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Spatial Autocorrelation in Housing Prices: Analysis of the Brno Metropolitan Area

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ABSTRACT

This study examines the persistence of spatial autocorrelation in housing prices within the Brno metropolitan area, focusing on the dynamics between the core city and its peripheral municipalities. The aim of the study is to test whether spatial autocorrelation exists and the extent to which it can be explained by traditional variables. Using a log-linear specification, the analysis employs a hedonic price model estimated separately for the city's central and peripheral areas. The dataset comprises 19,286 residential transactions from the period 2020–2023. Explanatory variables include structural characteristics, land use, crime rates, and accessibility to services. Spatial autocorrelation is measured using Moran's I and Local Indicators of Spatial Association, both on raw data and model residuals. The results reveal that price clustering is substantially stronger in peripheral areas, where lower market liquidity and limited substitutability of dwellings amplify the transmission of price signals across municipal boundaries. The findings suggest that localized factors such as planning agreements and limited market liquidity affect price transmission across municipal borders. The study's findings highlight that spatial autocorrelation is not merely a statistical pattern but a mechanism shaping housing affordability, market efficiency, and the distribution of price shocks. In peripheral areas, prices are strongly affected by proximity to the city center and access to public infrastructure, indicating the need for coordinated metropolitan policies, particularly in rapidly growing suburban areas where spillover effects are most pronounced. The study contributes to housing economics by quantifying the structural sources of spatial dependence and demonstrating their relevance for metropolitan policy design.

1. Introduction

The privatization of the Czech housing market following the transition from a centrally planned to a market economy drove more than two decades of significant housing price appreciation. Much

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of the relevant research has examined the Czech housing market from either macroeconomic [1], behavioral [2], regional crisis impacts [3], [4], monetary [5] and most importantly sustainable urban development perspective [6]. However, intercity linkages and interactions at the most granular territorial level remain underexplored, despite their importance in the context of demographic shifts, particularly the predominance of suburbanization over the past decade. Addressing this knowledge gap could improve understanding of housing price co-movements and the targeting of policies, beginning with defining the appropriate level for policy intervention on the local level, which however crucial also for the regional development

The present research focuses on the Brno metropolitan area (BMA). In recent years, the concept of metropolitan areas has been introduced into the Czech system of local government. Although these areas share a legal framework and receive financing from the European Regional Development Fund, they lack integration and coordination in land use and planning policies in their constituent municipalities. The Brno case study suggests that greater metropolitan-level coordination could improve the effectiveness of affordable housing policies.

Applying a hedonic price model, the study tests the hypothesis that spatial autocorrelation persists as a potential driver of housing price spillover effects in the Czech residential housing market, with a focus on the Brno agglomeration. The model includes a comprehensive set of explanatory variables: lot-specific characteristics (e.g., number of rooms, presence of balcony), neighborhood-level indicators, accessibility metrics, and land use data. The dependent variable is the price per square meter.

The remainder of the paper is structured as follows: chapter 2 reviews related works on spatial patterns in housing prices; Chapter 3 describes the study area and dataset applied in the modelling process; Chapter 4 outlines the methodological framework; Chapter 5 presents empirical results; Chapter 6 discuss findings and provide implications while chapter 7 concludes the study.

2. Literature Review

Spatial autocorrelation has been defined in several ways, each emphasizing a different aspect of the concept. Ismail, [2] offers a straightforward definition: "Spatial autocorrelation is a phenomenon where the values of a variable located within certain a geographic area show similar patterns." Griffith, [7] defines spatial autocorrelation as "a measure of true but masked information content in geo-referenced data", highlighting its role in exploring hidden spatial relationships that may arise from factors such as the tendency for properties in close proximity to be developed and sold concurrently [8]. Key importance of spatial autocorrelation in pricing of properties is emphasized by Jamil, who puts this feature of property markets into the context of urban-rural disparities [9].

Spatial autocorrelation in real estate has been examined through multiple conceptual approaches. Lo *et al.,* [10] categorize the literature into two main strands: (i) studies focused on spatial features of housing markets and (ii) research centered on modelling procedures. The former includes works by Chen *et al.,* [11], Gillen *et al.,* [8], and Lo *et al.,* [10], and the latter includes Basu & Thibodeau, [12], and Valente *et al.*, [13]. The first strand identifies several sources of spatial autocorrelation. Bowen *et al*., [14] emphasize the valuation process as a key factor, noting that real estate professionals and agents apply local market knowledge when estimating property values. This practice can link prices with nearby locations, creating spillover effects between submarkets [10]. Another commonly cited source of spatial autocorrelation is the inability to fully capture local amenities and socio-cultural, ecological, and geographical contextual factors, such as crime rates [15], population density [16], and air quality [17]. Land use regulations and zoning policies are also frequently mentioned. Barrecca *et al*., [18], for example, find a statistically significant relationship between building characteristics and spatial autocorrelation. Design constraints, such as limits on developable areas, requirements for green space, or infrastructure elements such as walkways and escalators, may further contribute to spatial autocorrelation.

Recent studies also examine the price discovery process in housing markets. Hromada [19] found that lower mortgage rates paradoxically raise house prices through increased demand, highlighting the complex interplay between fiscal policy and market responses. This finding is particularly relevant for understanding price dynamics in metropolitan areas, where monetary policy effects may vary between core and peripheral markets due to different demand elasticities and market structures.

Market liquidity is a key component of the price information search framework [14]. When trading volume in a housing submarket declines, market participants may be forced to depend on prices of previously sold properties or transactions from more distant locations for valuation. This dependence increases spatial autocorrelation, as illiquid markets compel property owners to seek price information beyond their immediate areas, pushing price transmission across submarkets. This perspective relates to the findings of Can & Megbolugbe, [20], who demonstrate that incorporating information from earlier transactions improves the construction of housing price indices, specifically when not all locational and neighborhood attributes are observable.

Recent studies also investigate the vertical dimension of spatial autocorrelation, which refers to the relationship between different data types at a single spatial point. Morali and Yilmaz, [21] provide evidence that high rise residential complexes contribute to spatial autocorrelation; Lo *et al*., [10] report that market liquidity tends to increase vertical spatial dependence whereas market volatility has a stronger effect on horizontal spatial autocorrelation. This pattern reflects the efficiency of the Hong Kong property market, where price information is readily accessible in terms of both time and cost. However, researchers have noted a lack of theoretical foundations for hedonic models, ambiguity regarding the use of variables, and uncertainty about correct model specifications. Lo *et al.,* [10] further highlight that property pricing may use diverse data sources, including government records, professional reports, and subjective forecasts of market trends. Consequently, empirical findings may vary significantly across countries and should not be generalized without thorough testing in the relevant submarket context.

A distinct country-specific factor that may contribute to spatial autocorrelation in housing prices is the implementation of planning agreements. Over the past decade, many municipalities have adopted policies requiring developers to provide financial contributions as a condition for obtaining residential building permits. These funds are typically allocated to public infrastructure projects, such as roads, preschools, and playgrounds. However, the financial burden of these contributions is generally passed on to future homeowners through higher property prices, consistent with the principles of profit maximization.

This mechanism affects spatial autocorrelation through two main channels. The first is the direct impact of higher property prices; the second reflects the theoretical framework proposed by Stiglitz, [22], who suggests that communities with superior public services and infrastructure attract individuals willing to pay higher rents or purchase prices. Public infrastructure financed through planning agreements, independent of residents' tax contributions, disproportionately raises the value of existing properties as local governments seek to maximize land value. Consequently, the process reinforces housing price spillovers and amplifies spatial autocorrelation.

