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LOCAL VARIATION IN RATES OF RETURN ON RESIDENTIAL PROPERTY

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ABSTRACT

The rate of return on residential property is determined by a number of diverse factors, including macroeconomic determinants, the level of investment risk, the specific nature of the local market, and the structural characteristics of a particular property. One of the key factors affecting the spread of rates of return at the local level is the location. However, taking location into account in analyses of the rate of return presents significant methodological difficulties due to limitations in traditional calculation methods and analytical models, which generally do not refer to space. The aim of the study is to identify and analyze the spatial variation in rates of return on residential property in selected local markets in Poland, using, *inter alia*, geographically weighted regression. The methods applied enabled the determination of spatial heterogeneity in the relationship between income and price, which provided the basis for the development of maps showing the spatial distribution of rates of return for the local market area. The results indicate significant differences between individual locations, which emphasizes the importance of considering spatial factors when assessing the attractiveness and risk of investments in the property market.

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1. Introduction

Residential property existing within urban housing markets can serve a dual purpose: on the one hand, it is a fundamental consumer good providing conditions for everyday dwelling, while on the other hand, it can be treated as investment assets, generating passive income in the form of rental income. Return on the invested capital allocated for the purchase of a property may be realized not only through rental income, but also through the eventual sale price. In this context, the focus is on the income generated by the invested capital, that is, the rental income (excluding repair and maintenance costs). The key indicator of the effectiveness of property investments as a source of income is the rate of return, which plays an important role from the perspective of both individual and institutional investors. Its analysis enables an assessment of the capital attractiveness of the property market, taking into account the relationship between potential rental income and the costs incurred for the purchase and maintenance of the property. The significance of the rate of return arises from its direct effect on investment decisions, the level of activity in the property market, and price dynamics of individual market segments. A high rate of return attracts investment capital, promoting the development of the rental market and stimulating the supply of flats for rent, while a decline in the rate of return may result in an outflow of investors, and a reduction in market liquidity, with risk playing a significant role (Gregoir et al., 2012).

The rates of return in property markets show significant spatial variation resulting from the multidimensional interaction of local and macroeconomic factors (Dokko et al., 1991). This heterogeneity reflects the specific nature of individual urban markets, which are affected by both structural and demographic supply-and-demand conditions as well as broadly understood economic, financial and institutional determinants (Domian et al., 2015). The profitability of residential investments can vary significantly even within the same city, not only due to differences in the structural characteristics of the property, but also due to the value of the location, which has a key impact on prices, rent levels and the risk of vacant houses.

Despite the growing interest in analyzing the profitability of residential property investments, research to date has mainly focused on cities or entire regions, while often ignoring microstructural differences within individual local markets. Hence, the aim of the study is to identify and analyze the spatial variation in rates of return on residential property in selected local markets in Poland, using geographically weighted regression (GWR).

The paper is divided into several sections. The literature review provided a brief overview of research conducted to date on the spatial variation in the rates of return on residential property. Section Three provides a description of the source data and describes the research methodology. Section Four presents empirical results, while section Five discusses the consequences and significance of the results obtained. The paper ends with conclusions indicating the benefits of using the described method of return rate analysis, and further directions for research.

2. Literature review

The rate of return on residential property is determined by a number of global and local factors, as well as factors specific to a particular investment. Among macroeconomic factors, interest rates, inflation, and economic growth are particularly important (Agava & Gamu, 2024; Pavlov et al., 2015). Bond (2003) emphasizes the complex interaction of global and local factors, particularly in the context of opportunities for diversifying international property investments. The spatial variation in rates of return across regions and cities is highlighted by Samuels (2024), who stresses the importance of local economic conditions, investor expectations and market risk. The factors affecting these differences included the level of urbanization, ownership structure, government intervention and market size (Van der Vlist et al., 2002). Demers and Eisfeldt (2022) states that cities with higher average prices tend to see lower rates of return, which is due to the pursuit of capital gains, but also results in relatively lower rental income.

The rates of return on residential property are determined not only by global factors but also by local ones (Lin, 2022). Differences in rent-to-price ratios in local markets are correlated with factors such as local property tax rates, household incomes and age demographics (Pancak, 2017). Local determinants include, e.g., the elasticity of land supply and the dynamics of flat prices. These factors significantly affect the profitability of flats while recording systematic risks that vary geographically, thus affecting the overall rates of return on investments in residential property in different locations (Beracha & Skiba, 2013). In addition, the physical characteristics of flats in particular locations, as well as the risk of vacant buildings, contribute to the continuing heterogeneity of returns, thus affecting investment decisions in the housing market (Gregoir et al., 2012). According to Zhu and Lizieri (2024), the rates of return are also significantly affected by population density, accessibility of infrastructure, schools, health services, as well as changes in land use planning.

