The Invisible Hand of Geography: Spatial Determinants of Housing Rental Prices in Ukraine

by

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ABSTRACT

The study examines Ukrainian rental housing market during the 2025-2026 autumn-winter, investigating how prolonged war impacts residential value formation across 5 largest metropolitan areas. Using a dataset of 46,000 listings scraped from lun.ua, the study employs Ordinary Least Squares model to establish global price elasticities across 5 cities, Geographically Weighted Regression for a spatial case study of Odesa, and Quantile Regression as a distributional robustness check. The findings confirm a state of spatiotemporal normalisation: conventional amenities (such as proximity to the center) remain the primary determinants of rental value, while resilience amenities (such as generators) and war attacks show a secondary influence. The GWR analysis reveals that these effects are spatially heterogeneous, producing localised patterns that global models cannot capture. The results suggest that the fundamental economic logic of urban geography continues to organise residential space within cities even during the war.

Keywords: Ukrainian rental housing market, hedonic pricing model, geographically weighted regression, web-scraping, wartime adaptation.

Word count: 12,614

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LIST OF ABBREVIATIONS

GWR. Geographically Weighted Regression

HPM. Hedonic Pricing Models

OLS. Ordinary Least Squares

MAUP. Modifiable Areal Unit Problem

OECD. The Organization for Economic Cooperation and Development

FUA. Functional Urban Areas

CBD. Central Business District

GHSL. Global Human Settlement Layer

KDE. Kernel Density Estimation

VIF. Variance Inflation Factor

KMO. Kaiser – Meyer – Olkin

AIC. Akaike Information Criterion

QR. Quantile Regression

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1 INTRODUCTION

1.1 Background and Rationale

The full-scale invasion of Ukraine in February 2022 fundamentally disrupted country's urban fabric. Beyond the physical destruction of over 200,000 residential buildings (Adrienko et al, 2025), the war has fundamentally reconfigured the relationship between Ukrainian population and their domestic spaces (Khelashvili et al, 2025). In this context, the rental housing market has emerged as a vital mechanism for resilience. As millions of internally displaced people moved to relatively safer areas, traditional Ukrainian preference for homeownership has been replaced by a forced reliance on the rent. Moreover, this sector exhibits high informality (Bobrova et al, 2025), where a significant majority of transactions occur through non-notarized agreements, which makes it harder to analyze this market.

In a wartime economy, housing utility can no longer be explained merely through the traditional “location” approach, but is additionally shaped by considerations of urban resilience. While the beginning of full-scale war with first russian attacks on energy infrastructure represented a critical juncture in the evolution of housing market, the winter season of 2025-2026 should not be seen as an unprecedented shock. Because such disruptions have persisted over several years, households have gradually adapted to conditions of energy and physical insecurity. Over time, resilience features have become more normalized. Now they function more as expected amenity than as primary drivers of choice. As a result, traditional determinants of housing value, such as proximity to the city center, access to major transportation hubs play a central role in shaping tenant decision-making.

1.2 Analytical Problem

Despite the social and economic importance of these shifts, traditional real estate modeling often fails to capture the high-frequency, spatiotemporal volatility that is present in current rental market. Official registers are frequently too static or inaccessible to reflect the real-time adaptations of urban residents. This research addresses this gap by utilizing large-scale web-scraped data from lun.ua, Ukraine’s popular real estate aggregator. By analyzing a dataset of almost 46,000 rental advertisements collected between August 2025 and February 2026, this study provides a granular view of how the market evaluates both physical risk and adaptive resilience.

Methodologically, this thesis moves beyond global regression models to adopt a Geographically Weighted Regression (GWR) framework. This approach acknowledges that rental housing market is not uniform; the economic penalty of a missile strike or the value of a generator varies neighborhood by neighborhood.

The primary objective of this research is to quantify the marginal value of housing amenities in five largest metropolitan areas in Ukraine and to map the spatial non-stationarity of rental prices in one city as a case study. By doing so, this thesis contributes to broader fields of urban economics and conflict studies. The findings offer a structural account of how rental market is organized and priced in a major urban system operating under conditions of prolonged instability.

2 LITERATURE REVIEW

The study of housing markets is rooted in the Hedonic Pricing Model (HPM). This framework states that a property is not a single good but a "bundle" of heterogeneous characteristics, such as physical (number of rooms, furnishing), locational (proximity to center, public transport stops) or environmental amenities.