The assessment of territorial development and living standards, as examined by Luczak *et al.* [23], provides additional context for understanding spatial variations in housing markets. Their methodological framework for evaluating development positions of territorial units suggests that differences in sustainable development levels and living standards across municipalities within metropolitan areas may contribute to the observed spatial autocorrelation patterns, as these disparities influence both housing demand and price formation mechanisms at the local level.

Although spatial autocorrelation in housing prices is well documented, most existing research focuses on urban cores and ignores peripheral municipalities. Accessibility and institutional factors are also rarely analysed together, and evidence from Central and Eastern Europe remains limited.

3. Study Area and Data

3.1 Brno Metropolitan Area

The Brno metropolitan area (BMA), as defined by Ouředníček *et al.*, [24], covers 1,978 km^2 and had a population of approximately 722,000 as of December 31, 2023, representing 58% of the regional population. The area is mainly urbanized, with Brno serving as the dominant core city, home to approximately 55% of the metropolitan population. The municipal structure reflects the fragmented system of local governance in the Czech Republic, which includes 6,254 municipalities nationwide. Withing this framework, the BMA comprises 184 self-governing municipalities. Figure 1 illustrates the administrative boundaries of Brno and its broader metropolitan area within the Czech Republic.

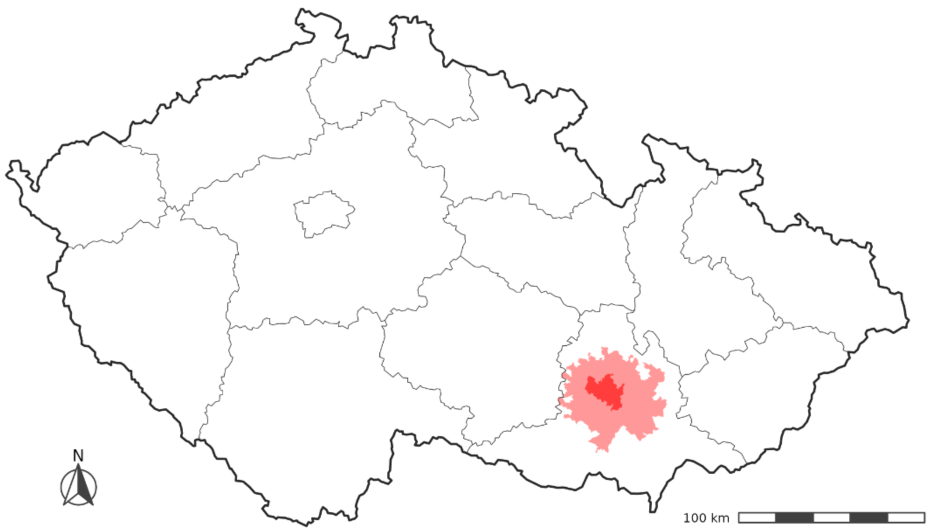


Fig. 1. City of Brno and the Brno metropolitan area in the Czech Republic

Table 1 summarizes the demographic changes in the BMA in the context of regional population trends. The table distinguishes between the city of Brno and its surrounding municipalities, highlighting the differences in population dynamics. The data indicate a gradual increase in the proportion of the regional population living within the metropolitan area, driven mainly by population growth in Brno. By contrast, peripheral municipalities exhibit only marginal growth.

Table 1
Population changes in South Moravia Region, the City of Brno, and the BMA

Population	2019	2020	2021	2022	2023
Region	1,191,989	1,195,327	1,184,568	1,217,200	1,222,558
BMA	699,080	702,203	697,084	721,263	726,417
BMA, excl. City of Brno	317,734	319,798	317,618	325,162	325,851
City of Brno	381,346	382,405	379,466	396,101	400,566
Proportion of BMA in region	58.65%	58.75%	58.85%	59.26%	59.42%
Proportion of City of Brno in region	31.99%	31,99%	32.03%	32.54%	32.76%
Proportion of City of Brno in BMA	54.55%	54.46%	54.44%	54.92%	55.14%
Proportion of BMA, excl. City of Brno, in region	23.19%	23.33%	23.44%	23.38%	23.33%

Although population inflow is concentrated in the regional capital, construction activity exhibits different dynamics. As indicated in Table 2, from 2022 onward, the number of completed dwellings increased in both the city of Brno and peripheral areas. However, between 2019 and 2023, the number of completed dwellings in the periphery grew more than threefold, compared to a comparatively moderate 50% increase in Brno. The slower pace of construction in Brno may partly be attributed to constraints imposed by the city's zoning plan, which has remained in effect since 1994 (a duration exceptional even by Czech standards). This plan may have depleted large, suitable sites for new development. Limited housing supply contributes to sharp price increases and may crowd out demand toward neighboring municipalities, producing spillover effects and driving price inflation in adjacent areas.

Table 2
Completed dwellings in apartment buildings in South Moravia Region, the City of Brno, and the BMA

Completed dwellings	2019	2020	2021	2022	2023
Region	2,084	1,966	2,098	4,461	5,171
BMA	1,721	1,514	1,771	2,306	3,447
City of Brno	1,274	930	972	983	1,918
BMA, excl. City of Brno	447	584	799	1 323	1,529
Proportion of BMA in region	82.58%	77.01%	84.41%	51.69%	66.66%
Proportion of City of Brno in region	61.13%	47.30%	46.33%	22.04%	37.09%
Proportion of BMA, excl. City of Brno, in region	21.45%	29.70%	38.08%	29.66%	29.57%

Table 2 also indicates that the COVID-19 pandemic had a discernible impact on construction activity within the city of Brno, which declined by approximately 27% in 2020 compared to the previous year, whereas construction patterns in the surrounding region and the rest of the metropolitan area remained largely unaffected.

3.1 Brno Metropolitan Area

The dataset contains 19,286 dwelling transactions within the cadastral territories of municipalities in the BMA, recorded between January 2020 and December 2023. To evaluate spatial autocorrelation, the study distinguishes between two zones: the cadastral territory of Brno (central) and the remaining municipalities of the metropolitan area (peripheral). The central zone accounts for 13,600 transactions; peripheral areas comprise 5,683 housing purchases.

Figure 2 illustrates the distribution of sales according to year. Except for 2022, when monetary restrictions peaked[1], the sample for the central zone remains evenly distributed, indicating stable demand. By contrast, the sample for peripheral areas indicates a pronounced concentration of transactions in 2023. The pattern observed in 2022 reflects the impact of monetary tightening and rising mortgage rates, whereas the final year of the examined period represents a prominent deviation from this trend.

Figure 3 illustrates the housing price variation across the two samples. The mean price in peripheral areas was CZK 75,000 per square meter, approximately 25% lower than the average price in the city of Brno. This disparity perhaps reflects differences in locational attributes and housing characteristics between the two areas.

Figures 4 and 5 compare housing characteristics across both zones.

[1] *The first increase in the base interest rate of the Czech National Bank from 0.25% to 0.50% occurred in June 2021 and culminated in June 2022 at 7%. This was mirrored by the development of the average mortgage rate, which peaked in December 2022 at 5.93%*

A much higher proportion of apartment transactions involving concrete panel buildings is observed in the central metropolitan area. This trend corresponds to the historical distribution of panel buildings, which were constructed in large cities during the period of centrally planned economies. Despite this, brick construction remains the dominant building type in both areas.