Research conducted to date on the rates of return on residential property indicates that their average value is relatively stable, with the observed variation resulting from both national determinants and the specific characteristics of individual cities. Chambers et al. (2021) found that annual actual total returns, after deducting costs, amounted to approximately 2.3% for residential property in the United Kingdom between 1901 and 1983. Francis and Ibbotson (2009) observed an average annual return of 5.68% for US residential property, which was lower than that for commercial and agricultural property. However, Eichholtz et al. (2021) reported higher actual total net returns of 4.9% for the city of Paris and of 5.3% for the city of Amsterdam, highlighting the importance of quality-adjusted data at the property level. Current data for Poland indicate that rates of return on residential property, depending on the city, range from 4.6 to 5.8% (bankier.pl). Against this backdrop, research conducted in Eastern Europe appears interesting. For example, research conducted in Ukraine before the Russian invasion shows that, in Kharkiv, average returns on residential property were 10%, with certain areas yielding higher returns of up to 12.36% (Kobzan & Nesterenko, 2020).

Local rates of return on residential property are estimated using different methods, including hedonic regression, taking into account both capital gains and rental income (DeRieux et al., 2005), yet for large data sets, these calculations can represent a significant research problem (Domian et al., 2015; Hungria-Garcia et al., 2004). Giaccotto and Clapp (1992) suggested estimating the rates of return on residential property using exponential smoothing and Kalman filter rules. Cajias (2019) suggested using semi-parametric hedonic models to calculate initial net capitalization rates for residential property, using large data sets from digital listing systems. This approach increases market transparency and allows the spatial patterns of profitability in German markets to be identified. In contrast, Erpolat Taşabat et al. (2018) used deep learning methods, in particular LSTM networks, on big data platforms to predict gross rates of return based on property and location attributes. Their model exhibited high accuracy in estimating profits for particular flats. Szweizer (2019), on the other hand, introduced a cross-sectional approach, adapting physics equations to model the rates of return on residential property in Auckland. This method combined macroeconomic and microeconomic factors, taking into account both the investment size and the property size.

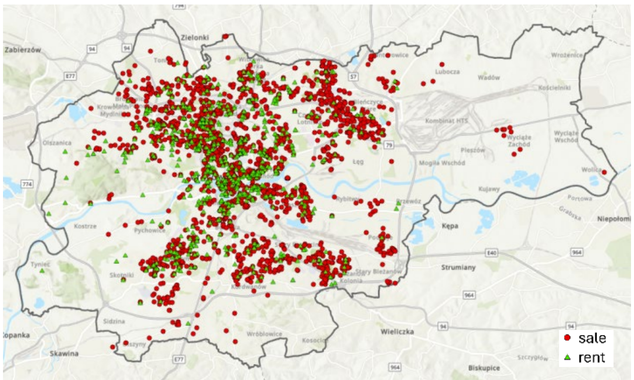
Based on the literature review, it can be concluded that research to date has been focused on determining rates of return for relatively large areas (countries, regions or cities), while few studies take into account the local nature of rent-price relationships. Although there is a wide range of literature on the use of GWR models to analyze prices and rents in the property market (Fotheringham et al., 2024), there is a noticeable lack of research using this method to analyze local rates of return on residential property. This may be due to the fact that calculating the rate of return requires simultaneous access to data on both the income generated by the property and its price, which is a significant challenge in view of the limited availability of such information. Hence, the literature review identified a research gap that needs to be explored further.

3. Materials and methods

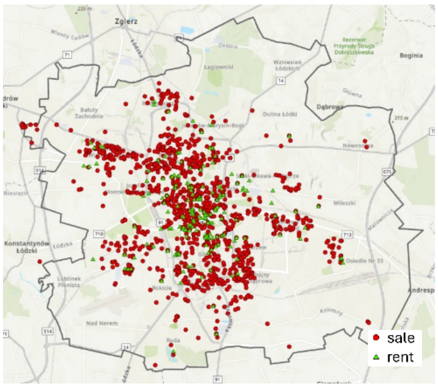
Most published housing market research results are based on actual rents and transaction prices of property, but listings can also be a valuable source of data due to their easy access and timeliness (Park & Bae, 2015). Although the asking prices and rents may not accurately reflect transaction prices, they can still provide information on trends in the property market (Mora-Garcia et al., 2022). The asking prices and rents reflect sellers' expectations and serve as a reference point for negotiations, meaning that, from an investment analysis perspective, they may reflect actual market trends and dynamics. While information on transaction prices is available in the state price register, access to data on actual rents paid for renting flats is significantly restricted. If the rate of return is considered in a simplified manner as the ratio of rents to property values (prices), the asking prices for flats correspond better to the asking rental rates, which reduces the problem of methodological inconsistency. Despite the advantages of using asking prices and rents for market analysis, certain disadvantages have also been indicated, resulting from excessive optimism on the part of sellers (or landlords), or susceptibility to manipulation (Rico-Juan & Taltavull de La Paz, 2021). However, an unquestionable advantage of using this source of information is the ease with which it can be obtained using web scraping (Üzümcü & Eliguzel, 2023).