A number of papers (Goodman, 1998; Colwell and Dilmore, 1999; Malpezzi, 2003; Sirmans et al, 2005) discuss in great detail the history behind the HPM, and who can be considered to be the early inventors of the Hedonic Pricing. There is no consensus among scholars on the very first founder of the method. Some papers (Goodman, 1998) refer to Court's article, published in 1939, as "foundational"; while others (Colwell and Dillmore, 1999; Sirmans et al, 2005) point out Haas' 1922 work that used a hedonic model to evaluate the price of land, therefore he was the first inventor of the method. In his work, Haas used transaction data to analyze land value, based on characteristics like building costs or distance to city centers.

However, it is less disputed that Lancaster (1966) and Rosen (1974) are among the most significant contributors to the development of the modern perception of HPM. The former paper established a microeconomic basis that estimated the value of utility-generating characteristics. While the latter is more focused on how prices are determined by these characteristics. Several papers (Malpezzi, (2003); Sirmans et al, (2005)) point out that Rosen's work, dated 1974, created the theoretical groundwork for the development of nonlinear HPMs.

Access to reliable and granular real estate market data has made the HPM a widely applied approach in housing market research. Sirmans et al. (2005) provide a comprehensive 10-year retrospective on nearly 125 papers that utilized HPM, identifying over 20 core physical and locational attributes that consistently drive rental prices. This research builds upon this foundation by quantifying previously understudied "resilience amenities", such as intensity of war events, distance to bomb shelters, which have emerged as more critical determinants in the contemporary Ukrainian housing market (Terzi, 2025).

The growing availability of digital platforms has created new opportunities to measure housing market data using alternative data sources such as property aggregators. The datasets with web-scraped observations can provide more detailed information that is often unavailable in administrative statistics. At the same time, the increasing role of digital data requires careful incorporation of such sources, while maintaining standards of reliability and quality (Ricciato et al. 2020). Given that the State Service of Statistics of Ukraine does not publish detailed data on the rental housing market, I used the web-scraped rental data that I had collected from a local property aggregator lun.ua. Lun.ua is one of the most widely used real estate aggregators in Ukraine. It provides users with information on rental listings, properties available for purchase and aggregated market statistics. Registered users can post listings to advertise properties for rent or sale, while the listings themselves are publicly accessible and can be viewed by anyone.

Web-scraping allows to observe rent prices, property characteristics and spatial variation in the housing market at a much finer temporal and geographic resolution than traditional sources. This approach has been increasingly used in housing market research for diverse types of analysis. (Boeing et al. (2016); Bricongne et al. (2021); Harten et al. (2020); Souza et al. (2021); Üzümcü & Eliguzel (2023); Chapelle & Eyméoud (2022); Antonov & Laktionova (2020); Meyberg et al. (2024); Groiss & Syrichas (2025); Hess & Chasins (2022)). This data collection method allows researchers to rapidly analyze shifting market dynamics, including responses to sudden shocks, such as COVID (Bricongne et al. (2021)), environmental hazards (Moulton, et al (2024)), or economic disruptions, like those in Russia (Palumbo (2023)). As a result, web-scraped data are particularly valuable for studying markets where traditional data sources are limited or outdated. My research examines the rental housing market in Ukraine in the context of the ongoing war. It builds on existing analyses of the real estate sector conducted after the escalation of the war in 2022 (Hrabynskyi et al, 2022); Husakov (2024)), while focusing specifically on the rental segment, which remains relatively understudied. By analyzing rental market dynamics during wartime, the study aims to contribute to the emerging body of literature on how war reshapes housing markets.

However, there is a large number of limitations associated with the web-scraping method. Listing data typically represent advertised rather than transacted rents (Chapelle & Eyméoud (2022)). Additionally, the collected data typically contains missing attributes or platform-specific selection biases (Meyberg et al, 2024), which require careful data cleaning. As discussed in a study on real and fake data in Shanghai's informal housing market (Harten et al, 2020)), web-scraped online listings may not always accurately reflect actual market conditions.