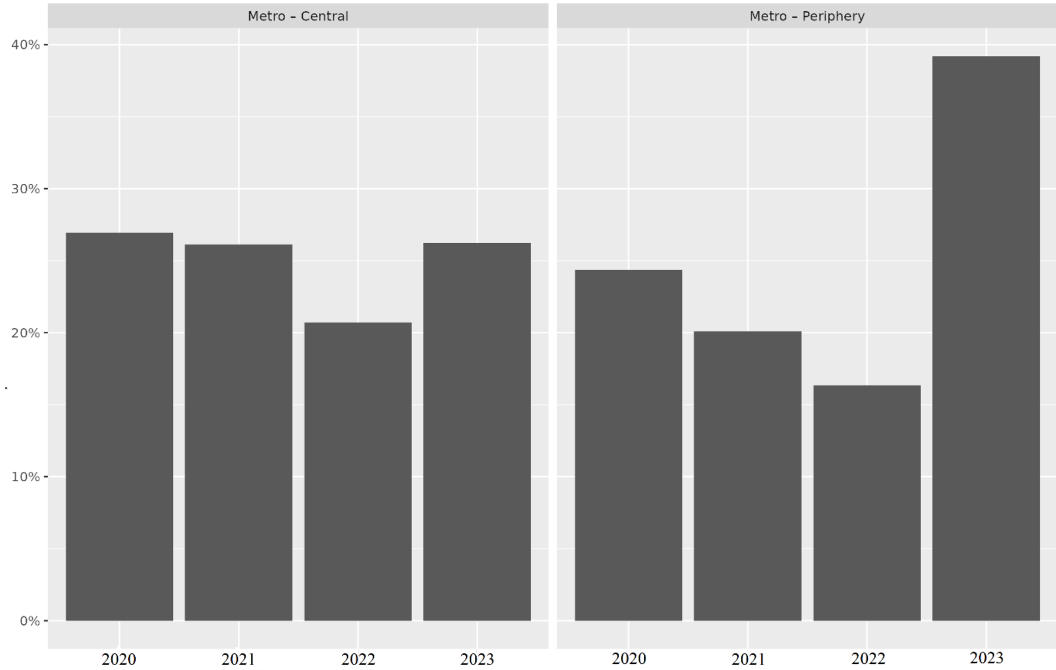


Fig. 2. Distribution of transactions according to year

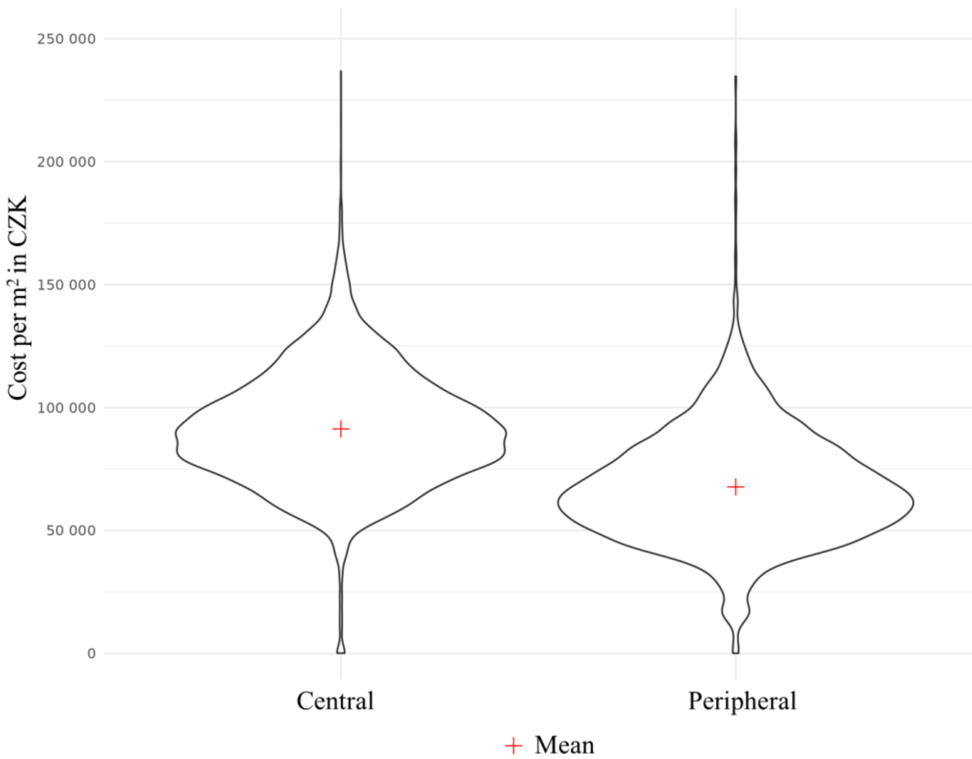


Fig. 3. Variance in prices in the central and peripheral areas of Brno

In both samples, privately owned housing constitutes the majority of transactions. The central zone, however, is more homogeneous, with over 80% of sales involving private ownership. By contrast, the peripheral areas exhibit greater diversity in ownership structures, with alternative forms such as public ownership being more common. Another notable ownership category in the dataset is housing cooperatives. This form emerged in the Czech Republic during the period of transition from public to private ownership, when most dwellings were privatized as the legal representatives of former tenants (i.e., housing cooperatives).

Surprisingly, the proportion of cooperative-owned properties is similar in both zones, despite the majority of privatized units originally being concentrated in larger cities.