The study covered all voivodeship capitals in Poland, with the results presented for four selected cities, namely Krakow, Lodz, Wroclaw and Poznan. The source data originates from the www.oferty.net portal, and was sourced in January 2025 (in the winter period, there is usually relative stability in both the sales and rental markets). In order to analyze the three selected cities, approximately 10,000 flat sale offers and approximately 1,800 flat rental offers were used. The spatial distribution of the analyzed data is shown in Figure 1.

Krakow



Lodz



Wroclaw

Poznan

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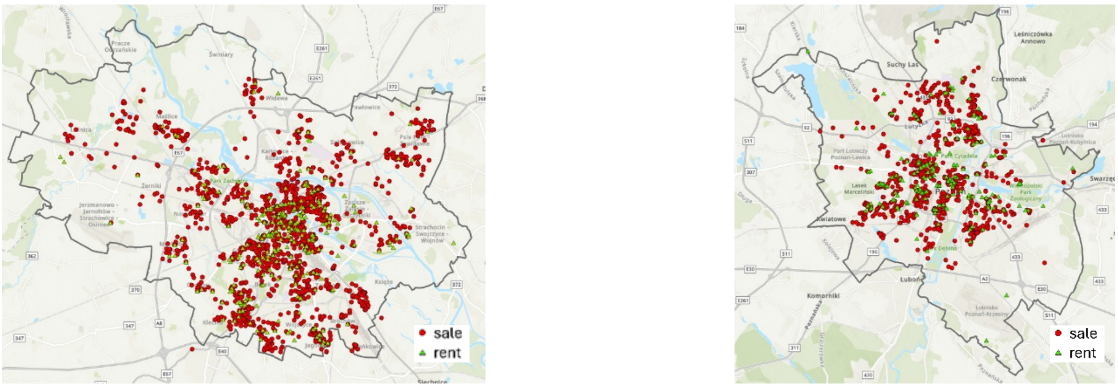

Fig. 1. The spatial distribution of flat sales and rental offers. *Source*: own study.