As noted earlier, housing market data has been extensively studied across the world, with numerous methods developed to examine it. This includes Descriptive Analysis (Boeing, et al (2016); Bricongne et al. (2021); Antonov & Laktionova (2020)) Hedonic Models (Chapelle & Eyméoud (2022); Groiss & Syrichas (2025); Husakov (2024); Spatial Analysis (Souza et al (2021); Market Segmentation and Clusterization (Hrabynskyi et al (2022); Wiersma et al (2022); Skovajsa (2023)), Machine Learning Algorithms (Meyberg et al, (2024); Üzümcü & Eliguzel (2023); Yazdani, (2021)); Geographically Weighted Regressions (Huang, et al (2010); Zhang, et al (2019); Tomal, (2020); Cellmer, et al (2020); Wu, et al (2018)).

A traditional OLS (Ordinary Least Squares) regression method assumes spatial stationarity – the idea that the value of an amenity is constant across an entire city. However, Anselin in a book “Spatial econometrics: methods and models” (1988) argued that spatial data are characterized by spatial autocorrelation (nearby properties influence each other) and spatial heterogeneity (relationships vary by location). Additionally, several studies argue that traditional hedonic regression models have limitations in housing market analysis (Hoxha, (2024); Yazdani, (2021)). In particular, these models cannot capture non-linear relationships between housing prices and their attributes.

To address spatial heterogeneity Fotheringham et al. (2002) introduced Geographically Weighted Regression (GWR), which allows regression coefficients to vary across space with the help of local kernels. Over the past 20 years this model has evolved to a whole family of models, such as Multiscale GWR (MGWR) (Fotheringham et al., 2017), which accommodates different spatial scales, and Geographically and Temporally Weighted Regression (GTWR) (Huang et al., 2010), which incorporates a spatiotemporal kernel that can capture also time. These extensions are well-suited to the complexity of Ukrainian market, but their computational demands exceed the scope of this study. This thesis uses a standard GWR as a framework for quantifying the spatial variation of neighborhood-level amenities.

Another recurring challenge in urban economics is the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984), where results are biased by arbitrary administrative boundaries. Thus, it is not ideal to "truncate" the market by excluding suburbs. To avoid this, this research utilizes the OECD (2020) / GHSL (2019) definition of Functional Urban Areas (FUA). According to OECD methodology, FUA is either based on population density thresholds (at least 1,500 people per square kilometer) or by identifying surrounding commuting zones that are connected to the city. In the case of Ukraine, the latter approach was used. This allows for a robust distinction between the urban core and the suburbia, which provides a scientifically standardized platform to compare Ukraine’s five largest metropolitan centers (Kyiv, Lviv, Odesa, Dnipro, and Kharkiv).

A substantial number of studies investigate the impact of spatial violence on housing markets, consumer behavior, and urban development in different contexts. Some authors focus more on immediate localized effects of spatial violence. For example, Besley and Mueller (2012) demonstrated in their study of Northern Ireland that housing prices rapidly respond to localized violence, stating they are high-frequency indicator of conflict. The study of Abadie and Gardeazabal (2003) supports the latter on a broader economic level – the terrorist risk in Basque country led to a 10% decrease in GDP, when compared to a safer region. Linden and Rockoff estimated in their study a significant economic penalty for owning property close to houses of registered sex offenders. Finally, in Ukrainian context, several studies highlight the shift of housing market preferences (Terzi, (2025); Hrabynskyi et al, (2022)) with more people prioritizing options perceived as safer.

Other studies dive more into long-run, structural resilience of cities after a prolonged exposure of spatial violence. Davis and Weinstein (2002) in their study demonstrate that even despite nearly the total destruction of Japanese cities during the WWII, the cities returned to their original size and economic importance. Brakman et al, (2002) in a similar study on post-war German cities also achieved comparable results. Glaeser and Shapiro (2002) suggest that terrorism or wars do not change the urban form significantly, and US cities are not likely to be affected by terrorism.

In summary, while existing literature has explored either spatial modeling or the economic impact of spatial violence in isolation, there is a lack of research that integrates GWR with granular attack data at the individual listing level. This thesis fills that gap by analyzing a large-scale dataset to quantify how the value of housing resilience and the penalty for physical risk is negotiated in a market characterized by high spatial volatility.

3 ANALYTICAL FRAMEWORK

The analytical framework of this study is grounded in the New Urban Economics paradigm, specifically the Hedonic Pricing Theory (Rosen, 1974). However, it adapts this classical model to a wartime adaptation paradigm. This idea assumes that while the fundamental economic structures of a city (accessibility or density) remain the primary drivers of value, they are now overlaid with a high-frequency resilience amenities necessitated by ongoing external shocks.

