use of $k = 10$ gives the best model performance in terms of AIC and AICc criteria (see Table A1). In addition, the use of a row-standardised matrix enables the interpretation of β_k as the direct marginal effect, whereas the total marginal effect can be expressed as $\beta_k / (1 - \rho)$ for the SAR model [58]. Furthermore, row-standardising of W allows to interpret Wy as the average rental price of the neighbours.

　　When analysing an area as large as the city of Cracow, it can be expected that the strength of the influence of particular determinants of rental prices may vary in given locations. Therefore, when modelling house or rental prices, one should also take into account spatial heterogeneity. It should be noted that the spatial autoregressive parameter may also be unevenly distributed over space. The occurrence of spatial heterogeneity, however, is not certain for all parameters. Therefore, it is possible that some of the variables may affect rental prices in a global way, that is, the strength of their influence on the dependent variable will be the same at every point of the analysed area. In order to take into account all of the above demands, the MGWR-SAR model outlined by Geniaux and Martinetti [17] should be used for modelling rental prices. In particular, the model that takes into account the possibility of the existence of global and local variables (including the spatial autoregressive parameter) takes the form:

$$y = \rho(u_i, v_i) W y + \beta_c X_c + \beta_v(u_i, v_i) X_v + \varepsilon \tag{3}$$

where (u_i, v_i) denotes the longitude and latitude of rental price i, X_c are k_c independent variables with constant coefficients (β_c), and X_v represents k_v independent variables with spatially varying coefficients (β_v). It should be noted that $k = k_c + k_v$.

　　In order to select an appropriate model specification, the spatial non-stationarity of all parameters, both the tested determinants, and the spatial autocorrelation term should be assumed at the first stage (this type of model will be named GWR-SAR in this study, because in this case, there are no global variables). Then, the Monte Carlo test for spatial variability should be performed to identify global variables. With information on global as well as local variables, it is possible to choose an appropriate model and then make its estimation. In this study, in models based on geographically weighted regression (GWR), a bi-square kernel function and an adaptive bandwidth were used. The latter was selected based on the AICc criterion.

　　Moreover, taking into account the spatially lagged dependent variable, the issue of endogeneity appears. Therefore, in order to estimate models in which spatial autocorrelation occurs, the spatial two-stage least squares technique was used with X and WX as a set of instruments [59].

　　There is another problem when estimating the GWR model. In particular, the subsamples used in the local GWR estimates often overlap, which artificially increases the t-values obtained [47]. Therefore, an adjusted significance level for the estimates will be applied in this study, which can be expressed by the following formula [60]:

$$\alpha = \frac{\xi_m}{\frac{p_e}{p}} \tag{4}$$

where ξ_m is the usual α, p_e is the effective number of parameters, and p is the number of parameters. In order to synthesise the research methodology presented in Section 3, and in particular, its subsequent steps, the whole procedure is presented in Figure 5.
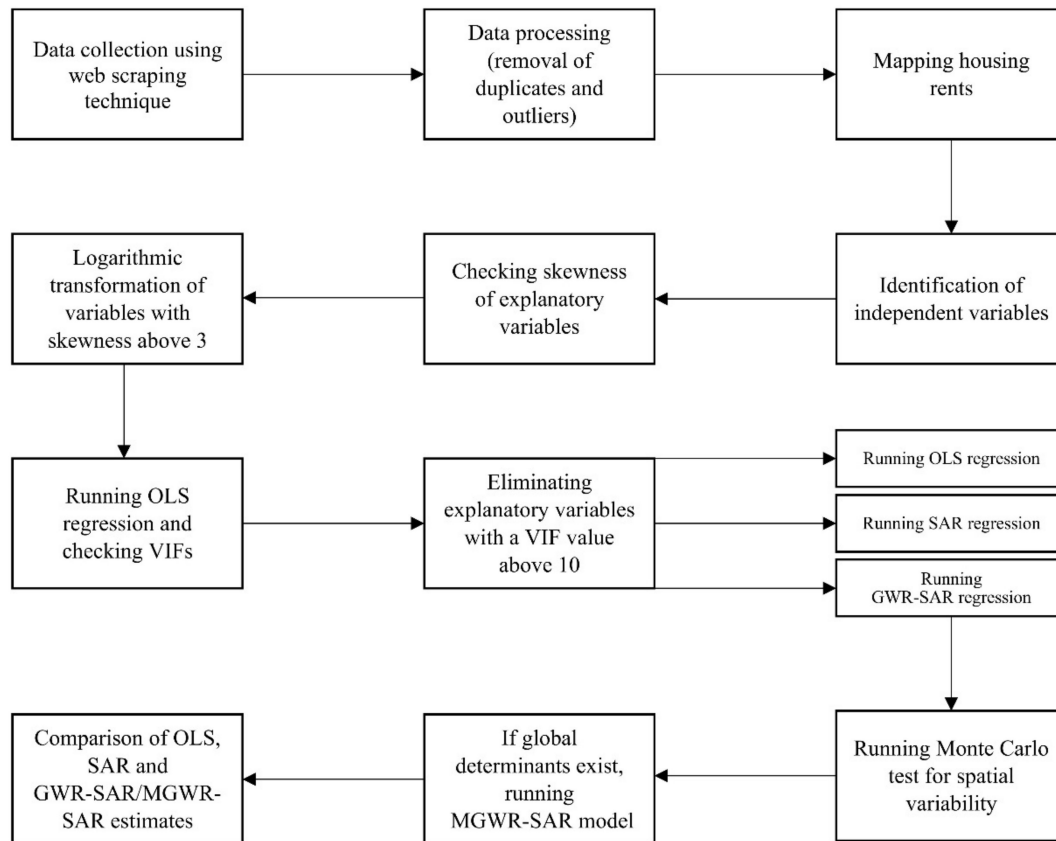

Figure 5. Procedure for exploring the determinants of rental prices in Cracow.

4. Results and Discussion

4.1. OLS and SAR Model Estimates

Analysing the results of OLS model estimation, it can be stated that rental prices are affected by structural, locational, and neighbourhood variables (Table 2). In particular, among structural attributes, the dependent variable is negatively influenced by floor area, as well as age and building size (measured by the number of floors). In turn, the availability of an elevator has a positive impact on the level of housing rents. Very similar results can be observed taking into account the SAR model. In the latter, one more variable turned out to be significant. It concerns the attribute describing the location of the flat on a given floor. It should be noted that all the above results are in line with previous research.