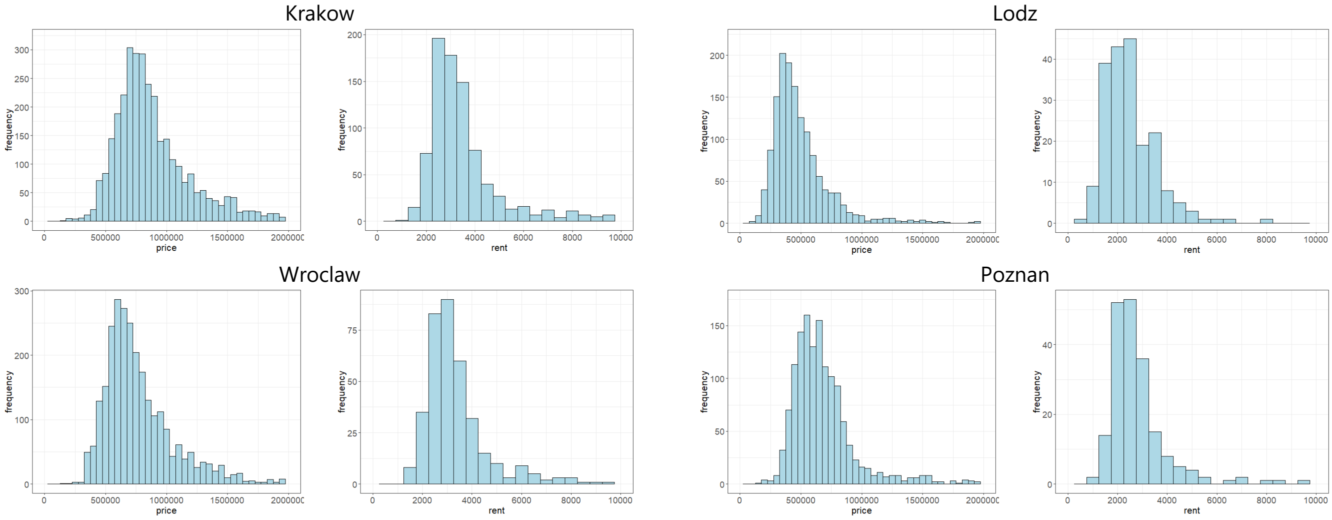

Fig. 2. Histograms of the distribution of transaction prices and rental rates in four cities under analysis. *Source*: own study.

Residential property is characterized by significant heterogeneity in terms of physical characteristics, which are commonly included in market analyses as an important factor affecting price formation, both within individual cities and between them. Although both rents and prices reflect these diverse characteristics, estimating local rent-to-price ratios can be challenging due to the limited availability of data on properties for which both the prices and rental rates are known. Therefore, the analysis also took into account such characteristics as the size of the flat and the year of construction. Fig. 2 shows histograms of the distribution of transaction prices and rental rates in the analyzed cities.

The study used a log-linear multiple regression model, a mixed geographically weighted regression model and, for the purpose of result visualization, simple kriging. The classic linear regression model can be formulated as follows:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \varepsilon \tag{1}$$

where β_0, β_1,..., β_2 represent model parameters, while ε represents a random error with distribution N(0,σ). Model parameters are usually estimated using the Ordinary Least Squares (OLS) method, while significance tests are performed using F statistics and t statistics (Rencher & Schaalje, 2008). The geographically weighted regression (GWR) model is an extension of the classic linear regression model, as it takes into account spatial relationships by assigning weights to individual observations depending on their location. It originates from non-parametric regression (Mei et al., 2006), and its essence is to construct local linear regressions at each point where measurement data exist. The GWR model can be formulated as follows (Fotheringham et al., 2002):

$$y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) x_k + \varepsilon_i \tag{2}$$

where (ui, vi) specifies the location expressed by coordinates u_i and v_i. The GWR model parameters are usually estimated in a way similar to that used for classic models, but with the weights of observations depending on location taken into account:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) y \tag{3}$$

where $W(u_i, v_i)$ is a diagonal matrix of weights representing the distance function between the location defined by coordinates (u_i, v_i) and the location of each point at which the observation has been made. Most often, functions similar in shape to the Gaussian distribution are used to determine weights, e.g. in the form of the bisquare kernel function (Fotheringham et al., 2002). The use of the GWR model results in a series of areas determined by the estimated parameters. The spatial variation in the values of these parameters indicates local variability in the influence of the dependent variables on the explanatory variable, and thus spatial heterogeneity of the phenomenon under study.

Local GWR regression coefficients may have varying degrees of variability across the study area. Some of them can be seen as permanent (i.e. global, stationary), while others can be local in nature (non-stationary). Then, a mixed MGWR model can be determined (Fotheringham et al., 2002), which can be expressed as follows (Lu et al., 2014):

$$y = X_a a + X_b b + \varepsilon \quad (4)$$

where y is the vector of the dependent variable, X_a is the matrix of global variables, a is the vector of global coefficients, X_b is the matrix of local variables, and b is the matrix of local coefficients. In the MGWR model, some coefficients are regarded as global (constant across the entire analyzed area), while others are regarded as local (variable depending on location). This means that this model enables a more flexible approach to spatial variability, regarding some coefficients as constant for the entire area, and others as variable. Mixed model parameters can be estimated iteratively (Lu et al., 2014), under the assumption that:

$$\hat{y} = \hat{y}_a + \hat{y}_b, \text{ where } \hat{y}_a = S_a y, \text{ and } \hat{y}_b = S_b y \quad (5)$$

where S_a and S_b represent hat matrices, i.e. matrices which, when multiplied by the empirical values of the dependent variable, yield theoretical values. The model fitting procedure can be described in the following six steps (Lu et al., 2014):

Step 1. Supply an initial value for $\hat{y}_a$, say $\hat{y}_a^{(0)}$, using OLS
Step 2. Set *i* = *1*
Step 3. Set $\hat{y}_b^{(i)} = S_b\left[y - \hat{y}_a^{(i-1)}\right]$
Step 4. Set $\hat{y}_a^{(i)} = S_a\left[y - \hat{y}_b^{(1)}\right]$
Step 5. Set *i* = *i* + *1*
Step 6. Return to Step 3 unless $\hat{y}^{(i)} = \hat{y}_a^{(i)} + \hat{y}_b^{(i)}$ converges to $\hat{y}^{(i-1)}$

A slightly different method for estimating the mixed GWR model is presented by Fotherihngham et al. (2002), who applied the method presented by Speckman (1988). In turn, Wei and Qi (2012) proposed constrained two-step estimation by transforming the MGWR model into the form of GWR, and performing estimation using the Lagrange Multiplier procedure.