To investigate the dynamics of Ukrainian rental market, this study conceptualizes two key terms that define the interaction between urban space and war.

1. Resilience amenities. Traditional real estate literature classifies amenities as structural (e.g., area) or neighborhood-based (e.g., parks). This study develops a new typology: resilience amenities. These are either defined as characteristics that allow to maintain household’s utility during disruptions (e.g., power generators); or these are amenities that provide citizens with physical risk reduction (e.g., bomb shelters, lower floors, etc).
2. Spatiotemporal normalization. After more than four years of ongoing full-scale war, this study conceptualizes the market is in a state of spatiotemporal normalization. This is defined as the process by which market accounts for a baseline level of systemic risk. This leads to the reemergence of classical determinants as primary value drivers.

3.1 Theoretical Framework and Hypotheses

The theoretical framework outlines the expected causal relationships between the concepts identified above, moving from classical urban theory to the specificities of the 2025-2026 autumn-winter season.

3.1.1 Research Question

What is the relative marginal contribution of conventional characteristics, resilience amenities, and war attacks to rental prices in the largest Ukrainian cities during the winter of

2025-2026; and does the urban housing market exhibit spatiotemporal normalization to sustained war?

3.1.2 Conceptual Framework

The central theoretical premise of this study is that cities are structurally resilient economic entities. After four years of full-scale war, Ukrainian cities continue to function as economic engines. This study argues that prolonged war induces a process of spatiotemporal normalization within cities. The market re-equilibrates around its classical price determinants, absorbs new war-related factors as background conditions rather than sudden shocks. Under this framework, individual war events produce localized, temporary information shocks rather than market-wide repricing (Moulton et al., 2024).

3.1.3 Hypotheses

H1: Primary Role of Conventional Amenities

Following classical bid-rent theory (Alonso, 1964), this study hypothesizes that conventional amenities, such as proximity to the central business district (CBD), transport networks, remain primary determinants of rental prices. With four years into the full-scale invasion, the bid-rent gradient is assumed to have stabilized.

H2: Secondary Role of Resilience and Conflict Amenities

Resilience infrastructure (generators, bomb shelters) and war-related effects are expected to demonstrate a statistically significant but secondary influence on rental prices.

4 METHODOLOGY

4.1 Data Collection

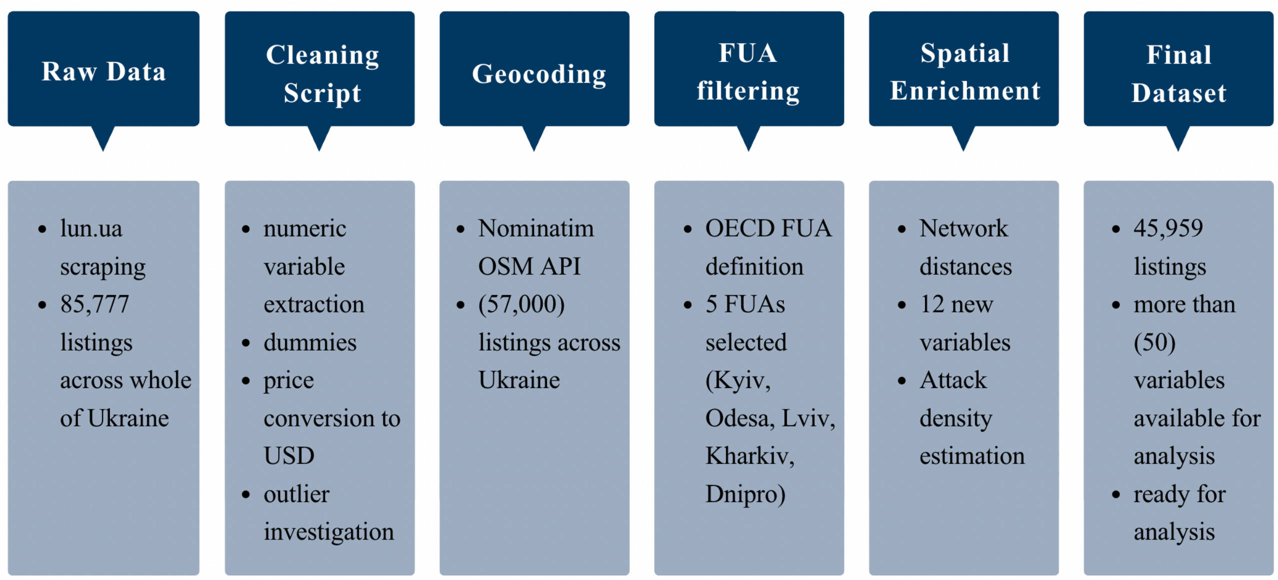
Primary data were collected from lun.ua, Ukraine's popular residential real estate aggregator. The collection was limited only to long-term apartment rental listings, excluding short-term, commercial and private house offerings. The data were collected across whole government controlled area in Ukraine using a two-stage scraping approach implemented in Python. A first scraper crawled search-result pages and compiled unique listing URLs across the whole of Ukraine. A second scraper visited each URL and extracted all structured and semi-structured HTML fields, including price, area, rooms, floor, construction characteristics, amenity strings, and text descriptions.