With regard to locational variables, tenants are willing to pay a higher price for rent in the case of near proximity to public transport facilities. This relationship in the SAR model, however, is insignificant, which calls into question the impact of this variable on rental prices. This may result from the fact that the vast majority of flats for rent in Cracow are located in the city centre and are close to main roads. Therefore, both landlords and tenants may ignore the question of distance to bus stops when setting the rental price, because they believe that the general location of the apartment guarantees easy access to public transport. When examining the results of neighbourhood variable estimations, special attention should be paid to natural amenities. In OLS and SAR models, both good access to parks and water bodies are added value for the rental price level. In this context, the determinants of rents show very high similarities to the determinants of housing prices in Cracow. In particular, one can

refer to studies by Małkowska and Palus [61], as well as Nalepka and Tomal [51], in which variables concerning distance to the park or to the Wisła River were negatively correlated with house prices. Such a strong impact of natural amenities on both rental and house prices is the result of the specificity of the city of Cracow, which, in recent years, has been characterised by a high level of air pollution. This encourages potential sellers and landlords to increase the prices of properties located in a greener natural environment, because they know that there is demand for this type of real estate on the market. A similar consistency of the estimated models in terms of determinants of rental prices can be observed in the case of education facilities, that is, the smaller the distance to schools and universities, the higher the rental price in the analysed market. The above results are not surprising because a very large part of the rental market in Cracow is offered to students, as well as to pupils whose families rent a flat closer to prestigious schools. The results obtained in relation to education facilities are in line with the research conducted by Adamkiewicz and Radziszewska-Zielina [62], in which the determinants influencing the choice of residential properties by the inhabitants of Cracow were examined. Very interesting results in terms of neighbourhood variables concern also the determinant describing distance to the nearest supermarket. On the basis of common sense, the relationship between rental prices and the above variable should be negative. OLS regression results, however, indicate the opposite, that is, the higher the distance to the nearest supermarket, the higher the rent. This may result from the fact that negative externalities related to noise around supermarkets outweigh the positive aspects of locating this type of facilities in the vicinity of a given flat. It should be noted that the estimates obtained in this respect are in contradiction with the research conducted by Gluszak [63] for the real estate market in Cracow, in which the author identified retail sales as a desired amenity affecting one's willingness to buy or rent a flat.

Table 2. OLS and SAR model estimates.

Variable	OLS	SAR
Intercept	59.261 ***	25.656 ***
	Structural variables	
FA	−0.059 ***	−0.072 ***
NR	−0.803	−0.462
FL	0.135	0.352 **
AA	−0.621	−0.410
AB	−0.067 ***	−0.061 ***
NF	−0.691 ***	−0.483 ***
AL	8.165 ***	4.870 ***
	Locational variables	
DPT	−0.011 ***	−0.002
DR	0.001	0.000
	Neighbourhood variables	
DG	−0.001 ***	−0.000
DW	0.103	−0.159
DS	−0.005 ***	−0.002 *
DU	−0.004 ***	−0.001 ***
DP	0.604	0.444
DSM	−0.000	0.001
DSU	1.380 ***	0.173
DPA	−1.171 ***	−0.984 ***
DRR	−0.003 ***	−0.001 *
Wy	NA	0.665 ***
N	2336	2336
AIC	18,518.60	18,373.00
AICc	18,520.96	18,375.40
R^2	0.24	0.28

Notes: *** one percent level of significance; ** five percent level of significance; * ten percent level of significance.

4.2. GWR-SAR Model Estimates

The next stage of studying the determinants of housing rents in Cracow was the estimation of the GWR-SAR model (Table 3). Then, using the Monte Carlo test, the estimated parameters of the model were checked for spatial variability. The above test indicated that all variables could be characterised as local, including the spatial autocorrelation term (Table 3). Therefore, the model presented in Table 3 can be considered as final. The first look at the results of the GWR-SAR model estimation reveals that the problem of collinearity occurs for some neighbourhood variables. For the latter, caution should be exercised when interpreting the parameter estimates.

Table 3. GWR-SAR model estimates.

| Variable	Mean	SD	Min	Median	Max	Percent of Significant Cases at 95%	Percent of Cases with Local VIF > 10	MC
Intercept	51.486	49.589	−195.165	46.798	283.054	10.74%	–	SN
					Structural variables			
FA	−0.243	0.222	−0.734	−0.239	0.825	52.40%	0.00%	SN
NR	1.862	3.879	−14.150	2.045	17.324	9.85%	0.00%	SN
FL	0.331	0.746	−3.126	0.142	3.111	7.58%	0.00%	SN
AA	0.428	2.210	−8.033	0.372	4.893	0.21%	0.00%	SN
AB	−0.166	0.174	−1.955	−0.144	0.068	35.40%	0.00%	SN
NF	−0.113	1.303	−3.356	−0.262	4.608	4.79%	0.09%	SN
AL	2.978	5.087	−15.567	2.382	15.395	14.04%	0.00%	SN
					Locational variables			
DPT	−0.005	0.028	−0.089	−0.002	0.102	8.82%	6.77%	SN
DR	0.001	0.018	−0.103	−0.001	0.082	6.46%	13.16%	SN
					Neighbourhood variables			
DG	0.007	0.022	−0.043	0.002	0.183	6.55%	22.03%	SN
DW	−0.561	2.623	−9.426	−0.422	8.061	5.31%	1.20%	SN
DS	−0.001	0.017	−0.061	0.000	0.119	7.15%	12.69%	SN
DU	−0.003	0.028	−0.057	−0.003	0.260	6.46%	21.30%	SN
DP	0.330	2.741	−9.234	0.128	9.819	2.95%	3.90%	SN
DSM	0.002	0.015	−0.081	0.001	0.064	7.41%	22.29%	SN
DSU	0.826	3.215	−7.531	0.278	40.072	4.45%	5.57%	SN
DPA	−0.658	3.922	−19.560	0.264	11.465	5.39%	8.02%	SN
DRR	−0.007	0.023	−0.187	−0.001	0.036	4.49%	26.53%	SN
Wy	0.205	0.713	−3.893	0.308	2.140	6.85%	6.34%	SN
N					2,336			
AIC					17,508.26			
AICc					17,725.91			
R^2					0.66			

Notes: adj. critical t-value (95%) is equal to 3.063. In order to calibrate the GWR-SAR model, MGWR 2.2 software was used. MC denotes Monte Carlo test for spatial variability. SN denotes spatial non-stationarity at one percent level of significance. Bandwidth used: 223.