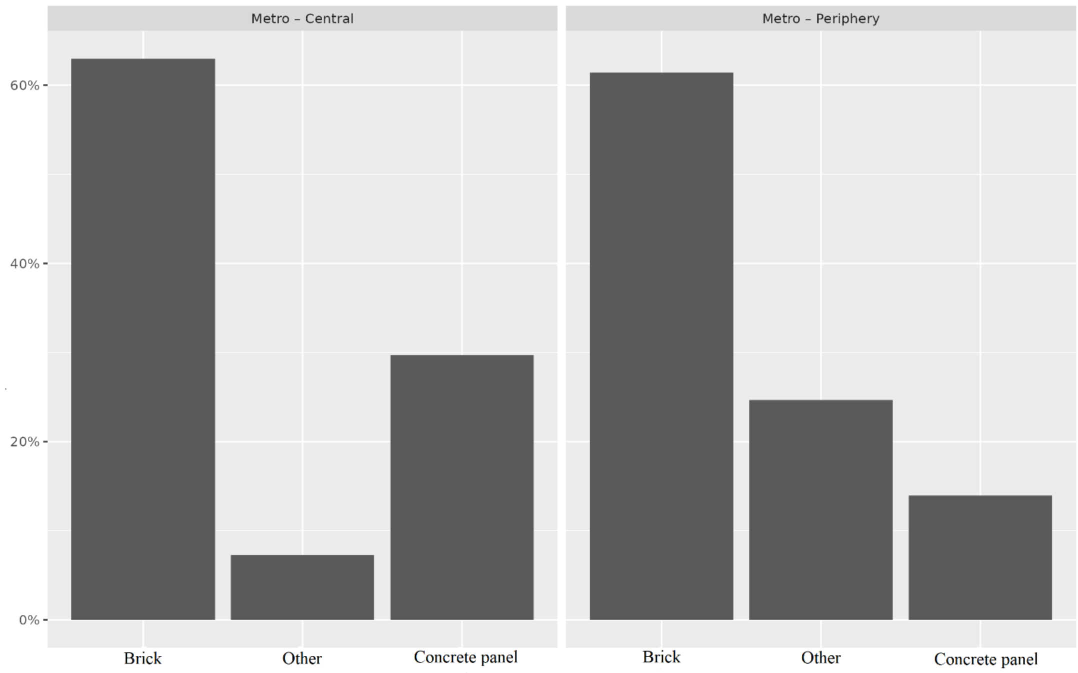


Fig. 4. Distribution of the samples according to construction type

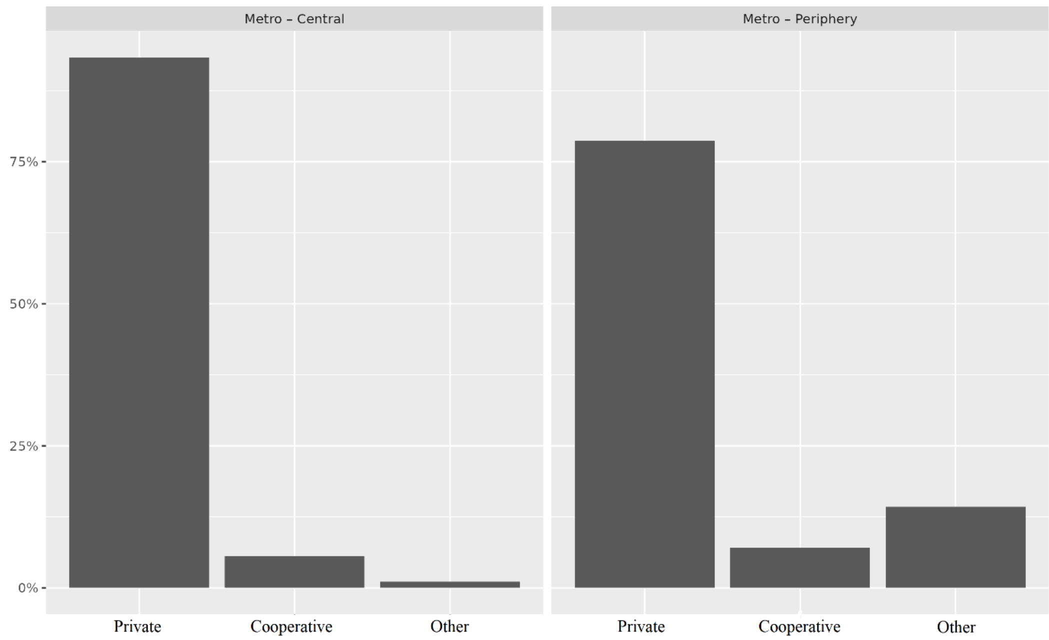


Fig. 5. Distribution of the samples according to ownership type

The variables included in the model are detailed in the table 3 below.

Table 3
Specification of variable used

Dependent Variable		
Variable	Type	description
Lot price	Continuous	Dependent variable representing the lot price in thousands of CZK per square meter.
Structural Characteristics		
Variable	Type	description
Lot Area	Continuous	Lot area in square meters.
Condition	Categorical	Six levels (new, very good, good, reconstructed, bad, other), with "good" as the reference level.
Construction	Categorical	Three levels (brick, panel, other), with "brick" as the reference level.
Disposition	Categorical	Number of rooms with six levels (1, 2, 3, 4, 5, other), with "3" as the reference level.
Ownership	Categorical	Three levels (private, cooperative, other), with "private" as the reference level.
Balcony	Boolean	Presence of a balcony, with "false" (no balcony) as the reference level.
Accessibility variables		
Variable	Type	description
Access to Bank	Boolean	Presence of a banking institution within 15 minutes of walking time.
Access to Post office	Boolean	Presence of a post office within 15 minutes of walking time.
Access to Supermarket	Boolean	Presence of a supermarket within 15 minutes of walking time.
Acces to Public transport	Boolean	Presence of a mass transit stop within 15 minutes of walking time.
Access to Primary education	Boolean	Presence of a primary school within 15 minutes of walking time.
Access to Secondary education	Boolean	Presence of a secondary school within 15 minutes of walking time.
Access to Preschool education	Boolean	Presence of a kindergarten within 15 minutes of walking time.
Access to Pharmacy	Boolean	Presence of a pharmacy within 15 minutes of walking time.
Access to medical institution	Boolean	Presence of a medical practice within 15 minutes of walking time.
Location characteristics		
Variable	Type	description
Time to Center	Continuous	Travel time in minutes to Central Brno (náměstí Svobody) using a car.
Petty Crime	Count	Offenses against peaceful coexistence (crime code 111) within a radius of 1200 meters from the lot over the years 2020–2024.
Theft	Count	Thefts (crime code 35) within a radius of 1200 meters from the lot over the years 2020–2024.

For land use variables, the seamless landscape cover layer (KVES) from the Nature Conservation Agency of the Czech Republic (AOPK) was applied, classifying the territory into 40 categories. The model incorporates the following landscape layers presented in table 4:

Table 4
Land use variables

Land Use		
Variable	Type	Description
KVES Woodland	Continuous	%share of land defined as forest in AOPK
KVES Farmland	Continuous	%share of land defined as farm in AOPK
KVES Housing	Continuous	%share of land defined as built-up area in AOPK
KVES Transport	Continuous	Transport infrastructure
KVES Parkland	Continuous	%share of land defined as city park in AOPK

Figure 6 illustrates the land use of Brno and highlights the spatial granularity of the dataset.