Each complete scraping round was executed approximately every three weeks, resulting a total of approximately 8 scraping cycles between 17th of August 2025 and 22nd of February 2026. This study period was selected deliberately to bracket the 2025–2026 winter season, during which Ukrainian cities experienced severe and sustained electrical blackouts caused by russian attacks. This provides a temporally structured shock against which the adaptation of rental markets can be evaluated.

The three-week sampling interval represents an analytically meaningful compromise between granularity and feasibility. It is sufficiently frequent to track the market across seasonal phases (late summer, autumn, peak and late winter) while keeping total data volume manageable. The main limitation of this approach is market-velocity bias. Short-term listings, which were withdrawn after hours, because they were immediately rented are systematically missed. Approximately 10-20% of URLs collected in Stage 1 returned HTTP errors by the time Stage 2 attempted extraction. This confirms that the most attractive listings are underrepresented. Only observations for which a numeric price was successfully extracted were retained. The total number of 85,777 unique listings were collected.

4.2 Data Cleaning and Quality Assurance

Figure 1: Data processing pipeline.



Six sequential stages transform raw data into a geo-enriched analytical dataset. Numbers in parentheses indicate approximate observation counts at each stage.

4.2.1 Cleaning Script

A Python script was developed to parse the raw HTML fields and clean columns and leave only cleaned numeric variables, such as: price, total area, kitchen area, living area, age of the buildings, street numbers, floor and ‘floority’, commission price, etc.

Dummy variables were also added for: furniture and appliance items (e.g. washing machine, tv, generator, dishwasher), owner type (whether the owner or real estate agent posted the listing), pet-friendliness, etc.

Beyond the raw cleaning step, several variables were constructed:

- Floor ratio: floor_ratio = floor/floority, which represents the apartment's relative position in the building.
- Price per square meter (in UAH): price_sq = price_cleaned/general_area
- Price per square meter (in USD): price_sq_usd = price_sq/ USD rate. The USD exchange rate was sourced from the National Bank of Ukraine (NBU) and applied at the specific date of each data scraping to account for temporal fluctuations.

4.2.2 Outlier Management

A two-pass quality audit was applied. In the first pass, price per square meter and cleaned prices were winsorised at the 5th and 95th percentile to identify candidates for manual review. In the second pass, suspicious observations were inspected against their textual description. For example:

- Listings at 6,000,000 UAH where the description clearly stated a monthly rent were corrected to 6,000 UAH.
- Listings with incorrect currency labeling were manually corrected to USD where explicitly stated in the description. Otherwise, they were removed when the intended currency could not be reliably determined (e.g., a penthouse in the center of Kyiv listed at 3,500 UAH).
- Listings with a floor ratio > 1 were manually inspected and corrected where possible; otherwise, removed.
- Buildings with reported floority exceeding realistic city limits (e.g., >47 in Kyiv or >27 in Lviv) were also deleted as implausible entries.
- Listings with suspicious area values (e.g., 7 square meters) were manually reviewed and removed if the description did not provide clarification.

These manual interventions preserved the integrity of the econometric models, as extreme outliers would otherwise inflate OLS standard errors and bias GWR kernel weights.

4.3 Geocoding and Spatial Preparation

4.3.1 Geocoding Strategy

Address strings were geocoded using the Nominatim (OpenStreetMap) API, implemented via the geopy Python library. Geocoding was attempted for all observations containing at least a street name; if the street number was missing, the API was queried at street-level, assigning the midpoint of the street segment as the coordinate.