When analysing the average values of the parameters of the GWR-SAR model, it should be stressed that they are quite similar to the estimates of OLS and SAR models. The minimum and maximum values, however, indicate how varied the influence of a given factor may be in a particular area. The above results underline the complexity of the real estate market in Cracow, whose analysis should take into account the detailed geographical location of the studied flats. The GWR-SAR model reveals that the most important determinant of housing rents for the real estate market in Cracow as a whole was the floor area variable (FA). Its significance was confirmed in 52.40% of cases (during GWR-SAR estimation, 2336 local regressions were calculated). On the basis of Figure 6a, it can be concluded that the FA variable has a negative impact on rent per 1 m^2 in almost the entire analysed area, which is to be expected. Generally, the strongest negative impact of the analysed determinant (FA) can be observed in the northern and south-eastern parts of the city. Conversely, closer to the city centre and the south-western areas, the negative correlation decreases. In some regions, a positive influence of the analysed determinant on the dependent variable can be noticed. This is mainly recorded in areas where new residential buildings have been constructed in recent years, as well as in luxury districts. In these latter locations in particular, the Veblen effect may be active, which, in the case under analysis, would result in an increase in rent for each additional square metre of floor area. This is because of the fact that, in luxury districts, larger apartments are a testament of prestige and tenants pay more for them. On the basis of Figure 6b, however, it must be concluded that, in a large number of

cases, this positive correlation is insignificant and, thus, the above conclusions cannot be considered as certain.
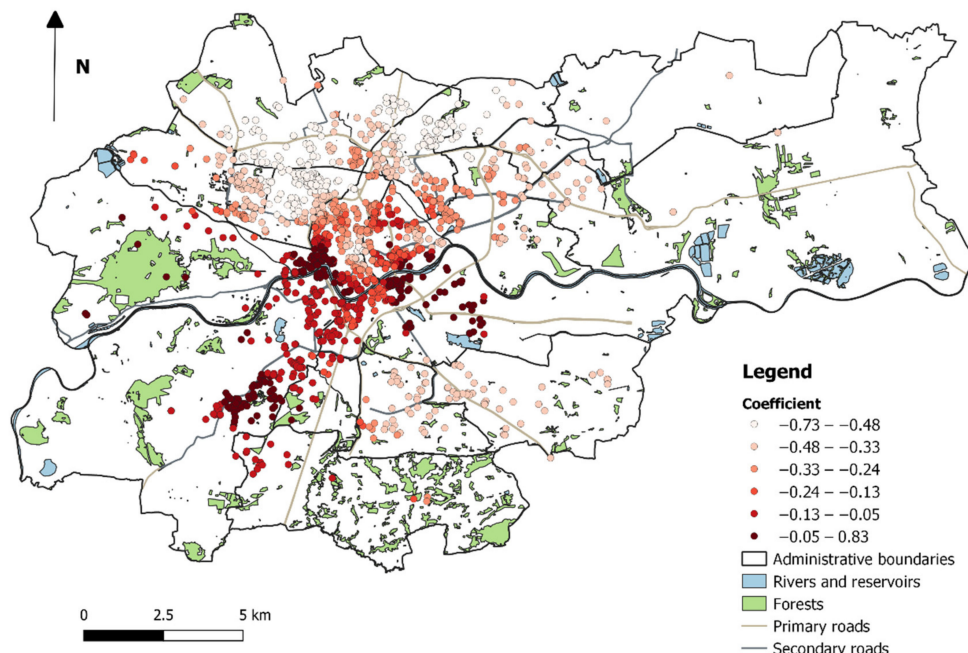

(a)
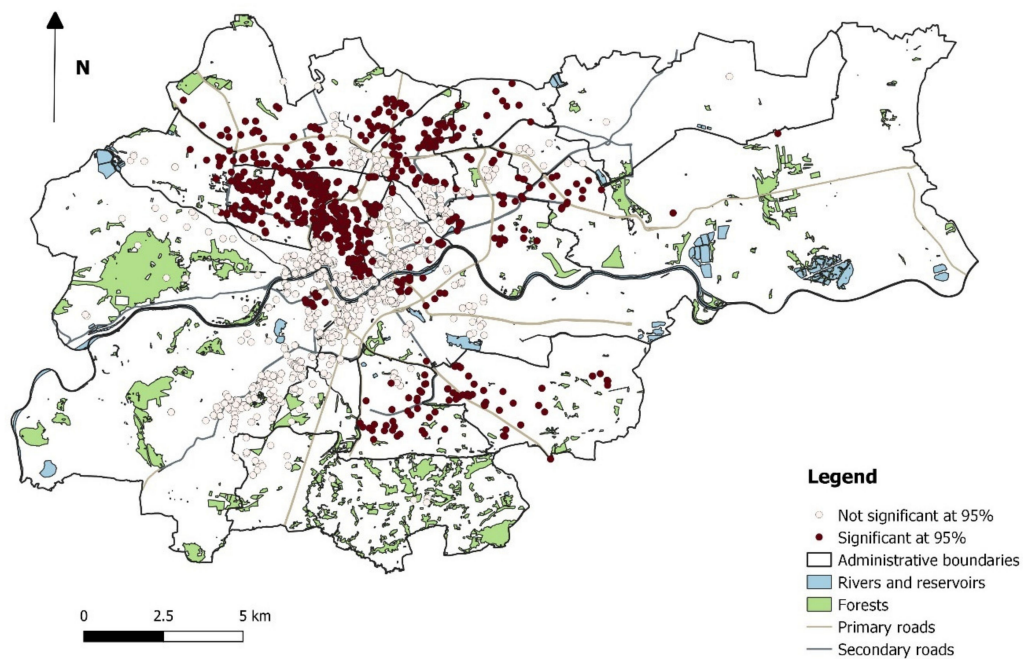
(b)

Figure 6. (**a**) Local coefficient estimates for FA (floor area). (**b**) Statistical significance of estimates for FA (floor area).

Another variable that mostly affects housing rents concerns the age of the building in which the flat is located. The results of spatial analysis of the estimated parameters for the above attribute are presented in Figure 7a,b. It can be observed that, closer to the city centre, the impact of the analysed

variable is weaker, that is, in these areas, older buildings do not significantly affect the reduction of rent. This may be because of the fact that residential buildings in the centre of Cracow may have a specific historical value, which eliminates the negative impact of age itself. This spatial relationship can be seen in Figure 7a, where historic places are marked. It should be stressed, however, that in the case of a weak impact of the investigated variable, the estimated parameter is usually insignificant, as presented in Figure 7b; therefore, the above conclusions should be treated with caution.