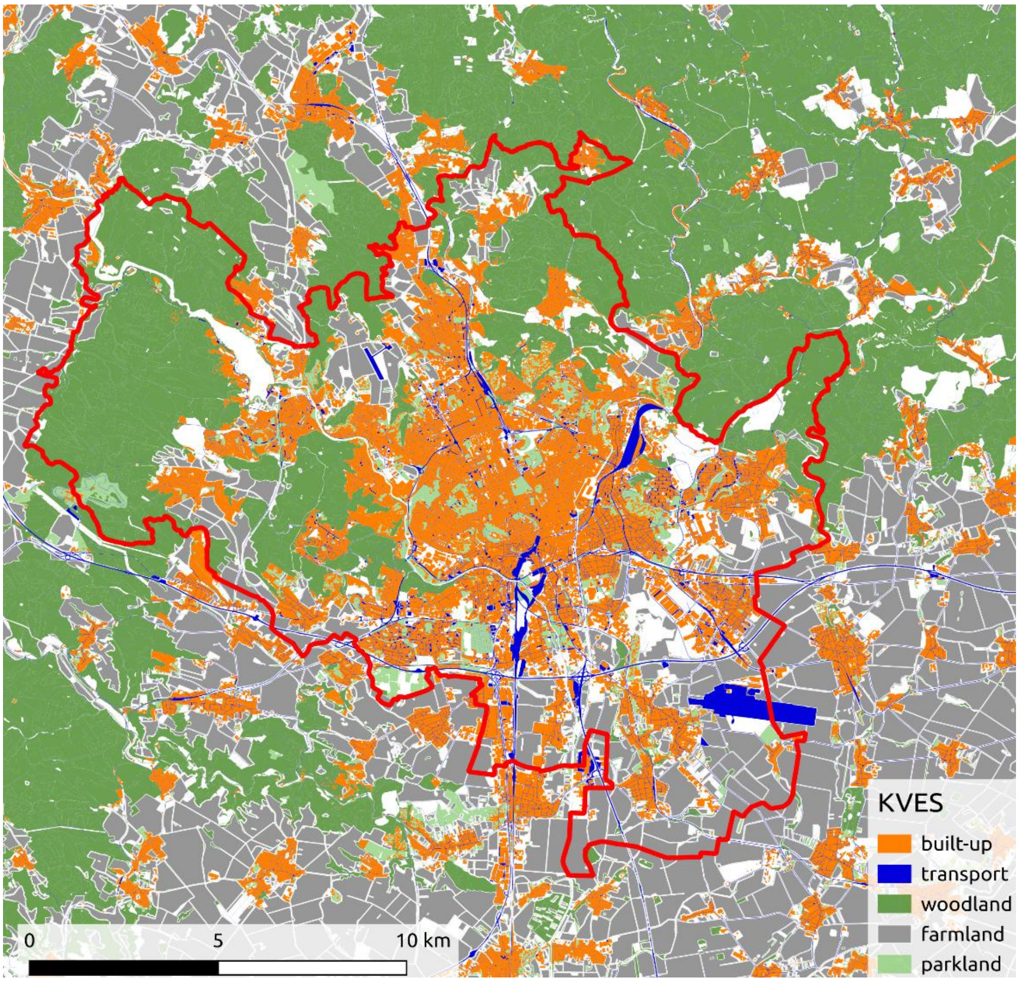


Fig. 6. Land use map of Brno

4. Methodology

The applied model assumes multiplicative (rather than additive) effects of independent variables, as expressed in Eq. (1):

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (1)$$

or more succinctly

$$y = exp(\beta_0) \times \prod_{i=1}^{n} exp(\beta_i x_i) \quad (2)$$

This multiplicative approach enables the interpretation of variables in relative terms (percentages), such as the premium associated with a balcony or the discount for cooperative ownership, rather than as fixed monetary amounts.

Spatial autocorrelation of both raw price data and model residuals was measured using Moran's I statistic (Eq. 3), following Bivand & Pebesma, [25].

$$I = \frac{n}{S_0} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

where n is the number of observations, x_i is the value of the variable of interest for observation i, $\bar{x}$ is the mean of the variable of interest, w_{ij} is the spatial weight between observations i and j, and S_0 is the sum of the matrix of weights. The spatial weights matrix is distance-based, with a neighborhood cutoff of 1,200 meters.

To visualize spatial autocorrelation and evaluate how individual lots contribute to the overall Moran's I, the Local Moran's I statistic introduced by Anselin, [26] was applied:

$$I_i = \frac{(x_i - \bar{x})}{m^2} \sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \tag{4}$$

where m^2 is the sample variance of vector x:

$$m^2 = \frac{1}{n} \sum_{k=1}^{n} (x_k - \bar{x})^2$$

$$y = exp(\beta_0) \times exp(\beta_1 x_1) \times \cdots \times exp(\beta_i x_i) \tag{5}$$

Local Indicators of Spatial Association (LISA) results were visualized by mapping z-scores to p-values and classifying the results according to the standard significance of stars convention ("***" for 0–0.001, "**" for 0.00–0.01, "*" for 0.01–0.05, and "." for 0.05–0.1); observations in the range 0.1–1.0 were labeled "insignificant".

The model was estimated separately for the central and peripheral datasets using an identical specification and explanatory variables. The comparative analysis examined:

i. The statistical significance of individual variables for each context (central or peripheral), evaluated with standard t-tests;
ii. The practical significance of individual variables, evaluated according to their contributions to the explained variance, measured through sum of squares regression (SSR);
iii. Spatial autocorrelation in raw price data;
iv. Spatial autocorrelation in model residuals.

For statistical inference on spatial dependence, Moran's I was transformed into a z-score to allow interpretation under the normal distribution. A Monte Carlo permutation test with 9,999 simulations was applied to determine the rank of the observed Moran's I. This approach permits evaluation of the extremity of the observed statistic without dependence on distributional assumptions.

5. Results

Table 5 summarizes the results of the log-linear model. The findings indicate a strong statistical significance for housing price inflation (captured by the year variable) and housing price characteristics throughout the period examined. Accessibility characteristics show a stronger effect on housing prices in the peripheral areas of the metropolitan region.

Preschool infrastructure and proximity to healthcare facilities show statistically significant effects on housing prices, whereas the presence of a public transport station near a dwelling shows no measurable effect, possibly reflecting a broad dependence on privately-owned vehicles. The distance of dwellings from the Brno central zone exerts a relatively stronger impact on housing prices as the distance increases. These findings align with the ongoing trend of population relocation toward Brno's periphery, driven primarily by the availability of more affordable housing. The temporal pattern of coefficients partly reflects pandemic-related shifts in housing demand, with 2021–2023 effects capturing both post-COVID relocation trends and monetary tightening. Nonetheless, proximity to the city center and access to essential services remain critical determinants of residential location choices, shaping property prices. Conversely, in central Brno, proximity to green spaces is a more influential factor on housing prices.

Table 5
Summary of model results

Variable	Central Zone	Peripheral Areas
year_2021	0.252***	0.284***
year_2022	0.283***	0.347***
year_2023	0.234***	0.308***
Area	-0.003***	-0.001***
Condition_bad	-0.033*	-0.130***
Condition_new	0.190***	0.206***
Condition_reconstructed	0.087***	0.091***
Condition_other	0.114***	0.105***
Condition_very good	0.052***	0.065***
Construction_other	0.019	-0.173***
Construction_panel	-0.075***	0.025
Disposition_1	0.069***	0.127***
Disposition_2	0.024***	0.072***
Disposition_4	0.022***	-0.056***
Disposition_5	0.016	-0.094***
Disposition_other	0.041**	0.004
Ownership_cooperative	-0.062***	-0.244***
Ownership_other	-0.049	0.044
Balcony	0.078***	0.071***
Variable	Central Zone	Peripheral Areas
Access_bank	0.012	0.016
Access_post	-0.06	0.015
Access_market	0.008	0.033***
Access_stop	0.040	-0.011
Access_preschool	-0.020	0.083***
Access_primary	-0.026*	0.034*
Access_pharmacy	0.013	-0.090***
Access_medic	0.003	0.070***
Center_time	-0.003*	-0.012***
Petty_crime	-0.0001***	-0.001***
Theft	0.001***	0.001***
Population	-0.0002	-0.02
Sales_population	-0.0002	0.0002***
Variable	Central Zone	Peripheral Areas
KVES_woodland	-0.168**	0.032
KVES_farmland	-0.0001***	0.076
KVES_housing	0.001***	0.854***
KVES_transport	-0.0002	-2.592***
KVES_parkland	-0.0002	0.059
Variable	Central Zone	Peripheral Areas
R2	0.187	0.335
Adjusted R2	0.185	0.330
Residual Std. Error	0.368 (df = 13561)	0.365 (df = 5643)
F-Statistic	82.114***	72.819***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Analysis of variance (ANOVA) presented in Table 5 further indicates the contribution of individual variables to the model’s R2 value.