Based on the results obtained by the MGWR method, local rates of return were visualized using geostatistical (kriging) methods. Kriging is a geostatistical interpolation technique that uses a weighted linear combination of known sample values to estimate unknown points. It also uses weighted averaging of neighboring points in such a manner that minimizes the prediction error variance (Goovaerts, 1997). These weights are selected based on the spatial structure of the data (semi-variogram), which distinguishes kriging from simpler interpolation methods such as the inverse distance weighting (IDW) method.

4. Results

The variation in rates of return on residential property in different cities is due to a combination of economic, demographic, institutional and spatial factors that shape both the demand and supply sides of the property market. It is the local factors shaping supply and demand for property in a particular city that account for a significant part of the differences in rates of returns on housing investments, with area-specific conditions often being more important than general economic trends (Lin, 2022). Therefore, the starting point for further research was to estimate rates of return in selected cities in Poland.

The determination of the rate of return requires knowledge of both the income generated by the property and its value (or, alternatively, its market price). If we have two separate data sets, one relating to sales, and the other to rentals, the simplest solution would be to use average prices and average rents. However, due to intra-group and inter-group differences, this solution would be subject to relatively high errors. Hence, the following log-linear multiple regression model was proposed to calculate rates of return, taking into account both sale and rental offers:

$$\ln Y = \beta_0 + \beta_1 \cdot AREA + \beta_2 \cdot YEAR + \beta_3 \cdot RENT + \varepsilon \quad (6)$$

where Y denotes the sale price or the annual rent (depending on whether the offer is for sale or rent), AREA denotes the property area, YEAR denotes the year of construction, and the binary variable RENT indicates whether the property is offered for rent. In this way, the coefficient for the binary variable, after appropriate conversion (R = exp(β_3)), directly indicates the rate of return as the ratio between income and property price. Table 1 shows the results of the estimation of multiple regression model coefficients for four selected cities.

Table 1

The results of the estimation of multiple regression model coefficients for four selected cities

Krakow	estimate	std. error	p-value
Intercept	12.4608	0.1814	<0.001
AREA	0.0128	0.0001	<0.001
YEAR	0.0002	0.00001	0.007
RENT	-3.0358	0.0090	<0.001
R^2=0.967 Adj. R^2=0.967			

Lodz	estimate	std. error	p-value
Intercept	3.5987	0.3045	<0.001
AREA	0.0142	0.0002	<0.001
YEAR	0.0043	0.0001	<0.001
RENT	-2.8144	0.0167	<0.001
R^2=0.953 Adj. R^2=0.952			

Wroclaw	estimate	std. error	p-value
Intercept	8.9735	0.2303	<0.001
AREA	0.0122	0.0002	<0.001
YEAR	0.0019	0.0001	<0.001
RENT	-2.9159	0.0128	<0.001
R^2=0.949 Adj. R^2=0.949			

Poznan	estimate	std. error	p-value
Intercept	7.9547	0.3501	<0.001
AREA	0.0119	0.0002	<0.001
YEAR	0.0023	0.0002	<0.001
RENT	-2.9079	0.0181	<0.001
R^2=0.948 Adj. R^2=0.948			

Source: own study.

In Krakow, the rate of return was 4.80% after conversion, in Lodz 5.99%, in Wroclaw 5.41%, and in Poznan 5.46%. The coefficients for all analyzed variables proved to be statistically significant at a significance level lower than 0.001. What is worth noting is the relatively high value of the coefficient of determination (approximately 0.95). The rates of return for other voivodeship capitals in Poland were determined in the same manner. The results are provided in Fig. 3.

The rate of return values show noticeable spatial variation. The highest values are observed in Bydgoszcz, Szczecin and Rzeszow, where the rates of return exceed the level of 6%. These are cities with relatively low asking prices for flats and stable demand for rentals, particularly among students and young household dwellers. These are also cities with relatively lower property prices and moderate rents, which translates into higher profitability of residential investments. The lowest values were noted in Bialystok and Krakow, where the profitability of residential investments does not exceed 5%. A low rate of return may be due to relatively high property purchase prices that are not fully offset by the rental rate achieved. As for the largest cities, like Krakow or Warsaw, other factors such as the growing short-term rental market, local regulations, or limits from spatial planning policies may also play a significant role.