Of approximately all 85,000 listings across whole of Ukraine roughly 57,000 (67%) were successfully geocoded. The 33% attrition, while substantial, is within the range reported in comparable urban studies (Goldberg et al, 2007). When narrowed to the five largest metropolitan areas (the primary geography of interest) geocoding quality improved considerably: of ~55,400 listings identified across these areas, ~46,000 (83%) were successfully geocoded.

Because of this geographic concentration I decided to focus on the five largest metropolitan areas. Of the ~57,000 successfully geocoded listings across Ukraine, more than 75% originated from Kyiv, Odesa, Lviv, Dnipro, and Kharkiv (cities). This concentration is not incidental, since users from larger cities were more likely to post standardized address formats. Restricting the analysis to the five largest FUAs aligns the study with the most economically significant rental markets in Ukraine. Also, it ensures that remaining geocoding gaps do not systematically bias the sample.

4.3.2 Functional Urban Area Definition

Administrative city boundaries were deliberately rejected in favour of the OECD Functional Urban Area (FUA) definition (OECD 2020), which delineates urban extents based on either:

1. Population density: all grid cells with ≥ 1,500 inhabitants per km2 and ≥ 50,000 total inhabitants, identified from the Global Human Settlement Layer (GHSL) population grid.
2. A commuting zone: all municipalities that where defined through a probabilistic approach performed through a logit model as part of commuting zone in the city.

This approach is scientifically better than fixed administrative buffers because it follows the actual economic connectivity of the city. It avoids the Modifiable Areal Unit Problem inherent in arbitrary administrative boundaries and naturally captures agglomeration.

The GHS-FUA R2019A dataset was used to filter listings, retaining only those falling within the FUA polygons of the five target cities – Kyiv, Odesa, Lviv, Dnipro, Kharkiv. A binary variable suburbia was created: suburbia = 1 if the listing falls outside the administrative boundaries of the city; suburbia = 0 if inside the urban core.

4.4 Spatial Variable Construction

4.4.1 Network Distances

Distances to urban amenities were calculated as shortest-path walking network distances using the QNEAT3 plugin in QGIS, operating on road network data filtered from OpenStreetMap via custom Overpass API queries (footway, residential, service, living street, pedestrian paths; excluding motorways and private access roads). It should be noted that amenity data in OpenStreetMap may be incomplete, with certain facilities, such as private hospitals and kindergartens, not fully captured in the dataset.

The following amenity types were processed (Table 1):

Table 1. Spatial amenity variables and OpenStreetMap tags used		
Variable	OSM Tag	Notes
cbd_network	Custom coordinates	Social/economic downtowns
hospital_network	amenity=hospital	Network distance
kinder_network	amenity=kindergarten	Network distance
tram_network	railway=tram_stop	Network distance
bus_network	highway=bus_stop	Network distance
subway_network	railway=subway_entrance	Kyiv, Kharkiv, Dnipro only
stop_count_500m	Combined transit	Count within 500 m buffer
shelter_dist	Records of civil defense shelter structures – SES of Ukraine	Network distance
shoreline_distance	Copernicus GSW	Euclidean to nearest shoreline
greenery	ESA WorldCover / NDVI	greenery within 500 m buffer
pop_mean	GHS population grid (2025)	Mean within 500 m buffer
attacks_kernel	Civilian harm in Ukraine timemap - Bellingcat	Kernel density estimation within 5 km buffer

4.4.2 Euclidean vs. Network Distance

For water bodies (Dnipro River, Black Sea, lakes), Euclidean distance to the nearest shoreline was preferred over network distance. This is justified on hedonic grounds: the primary utility of water proximity derives from scenic amenity and environmental quality (noise reduction, air cooling), which operate independently of road connectivity (Luttik, 2000).

4.4.3 Raster-Based Variables

- Population density was extracted by zonal statistics (mean within a 500 m buffer) from the GHSL-POP 2025 GeoTIFF, converted to persons/km^2.
- Greenery index is a proportion of pixels classified as tree cover (ESA WorldCover 2021) within a 500 m buffer around each listing.
- Shorelines were extracted from Copernicus Global Surface Water occurrence rasters (threshold: occurrence $\in [50, 100]$).