Table 6
ANOVA results

Variable	Central Zone		Peripheral Areas	
	Sum sq.	% of RSS	Sum sq.	% of RSS
Year	176.70	41.89 %	123.88	32.73%
Lot area	104.59	24.79%	30.98	8.19%
Condition	86.85	20.59%	66.64	17,61%
Construction	23.33	5.53%	23.56	6.22%
Disposition	3.82	0.91%	21.55	5.69%
Ownership	3.40	0.81%	36.11	9.54%
Balcony	8.99	2.13%	3.48	0.92%
Access_bank	2.09	0.50%	0.39	0.10%
Access_post	0.29	0.07%	2.43	0.64%
Access_market	0.13	0.03%	1.54	0.41%
Access_stop	0.11	0.03%	1.33	0.35%
Access_primary	0.01	0.00%	1.19	0.31%
Access_secondary	0.60	0.14%	0.05	0.01%
Access_preschool	0.14	0.03%	1.42	0.38%
Access_pharmacy	0.35	0.08%	0.21	0.06%
Access_medic	0.00	0.00%	4.61	1.22%
Center_time	4.01	0.95%	36.11	9.54%
Petty crime	0.39	0.09%	0	0.00%
Theft	1.46	0.35%	2.74	0.72%
Population	1.31	0.31%	0.02	0.01%
Sales/Population	0.10	0.02%	11.59	3.06%
KVES_Woodland	0.68	0.16%	2.68	0.71%
KVES_Farmland	0.00	0.00%	0.82	0.22%
KVES_Housing	0.47	0.11%	3.17	0.84%
KVES_Transport	0.91	0.22%	1.97	0.52%
KVES_Parkland	1.13	0.27%	0.01	0.00%

The ANOVA analysis reveals clear differences in the behavior of explanatory variables between the central and peripheral areas. Travel time to the city center accounts for a greater weight in the metropolitan hinterland, whereas housing characteristics contribute less. This disparity may partly reflect more price-sensitive demand in peripheral areas, where buyers tend to prioritize affordability over housing quality.

Tables 5 and 6 also show that the determinants of price variation differ clearly across metropolitan space. In the central zone, structural dwelling characteristics explain most of the variation, whereas in peripheral municipalities accessibility—especially travel time to the city center and proximity to preschool and medical services—plays a substantially stronger role. These results indicate that suburban price formation is more sensitive to spatial frictions and local service provision, while buyers in the core city place greater weight on dwelling quality.

The ANOVA results further support this interpretation: accessibility and ownership structure account for a much larger share of explained variance in peripheral areas, reflecting lower liquidity and stronger reliance on nearby transactions for price information. This helps explain why spatial autocorrelation remains higher in the metropolitan periphery even after controlling for a broad set of variables.

The final component of the analysis concerns the model's ability to eliminate spatial autocorrelation. In both central and peripheral locations of the BMA, spatial autocorrelation was not eliminated, a result that may stem from the aforementioned errors or an actual spatial pattern in housing prices, despite the log model incorporating a complex set of variables commonly applied in other studies. Figures 7 and 8 depict the results of the LISA analysis of housing prices at the street level before and after applying the log model.

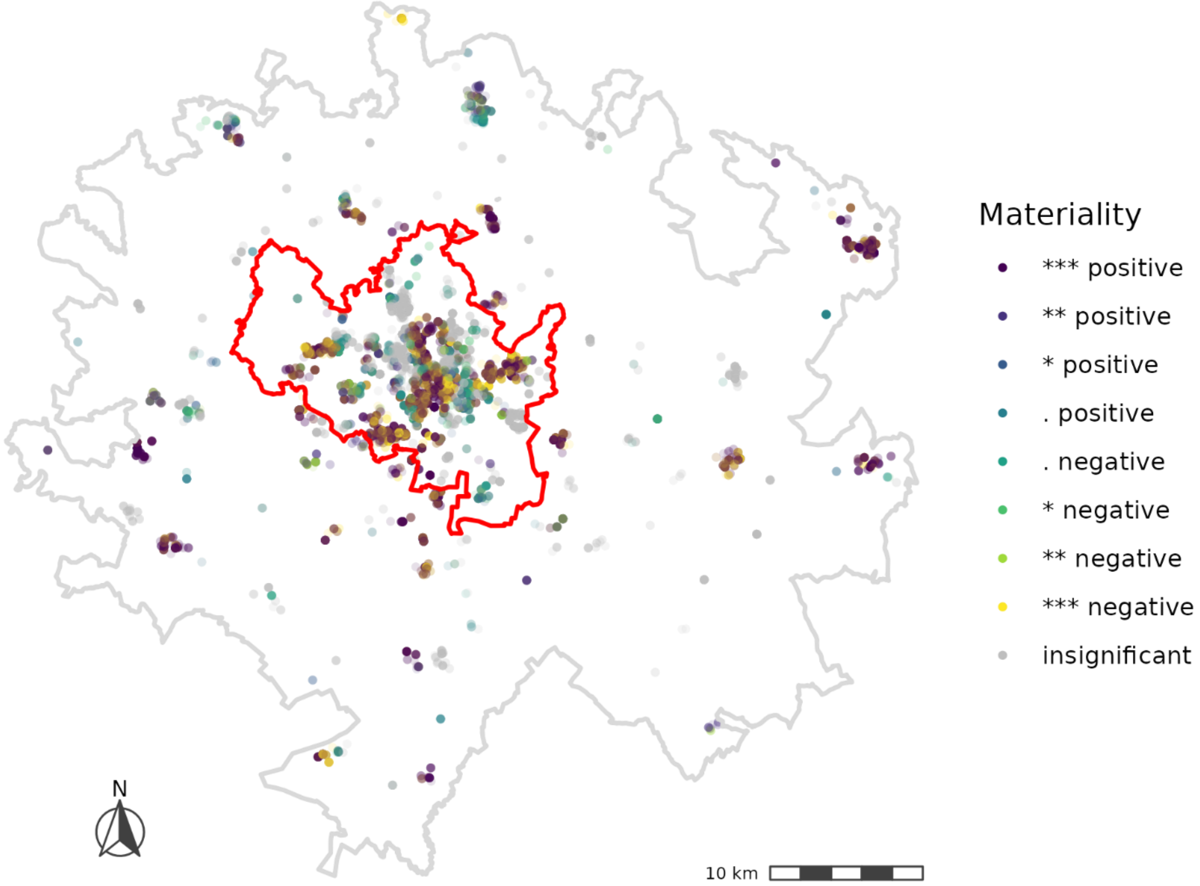


Fig. 7. Spatial autocorrelation of the raw data

Paradoxically, the central zone exhibits lower relative levels of spatial autocorrelation in the raw housing price data. Where spatial dependence is present, it is concentrated near the city's boundaries, suggesting the emergence of localized submarkets characterized by clusters of similarly priced transactions. By contrast, peripheral areas exhibit more consistent positive spatial autocorrelation, suggesting a stronger price clustering in suburban and exurban zones. This pattern may reflect a greater dependence on other transactions for asset valuation in the suburbs than the central zone, where the higher volume of sales supports the formation of aggregated prices.

Figure 8 illustrates a marked reduction in both the intensity and spatial extent of autocorrelation, particularly within Brno's urban core. The remaining clusters of spatial dependence appear mainly in peripheral areas, where positively correlated housing transactions persist.