(a)

(b)
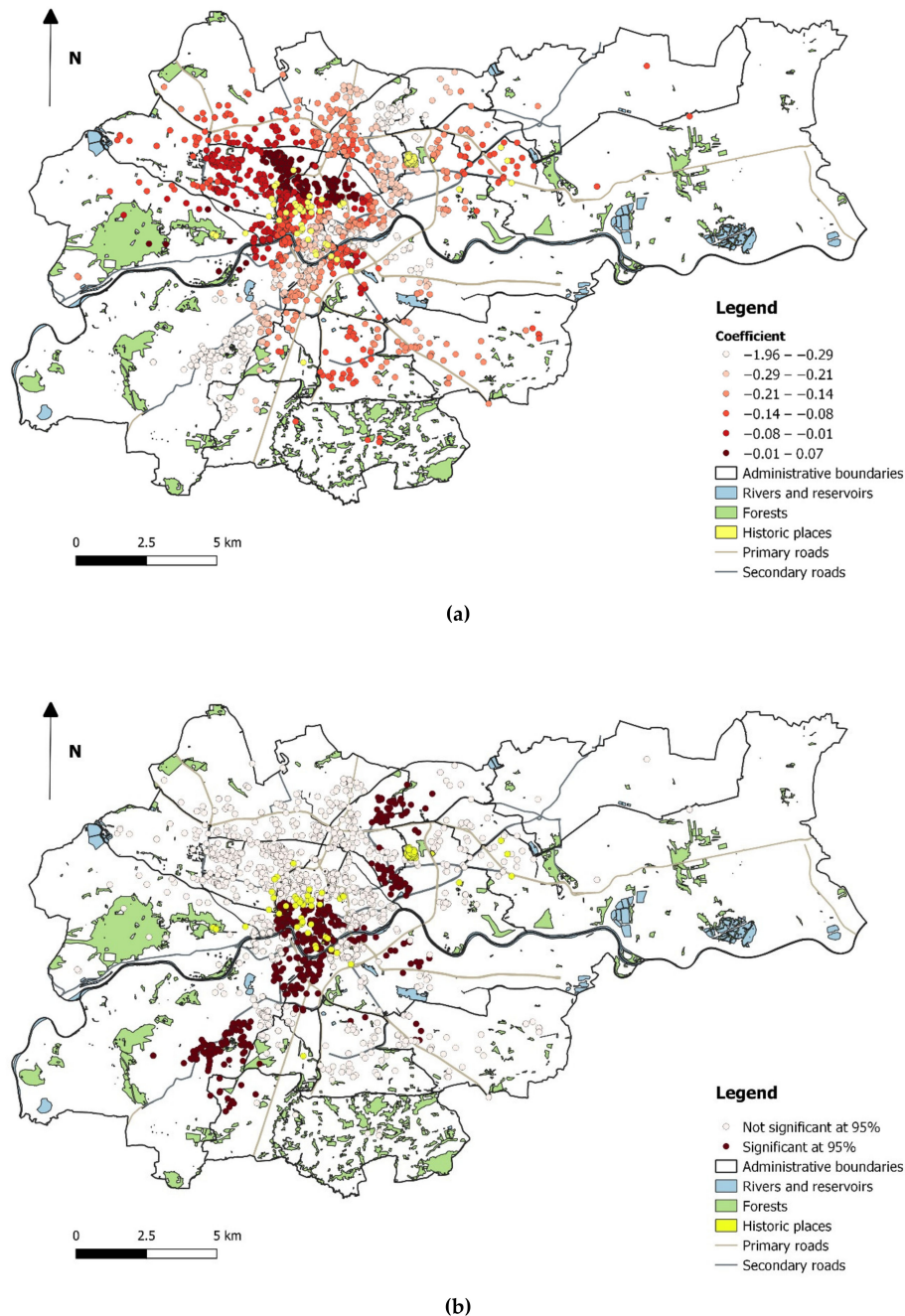
Figure 7. (**a**) Local coefficient estimates for AB (age of the building in years). (**b**) Statistical significance of estimates for AB (age of the building in years).

On the basis of the GWR-SAR model estimates, it is also possible to draw very interesting conclusions about the spatial autoregressive parameter (Figure 8a,b). In particular, the above-mentioned coefficient is not a constant value and changes significantly over space. Furthermore, it can be noted

that the spatial autoregressive parameter is significant mainly in areas with very high density of housing rents. Moreover, more rental offers in a given location strengthen the spatial autocorrelation of the dependent variable. This seems to be expected, resulting from the fact that, in the case of a large number of rental offers in a given area, each new offer will, to a large extent, imitate the prices in the immediate vicinity. Conversely, in areas of the city of Cracow where the number of lease offers is small, spatial dependence is low in intensity and usually insignificant at 95%. This implies that, in these cases, the basis for determining the price of each new offer is not the rents of apartments from distant locations, but an analysis of the attributes of the property itself and its immediate neighbourhood.

(a)

(b)
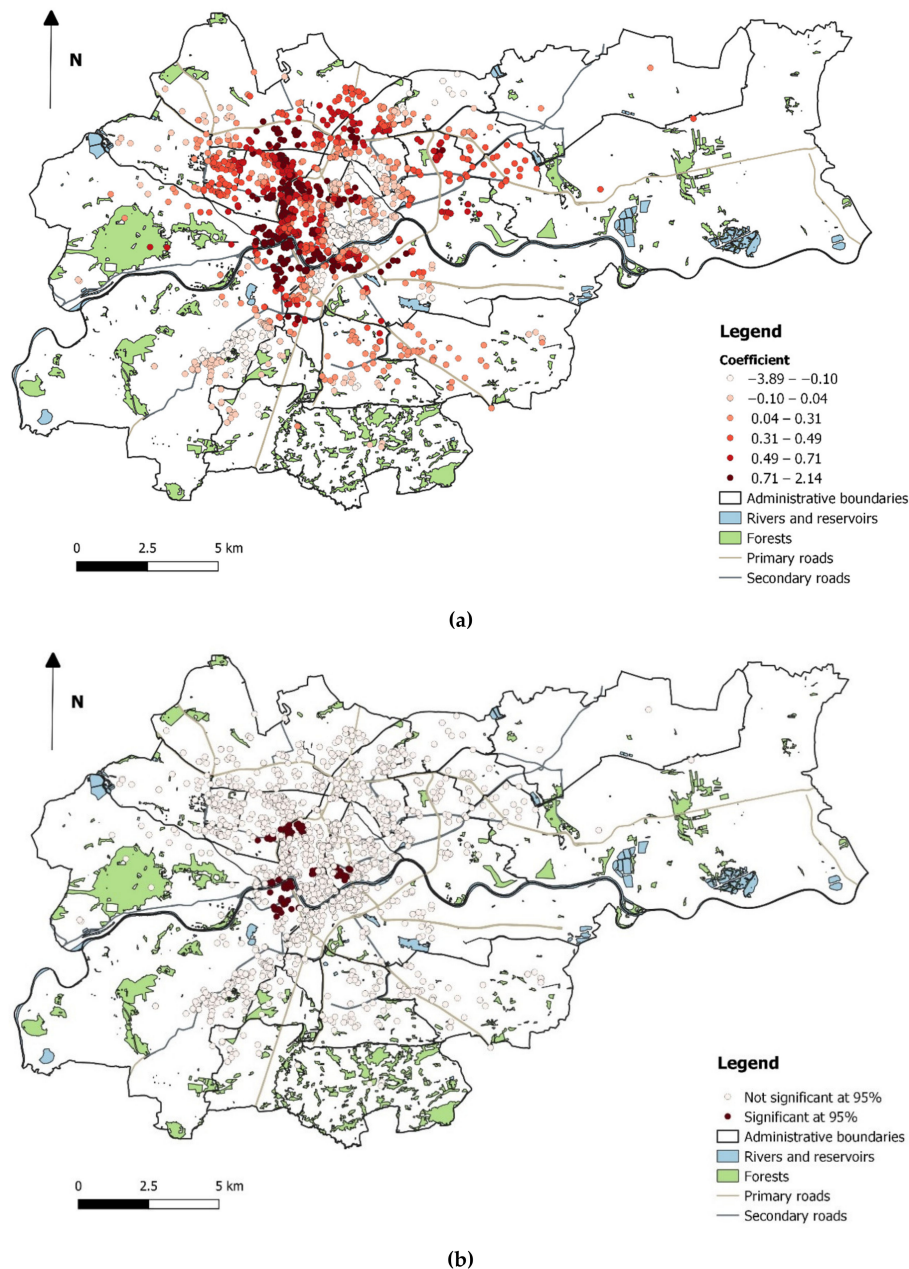
Figure 8. (**a**) Local coefficient estimates for the spatial autoregressive term. (**b**) Statistical significance of estimates for the spatial autoregressive term.