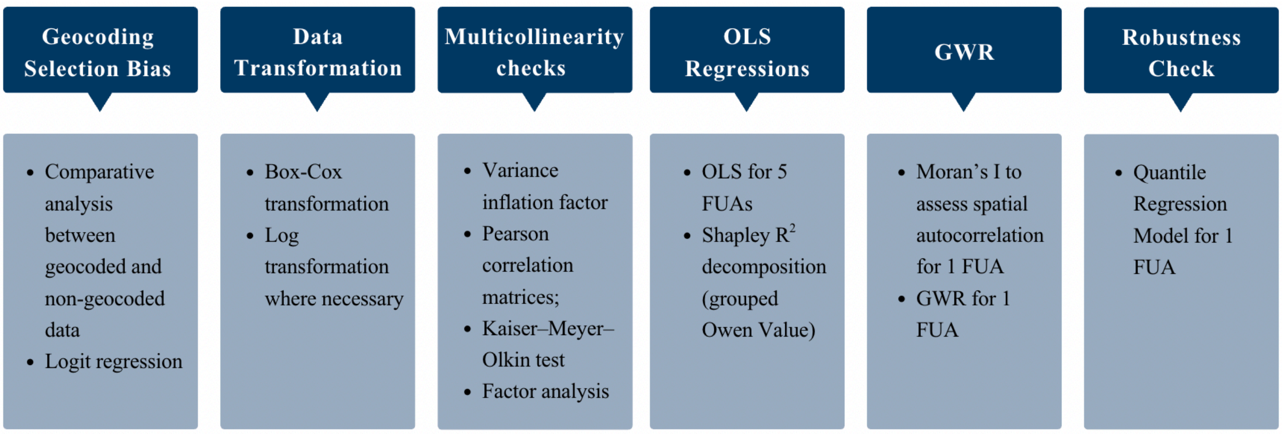
4.4.4 Conflict Exposure Variable

War-event data were obtained from the Bellingcat Civilian Harm in Ukraine Timemap. This dataset was selected over alternative conflict-coding sources due to its relatively high level of granularity and spatial detail in recording russian attacks across Ukraine. In contrast, datasets such as those provided by ACLED emphasize external validity by incorporating diverse and locally sourced Ukrainian-language reports; are continuously updated, which makes them generally more reliable. However, ACLED's methodology typically geocodes events to the centroid of a settlement, which limits the precision of spatial analysis. Triangulation of ACLED and Bellingcat data suggests that, while the latter is comparatively sparse and incomplete, it provides more spatially precise indications of conflict events and their localized impacts. Nonetheless, the incompleteness of these data constitutes an important limitation.

For each geocoded listing, a conflict kernel density estimate (KDE) was constructed by summing the Gaussian-weighted Bellingcat event counts within a 5 km radius 1 year prior to the first scraping date (August 2024 – August 2025); since more recent data were not available. In some cities (Lviv and Dnipro), the near absence of recorded events constrained meaningful cross-city comparison.

4.5 Data Analysis

Figure 2: Data analysis pipeline.



Six sequential stages advance from data diagnostics to econometric modelling.

4.5.1 Geocoding Selection Bias

To ensure the scientific rigor of the subsequent spatial analysis, it is necessary to account for the potential selection bias introduced during the geocoding process. Since the further analysis needs precise coordinates, only successfully geocoded subsample can be utilized for the final models. To assess this bias, a comparative analysis was conducted between the successful geocoded subsample and the non-geocoded subsample. By comparing these two mutually exclusive groups rather than the subset against the total population, we ensure statistical independence and more clearly identify characteristics that determine geocoding success (Heckman, 1979).

Additionally, to identify whether this geocoded subset is a representative mirror of the broader market, a Logit Regression Model was performed on the binary outcome of geocoding success (1 = Geocoded, 0 = Non-Geocoded). This analysis was restricted to settlements belonging to the five identified FUAs. Standard errors were estimated using the HC3 robust covariance estimator. The results of the full model can be found in Annex A.

The Logit model was highly statistically significant (LLR $p < 0.001$), with a McFadden's Pseudo R^2 of 0.099. This means that while geocoding success is not random, the vast majority of the variance in the geocoding mechanism remains unexplained by the property characteristics. This suggests that geocoded sample retains a high degree of generalizability. However, several findings were identified:

1. Critical structural variables (price_cleaned and general_area) showed almost negligible impacts on geocoding success. This is crucial for the validity of HPM. The odds ratio for price was almost 1.00, and the marginal effect of area was near zero ($\frac{\partial y}{\partial x} = 0.0005$). This indicates that the spatial sample is not biased toward either ultra-luxury or budget listings, nor is it skewed toward larger or smaller apartments.
2. The most significant limitation identified by this model is the "suburbia gap." Suburban advertisements were found to be 89% less likely to be successfully geocoded compared to those in the urban core. Thus, the final spatial results should be interpreted as being more representative of the urban center than suburbia.