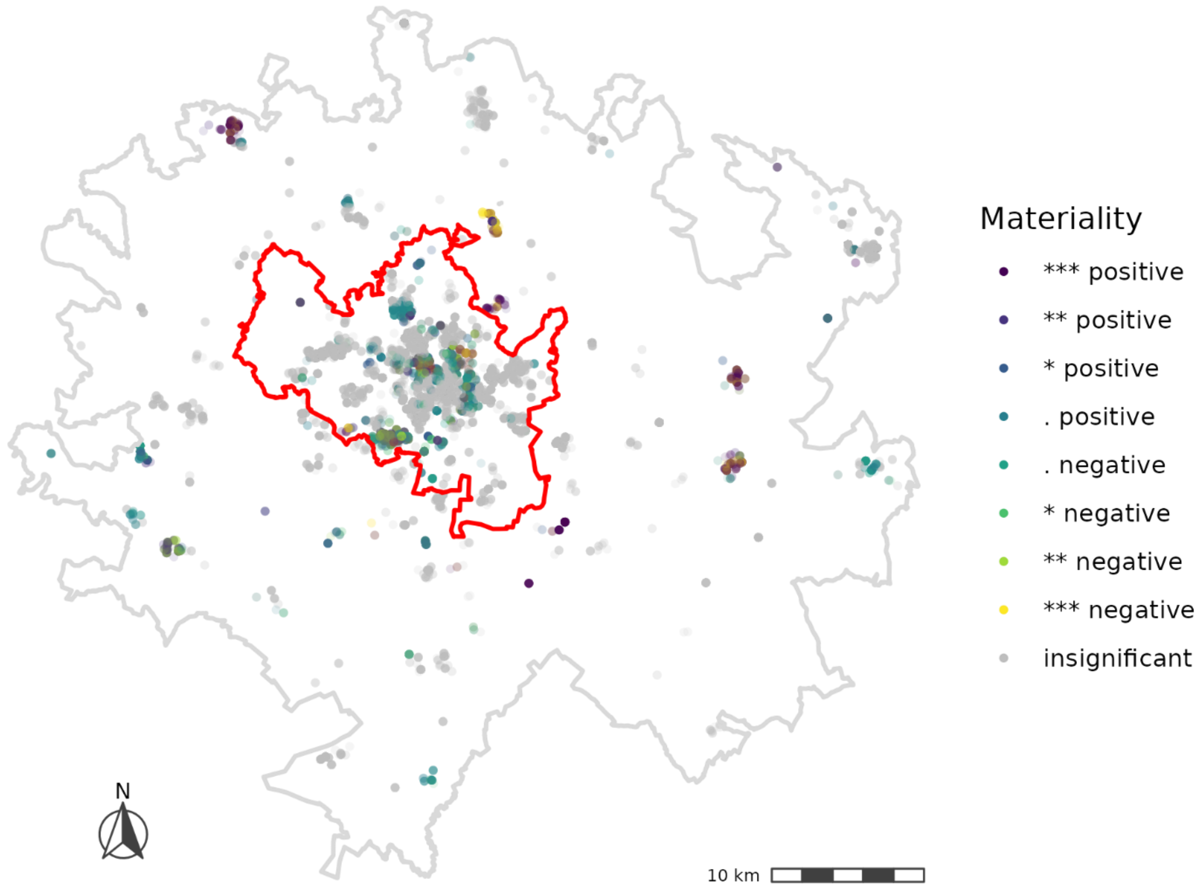
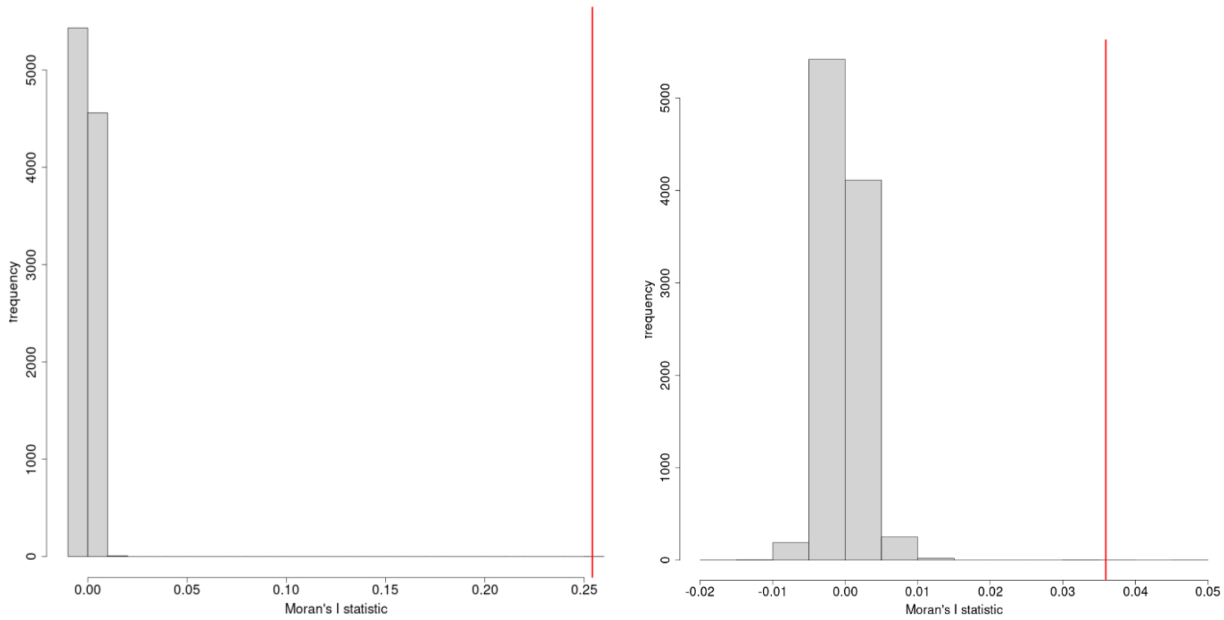


Fig. 8. Spatial autocorrelation of model residuals

Although the model substantially reduced spatial autocorrelation, it did not eliminate it entirely, as residual spatial dependence remains statistically significant. Figures 9 and 10 illustrate this by comparing the observed Moran's I statistics (red vertical lines) with the distribution of values obtained from 9,999 Monte Carlo permutations.