The rest of the visualised results of the GWR-SAR model estimation are presented in Figures S1–S32 in the Supplementary Material.

In order to further check the complexity of the housing rental market in Cracow, Figure 9 shows for each property the number of significant variables affecting the rental price. It should be noted that, the closer to the city centre, the greater the number of attributes that significantly shape the dependent variable. This is the expected situation because the city centre is the area where the residential rental market in Cracow is the most developed. Moreover, in the analysed context, it should be stated that the results obtained with the GWR-SAR model indicate the occurrence of the substitution effect between some rent determinants. As an example, one can give variables describing the location of the property on the floor in the building and the availability of the lift. Globally, both these variables have a significant impact on the level of rental prices. However, as can be seen in Figures S4 and S8, the above variables are usually not simultaneously significant when applying the GWR-SAR model.
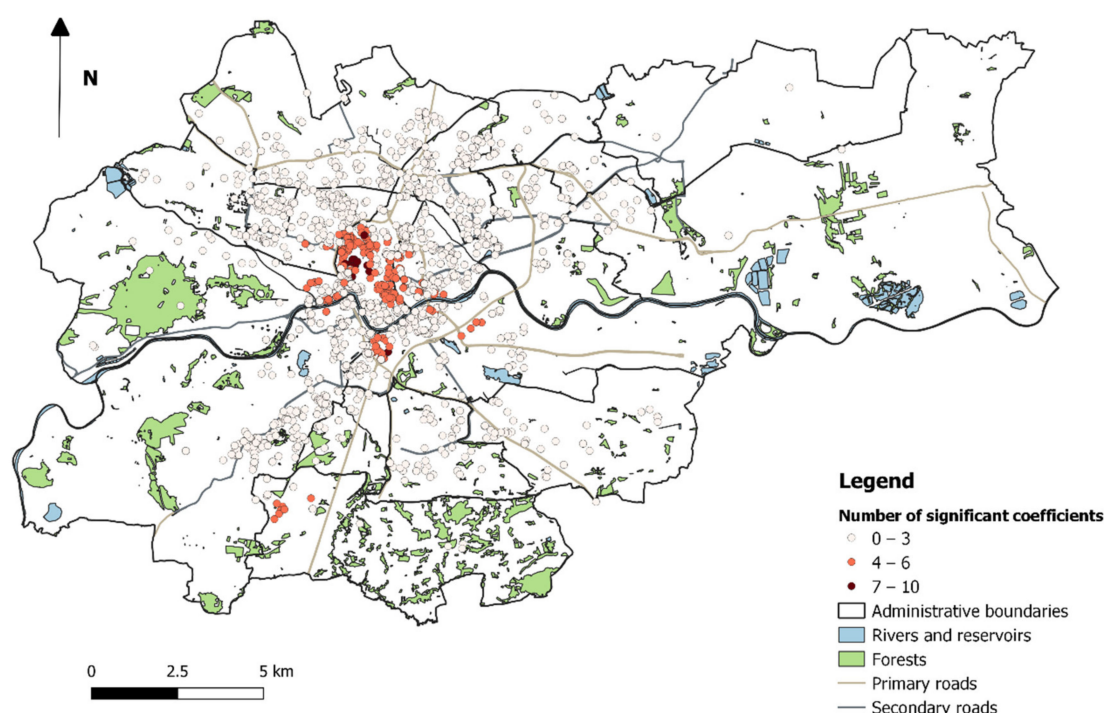

Figure 9. Number of significant coefficients for each property at 95%.

4.3. Comparison of the Models

OLS, SAR, and GWR-SAR model estimates have shown the diversity of the residential rental market in Cracow. A short comparison of the models used in terms of the AIC, root-mean-square error (RMSE), and R^2 criteria is presented in Table 4.

Table 4. Comparison of the models.

Model	AIC	RMSE	R^2
OLS	18,518.60	12.70	0.24
SAR	18,373.00	12.31	0.28
GWR *	17,520.78	8.59	0.65
GWR-SAR	17,508.26	8.50	0.66

Notes: * the GWR model is not described within the main text of this article; however, its characteristics are presented for comparison purposes. Moreover, estimates of the basic GWR are available in Table A2.

On the basis of Table 4, it can be concluded that the best model for studying rental prices is GWR-SAR. This is not surprising, as this approach allows both spatial non-stationarity of the parameters of determinants and change over space of the spatial autoregressive parameter. In particular,

the GWR-SAR model explains the variability of rental prices more than two times better than the OLS and SAR models. Moreover, with regard to the RMSE as well as the AIC criterion, significant improvements can be observed. It can, therefore, be concluded that the simple hedonic model (OLS) is far from sufficient in examining the determinants of both house and rental prices. This conclusion applies in particular when larger areas with detectable spatial relationships are tested. Therefore, an extremely interesting topic for future research would be to analyse in which areas OLS regression gives satisfactory results, and from what moment onwards spatial heterogeneity should be taken into account in modelling. A similar situation can be observed in the case of spatial autocorrelation. Taking the results of this study into account, it would be necessary to query how high the density of rental or sale offers in a particular area should be in order to take into consideration spatially lagged dependent variables during price modelling.

5. Conclusions

This study attempted to identify the determinants affecting rental prices in Cracow. To this end, OLS regression and spatial econometric methods were used. In particular, SAR and GWR-SAR models were employed, which made it possible to take into account the spatial heterogeneity of the parameters of determinants and the spatially changing spatial autocorrelation of housing rents. The results of OLS and SAR model estimations showed that rental prices are influenced by structural, locational, and neighbourhood variables. In-depth analysis of rent determinants using the GWR-SAR model revealed the complexity of the rental market in Cracow. Estimates of the above model showed that many local markets could be identified in Cracow, which differ in terms of the factors shaping housing rents. It is possible, however, to identify some determinants that are universal for almost the entire city. This concerns mainly the variables describing the area of the flat and the age of the building.