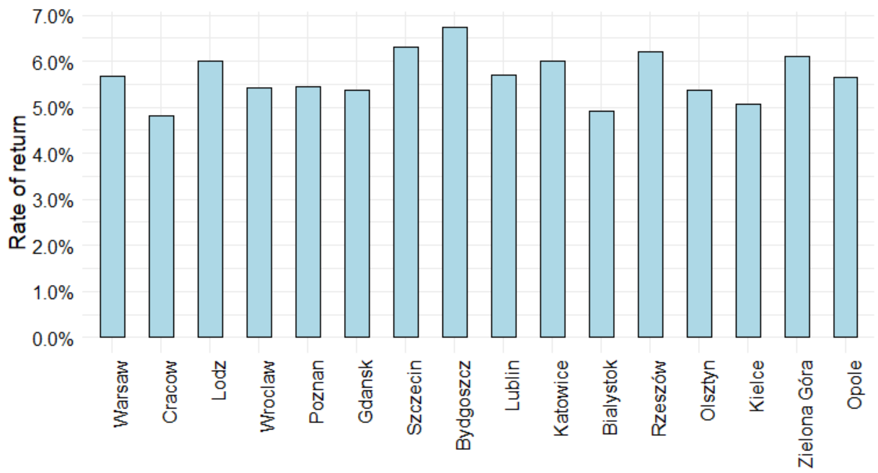

Fig. 3. A comparison of rates of return on residential property in voivodeship capitals of Poland (ranked by population). *Source*: own study.

Based on the analysis, it can be observed that peripheral markets and medium-sized cities may offer higher rates of return than large urban agglomerations, as high profitability is not always correlated with the

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size of a city. Warsaw and Krakow, despite their strong economic position, are characterized by relatively lower rates of return, which may result from comparatively high property prices in relation to the rents achieved. This relationship may limit the accessibility of these markets for investors expecting high current yields. The results indicate the need for a detailed analysis of local housing market conditions in the context of investment decisions. A high rate of return does not always go hand-in-hand with high potential for an increase in property value, while markets with low profitability may offer other benefits, such as greater liquidity or lower risk of vacant buildings. From the perspective of housing policy planning, the observed differences may also indicate areas requiring support regarding access to flats for rent.

The study also presents a detailed analysis, using a geographically weighted regression model, to determine the spatial variation in rates of return in Krakow, Lodz, Wroclaw and Poznan. The present study used a mixed GWR model (MGWR), which assumed that local characteristics would have a coefficient with the RENT variable, while the remaining coefficients, including the model constant, would reflect the analyzed phenomenon globally (a constant value across the entire analyzed area). A bisquare kernel function was used to determine the weights, while a method based on the AIC (Akaike Information Criterion) was used to determine the adaptive bandwidth. Table 2 shows the overall results of MGWR modeling.

Table 2

Overall results of estimation of the MGWR model coefficients for four selected cities

	Global			Local (RENT)					
	Intercept	AREA	YEAR	Min	Q1	Median	Mean	Q3	Max
Krakow	12.375	0.0128	0.0003	-3.356 (3.49%)	-3.054 (4.72%)	-2.962 (5.17%)	-2.952 (5.28%)	-2.837 (5.86%)	-2.507 (8.15%)
Lodz	3.6595	0.0143	0.0043	-3.136 (4.34%)	-2.930 (5.34%)	-2.860 (5.73%)	-2.848 (5.84%)	-2.774 (6.24%)	-2.495 (8.25%)
Wroclaw	8.8918	0.0122	0.0019	-3.488 (3.49%)	-3.054 (4.71%)	-2.962 (5.17%)	-2.952 (5.28%)	-2.837 (5.86%)	-2.507 (8.15%)
Poznan	7.6030	0.0118	0.0025	-3.350 (3.51%)	-3.032 (4.82%)	-2.960 (5.18%)	-2.959 (5.24%)	-2.879 (5.62%)	-2.261 (10.42%)

(return rates calculated based on the β_3 coefficient as $R=\exp(\beta_3)\cdot 100\%$ are given in brackets).

Source: own study.