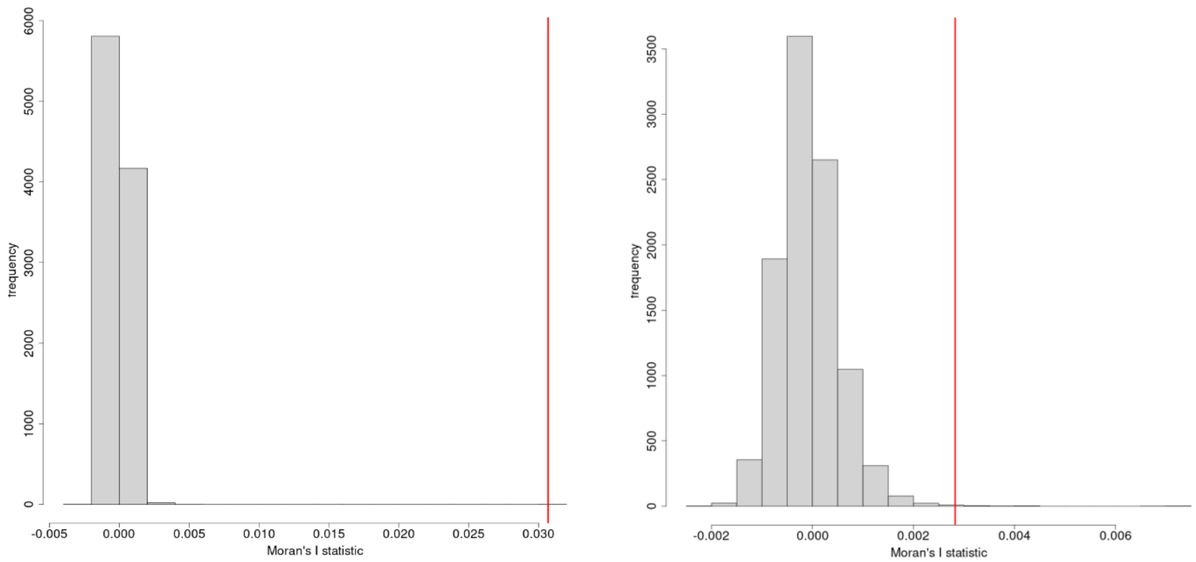
In each histogram, the red line marks the observed Moran's I statistic, and the gray bars show the distribution of simulated values under the null hypothesis of spatial randomness. In each chart, the observed Moran's I lies well outside the central mass of the simulated distribution, particularly for the raw data (left charts), indicating statistically significant spatial autocorrelation at conventional levels ($p < 0.01$). Even for the model residuals, where the effect is weaker, the observed value remains in the upper tail of the distribution, suggesting residual spatial structure not fully accounted for by the model.



(a) (b)

Fig. 9. Monte Carlo distribution of Moran's I for raw prices (a) and model residuals (b) in the peripheral municipalities of the BMA. The red line indicates the observed Moran's I statistic

These results indicate that although the model captured much of the spatial variation, some location-specific dynamics remain unexplained, possibly reflecting unobserved factors or localized processes absent from the explanatory variables.



(a) (b)

Fig. 10. Monte Carlo distribution of Moran's I for raw prices (a) and model residuals (b) in the central zone of the BMA. The red line indicates the observed Moran's I statistic

6. Discussion and Implications

The empirical results presented in the previous section reveal several structural mechanisms that shape price formation and spatial dependence within the Brno metropolitan area. This section discusses these findings in the context of metropolitan housing economics and outlines their implications for public policy.

The first important insight concerns the contrast between the urban core and the metropolitan periphery. In central Brno, higher market liquidity and better availability of price information contribute to relatively efficient price formation. This is consistent with the lower spatial autocorrelation observed both in raw prices and residuals. In peripheral municipalities, however, the significantly stronger clustering of prices suggests that buyers and sellers rely more heavily on nearby recent sales as reference points. Such dependence is typical of markets where liquidity is limited and transaction histories are sparse, creating conditions under which price signals diffuse more slowly. This mechanism is reflected in the consistently higher Moran's I values detected in suburban and exurban zones.

The ANOVA results deepen this interpretation by illustrating systematic differences in the importance of explanatory variables across metropolitan space. In the central zone, structural housing characteristics explain a relatively larger share of price variation, implying that quality differences within the housing stock play a major role. In contrast, accessibility variables—particularly travel time to the metropolitan core and proximity to essential services—contribute far more to explained variance in peripheral areas. These patterns align with economic models in which households in suburban municipalities trade off housing affordability against commuting costs and access to services. The strong impact of preschool and healthcare accessibility in the periphery further suggests that public service provision influences spatial price gradients and the formation of localized clusters of high or low prices.

The temporal dimension of the dataset also provides important context. The COVID-19 pandemic reshaped housing demand and mobility patterns across metropolitan areas, and its effects are visible in the distribution of transactions within the Brno metropolitan area. The marked increase in peripheral transactions in 2023 is consistent with post-pandemic preferences for larger or more affordable homes outside dense urban centers, as well as the increased prevalence of remote work. Although the model does not explicitly include a COVID-related variable, the timing and magnitude of the year effects suggest that pandemic-induced behavioral shifts reinforced existing spatial trends and likely amplified autocorrelation in peripheral zones. The subsequent monetary tightening in 2022 further constrained affordability, with delayed effects on demand visible in the final year of the sample.

Another key finding is the persistence of residual spatial autocorrelation despite the inclusion of a wide range of structural, neighborhood, and accessibility variables. This suggests that unobserved local factors continue to influence housing prices. One likely mechanism is municipal-level planning agreements, which require developers to contribute to local infrastructure. These contributions are typically capitalized into housing prices and vary widely across municipalities, potentially generating localized premiums. Other unobserved amenities—such as micro-scale environmental quality, informal community services, and localized infrastructure constraints—may also contribute to the remaining spatial structure.

Overall, the findings have significant implications for metropolitan housing policy. The strong spatial dependence in peripheral municipalities indicates that these markets do not function as isolated units; instead, price shocks and regulatory interventions can spill over across municipal borders. Policies aimed at increasing housing supply or improving affordability in one location may

produce unintended effects in adjacent areas, particularly where market liquidity is low. These outcomes highlight the value of coordinated metropolitan-level planning in areas such as land-use regulation, infrastructure provision, and strategic housing development. The results also suggest that investments in transportation infrastructure may not only improve mobility but also influence the spatial distribution of housing affordability within the metropolitan region.
In sum, the study demonstrates that spatial autocorrelation in housing prices arises from the interaction of structural characteristics, accessibility, liquidity constraints, and institutional settings. Understanding these mechanisms is essential for designing policies that aim to enhance market efficiency, reduce affordability disparities, and support balanced metropolitan development.

7. Conclusion

This study examined the persistence of spatial autocorrelation in housing prices within the Brno metropolitan area and demonstrated that spatial dependence reflects not only structural housing characteristics but also deeper institutional and accessibility-related mechanisms. The analysis shows that spatial autocorrelation remains significant even after applying a comprehensive hedonic model, particularly in peripheral municipalities where lower market liquidity and limited substitutability of dwellings amplify price clustering, which is in line with earlier literature findings [27]. These findings are consistent with theoretical perspectives on local public goods and price capitalization processes described by Stiglitz [22], as well as broader European patterns of spatially differentiated living standards and sustainability documented by Luczak et al. [3, 23].

The results highlight that metropolitan housing markets do not function as isolated submarkets; instead, price signals and regulatory effects spill over across municipal borders. This underscores the importance of coordinated planning at the metropolitan scale, particularly in the areas of land-use regulation, infrastructure provision, and the management of planning agreements whose costs may become embedded in local housing prices. Accessibility to essential services, especially in suburban municipalities, emerges as a key factor shaping spatial price gradients, reinforcing the need for integrated transport and public service policies. These insights contribute to the understanding of how structural, institutional, and spatial factors interact in shaping housing affordability and market efficiency. All above mentioned aspects may lead to deeper connection between local and regional urban planning [6] as peripheral areas in Czech Republic exhibit significant immigration patterns in the last decade which further strengthen the aforementioned problems.

The study is subject to limitations, particularly the persistence of residual spatial autocorrelation that may reflect unobserved local amenities, municipal policies, or micro-level environmental characteristics. Future research should incorporate additional institutional and planning-related variables, explore dynamic spatial models, and extend the analysis to other metropolitan regions to assess the generalizability of the findings.

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Data Availability Statement

Demographical statistics for Czech municipalities are available at https://csu.gov.cz/csu_a_uzemne_analyticke_podklady. Land use data are available at: https://data.nature.cz/ds/102.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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