Moreover, the Monte Carlo test indicated that the spatial autoregressive parameter also changes significantly over space, which additionally emphasises the fact that the rental housing market in Cracow is multi-faceted.

This study, however, has some limitations. First of all, offer instead of transactional data were used to identify the determinants of rental prices. As already mentioned, this is because of the unavailability of such information. Moreover, when modelling rental prices using the GWR-SAR model, future studies should take into account their change over time. In addition, future analyses could also include flexible bandwidths, as pointed out by Yang [55] and Wu et al. [13].

It is to be expected that housing shortages and changes in the housing preferences of young people will intensify the development of the rental market in Poland. Therefore, the present study is very important for local policy-makers and housing developers, as the first such comprehensive analysis on the determinants of housing rents in Cracow, and Poland in general.

Supplementary Materials: The following are available online at http://www.mdpi.com/2220-9964/9/6/346/s1: Figure S1: Local coefficient estimates for NR (number of rooms); Figure S2: Statistical significance of estimates for NR (number of rooms); Figure S3: Local coefficient estimates for FL (floor level); Figure S4: Statistical significance of estimates for FL (floor level); Figure S5: Local coefficient estimates for NF (number of floors in the building); Figure S6: Statistical significance of estimates for NF (number of floors in the building); Figure S7: Local coefficient estimates for AL (availability of lift in the building); Figure S8: Statistical significance of estimates for AL (availability of lift in the building); Figure S9: Local coefficient estimates for DPT (distance to nearest bus stop, tram stop, or train stop); Figure S10: Statistical significance of estimates for DPT (distance to nearest bus stop, tram stop, or train stop); Figure S11: Local coefficient estimates for DR (distance to nearest primary or secondary road); Figure S12: Statistical significance of estimates for DR (distance to nearest primary or secondary road); Figure S13: Local coefficient estimates for DG (distance to nearest local government building); Figure S14: Statistical significance of estimates for DG (distance to nearest local government building); Figure S15: Local coefficient estimates for DW (distance to nearest work center); Figure S16: Statistical significance of estimates for DW (distance to nearest work center); Figure S17: Local coefficient estimates for DS (distance to nearest school); Figure S18: Statistical significance of estimates for DS (distance to nearest school); Figure S19: Local coefficient estimates for DP (distance to nearest pharmacy); Figure S20: Statistical significance of estimates for DP (distance to nearest pharmacy); Figure S21: Local coefficient estimates for DSM (distance to nearest shopping mall); Figure S22: Statistical significance of estimates for DSM (distance to nearest shopping mall); Figure S23: Local coefficient estimates for DSU (distance to nearest supermarket); Figure S24: Statistical significance of estimates for DSU

(distance to nearest supermarket); Figure S25: Local coefficient estimates for DPA (distance to nearest park); Figure S26: Statistical significance of estimates for DPA (distance to nearest park); Figure S27: Local coefficient estimates for DR (distance to nearest river or reservoir); Figure S28: Statistical significance of estimates for DR (distance to nearest river or reservoir); Figure S29: Local coefficient estimates for AA (availability of additional space (garage, usable room, basement)); Figure S30: Statistical significance of estimates for AA (availability of additional space (garage, usable room, basement)); Figure S31: Local coefficient estimates for DU (distance to nearest university); Figure S32: Statistical significance of estimates for DU (distance to nearest university).

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. AIC and AICc values for SAR and GWR-SAR models depending on the method of calculating of the spatially lagged dependent variable.

Number of Nearest Neighbours (*k*)	AIC: SAR	AICc: SAR	AIC: GWR-SAR	AICc: GWR-SAR
6	18,417.57	18,419.98	17,514.89	17,733.49
8	18,397.45	18,399.85	17,514.13	17,732.02
10 *	18,373.00	18,375.40	17,508.26	17,725.91
12	18,377.28	18,379.68	17,522.07	17,739.70
14	18,374.65	18,377.05	17,527.10	17,743.97

Notes: * *k* = 10 gives the best performance of the SAR and GWR-SAR models according to the AIC and AICc criteria.

Table A2. Basic GWR model estimates.

Variable	Mean	SD	Min	Median	Max	Percentage of Significant Cases at 95%	Percentage of Cases with Local VIF > 10
Intercept	61.630	33.836	-201.480	59.322	148.515	45.74%	–
			Structural variables				
FA	−0.240	0.223	−0.734	−0.233	0.809	51.26%	0.00%
NR	1.817	3.921	−13.834	2.055	17.290	9.77%	0.00%
FL	0.314	0.772	−3.098	0.109	3.243	8.23%	0.00%
AA	0.395	2.254	−7.572	0.324	4.855	0.00%	0.00%
AB	−0.163	0.174	−1.960	−0.143	0.070	34.42%	0.00%
NF	−0.094	1.344	−3.457	−0.283	5.251	3.81%	0.00%
AL	3.185	5.101	−15.527	2.672	16.069	14.27%	0.00%
			Locational variables				
DPT	−0.008	0.025	−0.086	−0.006	0.088	10.03%	6.47%
DR	0.001	0.016	−0.082	0.000	0.071	5.44%	10.89%
			Neighbourhood variables				
DG	0.004	0.023	−0.054	0.000	0.186	5.62%	17.45%
DW	−0.246	2.637	−8.929	−0.091	8.595	6.26%	1.20%
DS	−0.003	0.017	−0.063	−0.001	0.089	9.34%	12.26%
DU	−0.005	0.029	−0.067	−0.004	0.266	12.82%	18.22%
DP	0.473	2.739	−10.937	0.322	9.507	5.53%	3.17%
DSM	0.003	0.014	−0.069	0.000	0.063	8.92%	20.27%
DSU	1.087	3.251	−6.698	0.564	30.373	7.76%	5.57%
DPA	−0.662	3.843	−18.275	0.216	9.206	5.53%	7.63%
DRR	−0.008	0.023	−0.19	−0.002	0.022	6.56%	25.72%

References

1. Hu, L.; He, S.; Han, Z.; Xiao, H.; Su, S.; Weng, M.; Cai, Z. Monitoring housing rental prices based on social media: An integrated approach of machine-learning algorithms and hedonic modeling to inform equitable housing policies. *Land Use Policy* **2019**, *82*, 657–673. [CrossRef]
2. Tomal, M. Moving towards a Smarter Housing Market: The Example of Poland. *Sustainability* **2020**, *12*, 683. [CrossRef]
3. Maalsen, S. Smart housing: The political and market responses of the intersections between housing, new sharing economies and smart cities. *Cities* **2019**, *84*, 1–7. [CrossRef]
4. Gilbert, A. Rental housing: The international experience. *Habitat Int.* **2016**, *54*, 173–181. [CrossRef]