The values of global coefficients (Intercept, AREA, YEAR) show a relatively similar level between cities, which suggests consistency in the overall relationships between the variables studied and the level of rates of return. The locally modeled coefficient for the RENT variable is characterized by significant spatial variation, which is noticeable in the interquartile range and extreme values of the coefficients. The greatest variation is observed in Poznan, where the coefficients (after conversion) range from 3.51% to 10.42%, with a median of 5.18%. At the same time, Poznan had the smallest interquartile range, indicating that the rates of return are clustered around the median, with extreme values occurring rather sporadically. The lowest variation in local effects of the RENT variable was observed in Lodz, where rates of return ranged from 4.34% to 8.25%.

Geostatistical interpolation was performed using simple kriging to visualize the spatial variation of rates of return. This method is based on the assumption that the expected value of a regional variable is known from external data or large samples and is constant throughout the study area. This may be particularly important in situations where data are irregularly distributed and extrapolated beyond the area defined by the sampled points. In this case, the global average was adopted based on multiple regression analysis (Table 1). Figure 4 presents the results of applying spatial interpolation in the form of maps showing the distribution of return rates in four cities under analysis.

In Krakow, the lowest return rate value was noted in the historic city centre. In this case, the profitability of property may be affected not only by high prices but also by regulations governing the short-term rental market, especially in cultural heritage protection zones. Tenement houses and older buildings in the centre of Krakow often require greater expenditure on renovation, modernization or ongoing maintenance, and are also burdened with high operating costs, which further reduces the actual profitability of the investment. In contrast, in the city of Lodz, the rates of return show relatively low spatial variation. The highest rates, reaching 7%, are found in the Stare Baluty district, near the Manufaktura shopping, service and cultural complex. In the inner centre, these range from 5% to 6%. In Wroclaw, as in Lodz, the highest rates of return on housing investments (close to 7%) are observed in the areas located in the immediate vicinity of the city centre, but not in its inner centre zone. In Poznan, the highest profitability of flats (over 8%) is found in areas located in the vicinity of the main railway station and a large shopping centre. In the remaining area, the return rate level ranges mostly between 5% and 6%. The fact that the highest rates of return are not observed in city centers may lead to the assumption that many investors buy flats with a view to an increase in the long-term property value (capital appreciation) rather than obtaining a high current rental income. This means that the acceptable rate of return on rent may be relatively low, yet the potential future profits from sales offset the lower current profitability for investors.