5. Rubaszek, M.; Rubio, M. Does the rental housing market stabilize the economy? A micro and macro perspective. *Empir. Econ.* **2019**. [CrossRef]

6. Czerniak, A.; Rubaszek, M. The Size of the Rental Market and Housing Market Fluctuations. *Open Econ. Rev.* **2018**, *29*, 261–281. [CrossRef]

7. Tomal, M. The Impact of Macro Factors on Apartment Prices in Polish Counties: A Two-Stage Quantile Spatial Regression Approach. *Real Estate Manag. Valuat.* **2019**, *27*, 1–14. [CrossRef]

8. Tomal, M. House Price Convergence on the Primary and Secondary Markets: Evidence from Polish Provincial Capitals. *Real Estate Manag. Valuat.* **2019**, *27*, 62–73. [CrossRef]

9. Geng, J.; Cao, K.; Yu, L.; Tang, Y. Geographically Weighted Regression model (GWR) based spatial analysis of house price in Shenzhen. In Proceedings of the 19th International Conference on Geoinformatics; IEEE: Shanghai, China, 2011; pp. 1–5.

10. Liang, X.; Liu, Y.; Qiu, T.; Jing, Y.; Fang, F. The effects of locational factors on the housing prices of residential communities: The case of Ningbo, China. *Habitat Int.* **2018**, *81*, 1–11. [CrossRef]

11. Liu, J.; Yang, Y.; Xu, S.; Zhao, Y.; Wang, Y.; Zhang, F. A Geographically Temporal Weighted Regression Approach with Travel Distance for House Price Estimation. *Entropy* **2016**, *18*, 303. [CrossRef]

12. Mou, Y.; He, Q.; Zhou, B. Detecting the Spatially Non-Stationary Relationships between Housing Price and Its Determinants in China: Guide for Housing Market Sustainability. *Sustainability* **2017**, *9*, 1826. [CrossRef]

13. Wu, C.; Ren, F.; Hu, W.; Du, Q. Multiscale geographically and temporally weighted regression: Exploring the spatiotemporal determinants of housing prices. *Int. J. Geogr. Inf. Sci.* **2019**, *33*, 489–511. [CrossRef]

14. Zou, Y. Air Pollution and Housing Prices across Chinese Cities. *J. Urban Plann. Dev.* **2019**, *145*, 04019012. [CrossRef]

15. Wu, B.; Li, R.; Huang, B. A geographically and temporally weighted autoregressive model with application to housing prices. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 1186–1204. [CrossRef]

16. Cohen, J.P.; Coughlin, C.C.; Zabel, J. Time-Geographically Weighted Regressions and Residential Property Value Assessment. *J. Real Estate Finan. Econ.* **2020**, *60*, 134–154. [CrossRef]

17. Geniaux, G.; Martinetti, D. A new method for dealing simultaneously with spatial autocorrelation and spatial heterogeneity in regression models. *Reg. Sci. Urban Econ.* **2018**, *72*, 74–85. [CrossRef]

18. Li, D.-K.; Mei, C.-L.; Wang, N. Tests for spatial dependence and heterogeneity in spatially autoregressive varying coefficient models with application to Boston house price analysis. *Reg. Sci. Urban Econ.* **2019**, *79*, 103470. [CrossRef]

19. Ma, Y.; Gopal, S. Geographically Weighted Regression Models in Estimating Median Home Prices in Towns of Massachusetts Based on an Urban Sustainability Framework. *Sustainability* **2018**, *10*, 1026. [CrossRef]

20. Fotheringham, A.S.; Crespo, R.; Yao, J. Exploring, modelling and predicting spatiotemporal variations in house prices. *Ann. Reg. Sci.* **2015**, *54*, 417–436. [CrossRef]

21. Yao, J.; Stewart Fotheringham, A. Local Spatiotemporal Modeling of House Prices: A Mixed Model Approach. *Prof. Geogr.* **2016**, *68*, 189–201. [CrossRef]

22. Lu, B.; Charlton, M.; Harris, P.; Fotheringham, A.S. Geographically weighted regression with a non-Euclidean distance metric: A case study using hedonic house price data. *Int. J. Geogr. Inf. Sci.* **2014**, *28*, 660–681. [CrossRef]

23. McCord, M.; Lo, D.; Davis, P.T.; Hemphill, L.; McCord, J.; Haran, M. A spatial analysis of EPCs in The Belfast Metropolitan Area housing market. *J. Prop. Res.* **2020**, *37*, 25–61. [CrossRef]

24. McCord, M.J.; McCord, J.; Davis, P.T.; Haran, M.; Bidanset, P. House price estimation using an eigenvector spatial filtering approach. *Intern. J. Hous. Mark. Anal.* **2019**. [CrossRef]

25. McCord, M.J.; MacIntyre, S.; Bidanset, P.; Lo, D.; Davis, P. Examining the spatial relationship between environmental health factors and house prices: NO2 problem? *J. Eur. Real Estate Res.* **2018**, *11*, 353–398. [CrossRef]

26. Huang, B.; Wu, B.; Barry, M. Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *Int. J. Geogr. Inf. Sci.* **2010**, *24*, 383–401. [CrossRef]

27. Dziauddin, M.F.; Ismail, K.; Othman, Z. Analysing the local geography of the relationship between residential property prices and its determinants. *Bull. Geography. Socio-Econ. Ser.* **2015**, *28*, 21–35. [CrossRef]

28. Stewart Fotheringham, A.; Park, B. Localized Spatiotemporal Effects in the Determinants of Property Prices: A Case Study of Seoul. *Appl. Spat. Anal.* **2018**, *11*, 581–598. [CrossRef]

29. Helbich, M.; Brunauer, W.; Vaz, E.; Nijkamp, P. Spatial Heterogeneity in Hedonic House Price Models: The Case of Austria. *Urban Stud.* **2014**, *51*, 390–411. [CrossRef]

30. Helbich, M.; Griffith, D.A. Spatially varying coefficient models in real estate: Eigenvector spatial filtering and alternative approaches. *Comput. Environ. Urban Syst.* **2016**, *57*, 1–11. [CrossRef]

31. Helbich, M.; Brunauer, W.; Hagenauer, J.; Leitner, M. Data-Driven Regionalization of Housing Markets. *Ann. Assoc. Am. Geogr.* **2013**, *103*, 871–889. [CrossRef]

32. Osland, L.; Thorsen, I.S.; Thorsen, I. Accounting for local spatial heterogeneities in housing market studies. *J. Reg. Sci.* **2016**, *56*, 895–920. [CrossRef]

33. Nordvik, V.; Osland, L.; Thorsen, I.; Thorsen, I.S. Capitalization of neighbourhood diversity and segregation. *Environ. Plann. A* **2019**, *51*, 1775–1799. [CrossRef]