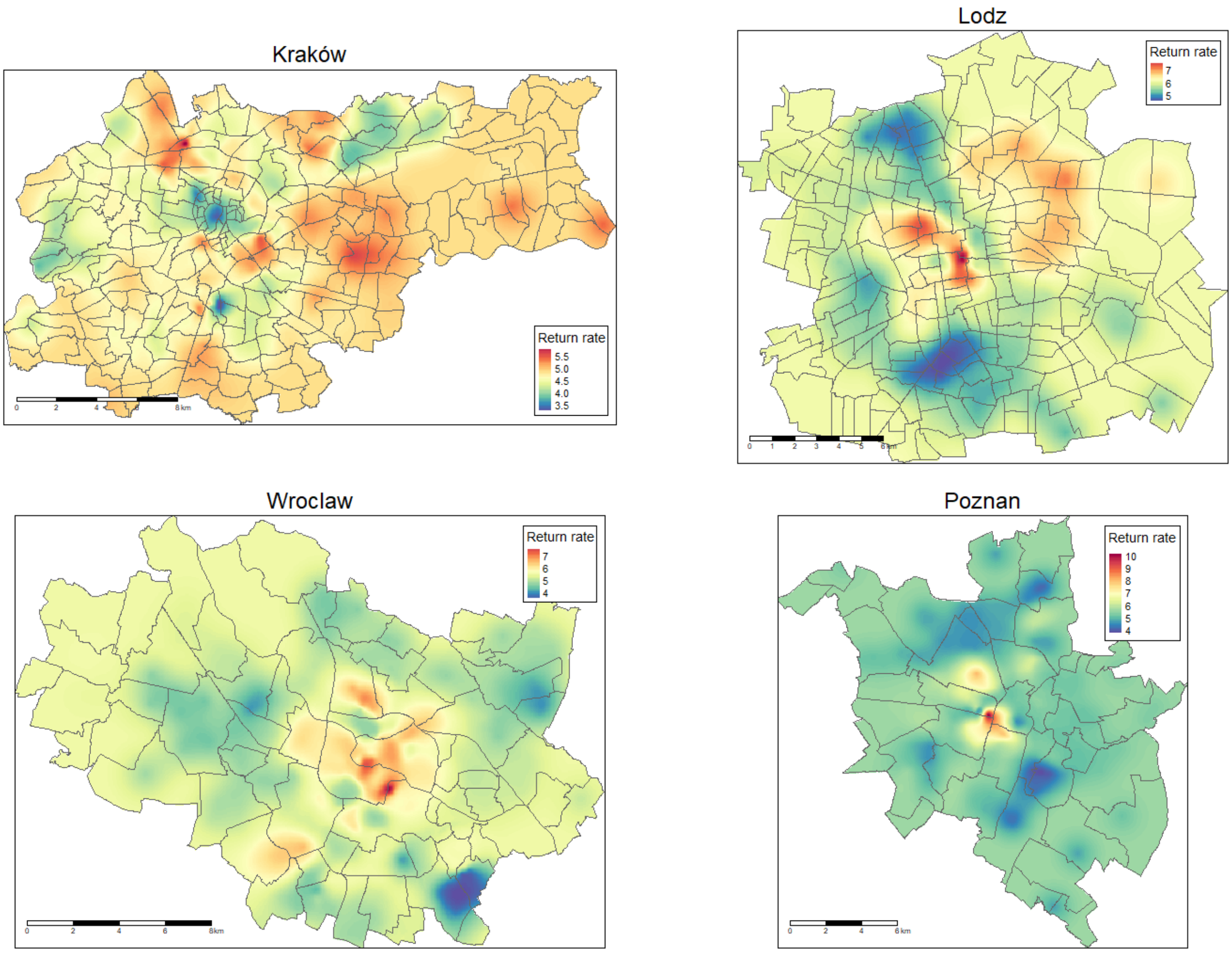

Fig. 4. Visualization of the spatial development of the rates of return on residential property in four analysed cities. *Source*: own study.

5. Discussion

The results of the analyses clearly indicate significant spatial variation in rates of return on residential property, both between voivodeship capitals and within selected agglomerations. The differences observed are not solely the result of macroeconomic determinants, but largely reflect local structural, demographic and institutional conditions affecting the relationship between purchase price and potential rental income, which may confirm the results of previous studies (Chae, 2023; Hanink et al., 2012). It is worth noting that higher rates of return, observed in smaller cities such as Bydgoszcz and Rzeszow, may result from low barriers to market entry combined with stable demand. This situation, however, may be associated with increased risk related to lower market liquidity and limited potential for property value growth over the long term (Thissen et al., 2010).

The spatial approach in the MGWR model enabled the identification of significant local deviations from global values, which would not have been possible using classic regression methods (Chae, 2023). In particular, the RENT variable, regarded as a local variable, showed significant variation in regression coefficients, which is directly reflected in the volatility of local rates of return. The results of spatial interpolation, carried out by the kriging method, additionally confirmed the heterogeneous nature of the residential rental market (Hoshino, 2011; Vanags et al., 2017). Therefore, the methodology used not only enables a more accurate estimation of the profitability of housing investments but also allows areas with above-average or below-average investment attractiveness to be identified. For example, in cities like Poznan or Wroclaw, locations with relatively high rates of return were identified, which may represent potential focal points of activity for private and institutional investors. At the same time, agglomerations with high asking prices (e.g. Krakow), despite favorable demographic and infrastructure indicators, show relatively lower profitability, which may be due to the saturation of the long-term rental market and growing competition from short-term rentals. A low rate of return in certain locations may not necessarily indicate low investment attractiveness, but rather but rather reflect the predominance of a strategy focused on capital gains (e.g., property value appreciation) rather than on current rental income.

6. Conclusions

The rates of return on residential property show significant spatial variation, both between cities and within them, which confirms the need to consider the location factor in investment analyses. The level of profitability is not clearly correlated with the size of the city or its economic position, suggesting that investors should take into account not only macroeconomic factors but also the microstructural characteristics of local markets.

The application of geographically weighted regression (GWR) and the MGWR model enables the capture of spatial non-stationarity of explanatory variables, which significantly improves the quality and precision of the estimation of profitability indicators. The maps obtained on the basis of the model not only enable the identification of areas with increased investment potential or increased risk, but can also be a useful tool to support investment decisions, especially in the context of selecting locations for rental property. From the perspective of housing policy planning, the identification of areas with low profitability may indicate a need for public intervention aimed at improving the availability of rental housing and supporting a balance between supply and demand in the residential property market.

It should be noted that the results are based on offer data, which may differ from actual transactions. What is more, the analysis did not take into account the potential factors affecting the rates of interest, including, e.g., infrastructure quality, accessibility of public services, or demographic changes. Future research should therefore consider extending the model to include additional explanatory variables.

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