34. Cellmer, R.; Bełej, M.; Konowalczuk, J. Impact of a Vicinity of Airport on the Prices of Single-Family Houses with the Use of Geospatial Analysis. *IJGI* **2019**, *8*, 471. [CrossRef]

35. Cellmer, R.; Trojanek, R. Towards Increasing Residential Market Transparency: Mapping Local Housing Prices and Dynamics. *IJGI* **2019**, *9*, 2. [CrossRef]

36. Kobylińska, K.; Cellmer, R. Modelling and Simulation of Selected Real Estate Market Spatial Phenomena. *IJGI* **2019**, *8*, 446. [CrossRef]

37. Olszewski, K.; Waszczuk, J.; Widłak, M. Spatial and Hedonic Analysis of House Price Dynamics in Warsaw, Poland. *J. Urban Plann. Dev.* **2017**, *143*, 04017009. [CrossRef]

38. Trojanek, R.; Gluszak, M.; Tanas, J. The effect of urban green spaces on house prices in Warsaw. *Int. J. Strateg. Prop. Manag.* **2018**, *22*, 358–371. [CrossRef]

39. Trojanek, R.; Gluszak, M. Spatial and time effect of subway on property prices. *J. House Built Environ.* **2018**, *33*, 359–384. [CrossRef]

40. Li, H.; Wei, Y.D.; Wu, Y. Analyzing the private rental housing market in Shanghai with open data. *Land Use Policy* **2019**, *85*, 271–284. [CrossRef]

41. Zhang, S.; Wang, L.; Lu, F. Exploring Housing Rent by Mixed Geographically Weighted Regression: A Case Study in Nanjing. *IJGI* **2019**, *8*, 431. [CrossRef]

42. Cui, N.; Gu, H.; Shen, T.; Feng, C. The Impact of Micro-Level Influencing Factors on Home Value: A Housing Price-Rent Comparison. *Sustainability* **2018**, *10*, 4343. [CrossRef]

43. Leung, K.M.; Yiu, C.Y. Rent determinants of sub-divided units in Hong Kong. *J. House Built Environ.* **2019**, *34*, 133–151. [CrossRef]

44. Efthymiou, D.; Antoniou, C. How do transport infrastructure and policies affect house prices and rents? Evidence from Athens, Greece. *Transp. Res. Part A: Policy Pract.* **2013**, *52*, 1–22. [CrossRef]

45. Crespo, R.; Grêt-Regamey, A. Local Hedonic House-Price Modelling for Urban Planners: Advantages of Using Local Regression Techniques. *Environ. Plan. B Plan. Des.* **2013**, *40*, 664–682. [CrossRef]

46. McCord, M.; Davis, P.T.; Haran, M.; McIlhatton, D.; McCord, J. Understanding rental prices in the UK: A comparative application of spatial modelling approaches. *Int. J. House Mark. Anal.* **2014**, *7*, 98–128. [CrossRef]

47. Suárez-Vega, R.; Hernández, J.M. Selecting Prices Determinants and Including Spatial Effects in Peer-to-Peer Accommodation. *IJGI* **2020**, *9*, 259. [CrossRef]

48. Santana-Jiménez, Y.; Suárez-Vega, R.; Hernández, J.M. Spatial and environmental characteristics of rural tourism lodging units. *Anatolia* **2011**, *22*, 89–101. [CrossRef]

49. Santana-Jiménez, Y.; Sun, Y.-Y.; Hernández, J.M.; Suárez-Vega, R. The Influence of Remoteness and Isolation in the Rural Accommodation Rental Price among Eastern and Western Destinations. *J. Travel Res.* **2015**, *54*, 380–395. [CrossRef]

50. Hanink, D.M.; Cromley, R.G.; Ebenstein, A.Y. Spatial Variation in the Determinants of House Prices and Apartment Rents in China. *J. Real Estate Finan. Econ.* **2012**, *45*, 347–363. [CrossRef]

51. Nalepka, A.; Tomal, M. Identyfikacja czynników kształtujących ceny ofertowe deweloperskich lokali mieszkalnych na obszarze jednostki ewidencyjnej Nowa Huta. *Świat Nieruchom. (World Real Estate J.)* **2016**, 11–18. [CrossRef]

52. Brzezicka, J.; Łaszek, J.; Olszewski, K.; Waszczuk, J. Analysis of the filtering process and the ripple effect on the primary and secondary housing market in Warsaw, Poland. *Land Use Policy* **2019**, *88*, 104098. [CrossRef]

53. Gluszak, M.; Marona, B. Discrete choice model of residential location in Krakow. *J. Eur. Real Est. Res.* **2017**, *10*, 4–16. [CrossRef]

54. National Bank of Poland. Sytuacja na Lokalnych Rynkach Nieruchomości Mieszkaniowych w Polsce w 2018. National Bank of Poland: Warsaw, Poland, 2019.

55. Yang, W. An Extension of Geographically Weighted Regression with Flexible Bandwidths. Ph.D. Thesis, University of St Andrews, St Andrew, UK, 2015.

56. Tomal, M.; Nalepka, A. The impact of social participation on the efficiency of communal investment expenditure. *Econ. Res. Ekon. Istraživanja* **2020**, *33*, 477–500. [CrossRef]

57. Basile, R.; Durbán, M.; Mínguez, R.; María Montero, J.; Mur, J. Modeling regional economic dynamics: Spatial dependence, spatial heterogeneity and nonlinearities. *J. Econ. Dyn. Control* **2014**, *48*, 229–245. [CrossRef]

58. Dubé, J.; Legros, D.; Thériault, M.; Des Rosiers, F. Measuring and Interpreting Urban Externalities in Real-Estate Data: A Spatio-Temporal Difference-in-Differences (STDID) Estimator. *Buildings* **2017**, *7*, 51. [CrossRef]

59. Anselin, L. Spatial Econometrics. In *A Companion to Theoretical Econometrics*; Baltagi, B.H., Ed.; Blackwell Publishing Ltd.: Malden, MA, USA, 2003; pp. 310–330.

60. da Silva, A.R.; Fotheringham, A.S. The Multiple Testing Issue in Geographically Weighted Regression: The Multiple Testing Issue in GWR. *Geogr. Anal.* **2016**, *48*, 233–247. [CrossRef]

61. Małkowska, A.; Palus, E. Wpływ sąsiedztwa rzeki Wisły na poziom cen ofertowych nowych lokali mieszkalnych w Krakowie. *World Real Estate J. (Swiat Nieruchom.)* **2017**, *101*, 63–68.

62. Adamkiewicz, D.; Radziszewska-Zielina, E. A housing market analysis for the city of Krakow. *Czas. Tech.* **2019**, *2019*, 57–70. [CrossRef]

63. Głuszak, M. Externalities and House Prices: A Stated Preferences Approach. *EBER* **2018**, *6*, 181–196. [CrossRef]