In summary, while the geocoding process and comparative analysis introduced a distinct geographic bias away from suburbia, it did not significantly distort the fundamental economic variables of price and size. This means that geocoded subsample is a robust proxy for analyzing the urban rental market. However, the results have to be interpreted with an awareness of the underrepresentation of suburbia.

4.5.2 Stage 2: Data Transformation

Table 2 presents descriptive statistics of all raw variables before transformations.

Table 2. Descriptive statistics of variables prior to transformation.

Variable	Observations	Mean	Standard deviation	Min	Max
Price per m^2 (USD)	45,959	9.38	5.71	.69	168.29
Area of listings (m^2)	45,959	60.44	37.01	9.7	706
Greenery index (ratio)	45,959	0.3	.18	0	1
Floority	45,959	13.01	7.84	1	47
Floor ratio	45,959	.59	.26	.04	1

Table 2 (continued)

Attack index (KDE)	34,737	1.26	1.44	0	7.43
Distance to tram stops (m)	45,959	2144.18	3236.56	24.25	44186.32
Distance to bus stops (m)	45,959	367.09	266.86	16.44	4997.71
Distance to the shoreline (m)	45,959	1634.25	1009.89	29.53	6032.86
Distance to shelters (m)	45,959	249.20	376.95	.20	15023.04
Distance to the center (m)	45,959	7089.12	5386.12	111.65	44020.08
Distance to subway stops (m)	31,516	2779.92	3265.77	12.42	36848.41
Distance to kindergartens (m)	45,959	1490.99	1331.89	57.96	27771.42
Distance to hospitals (m)	45,959	1490.45	1344.70	58.55	25103.34

To ensure a statistical validity of the regression models and to satisfy the assumption of normally distributed residuals, the functional form of continuous variables was determined using a Box-Cox transformation. It evaluates the optimal lambda (λ) value to minimize skewness and stabilize variance across the dataset.

Based on this analysis, several key variables were identified as highly right-skewed, requiring a logarithmic transformation to achieve a more normal distribution and to linearize their relationship with rental value. Specifically:

- Price per square meter: Log-transformation was applied to the dependent variable.
- General area: The area of the listings was log-transformed to reflect the diminishing marginal utility of additional square meters.
- Distances: All distance-based variables were log-transformed to model the non-linear distance decay of urban accessibility.

The adoption of a log-log specification for these continuous variables ensures that the resulting coefficients can be interpreted as elasticities. This provides a more intuitive measure of market sensitivity to various drivers.

4.5.3 Stage 3: Multicollinearity Diagnostics

Before estimating final econometric models, a diagnostic phase was conducted to identify potential multicollinearity among the variables. In large-scale urban datasets, spatial variables often exhibit high levels of internal correlation, which can inflate standard errors and lead to unstable coefficient estimates.

To address it, variance inflation factor (VIF) analysis was applied to detect the presence of multicollinearity among the explanatory variables. Additionally, the initial Pearson correlation matrix revealed a significant collinear relationship between three metrics: distance to the CBD, population density, and the count of bus stops within a 500-meter buffer. As hypothesized by classical urban theory, these variables move in synchronization: as distance from the CBD increases, both population density and the frequency of public transit infrastructure decline. Prior to factor analysis, the Kaiser–Meyer–Olkin (KMO) test was applied to assess the adequacy of the data, which confirmed that the data was suitable for factorization. Factor analysis confirmed the above-described finding, with these three variables loading onto a single primary component, which vaguely represents a dimension of "centrality." Despite this clustering, a decision was made not to factorize these variables into a single index. Constructing a composite factor from such diverse units is difficult to interpret within the context of a housing study. Instead, population density and transit stop counts were removed from the OLS specification to eliminate redundancy. Distance to the CBD was retained as the primary proxy for urban accessibility.

Given the structural differences between the cities, factor analysis was additionally performed for each city individually. This approach allowed for the identification of city-specific collinearity patterns that a global model would otherwise obscure.

Where significant local multicollinearity was detected, the model specification was adjusted for each city-level OLS. For example, in Dnipro a high degree of correlation was identified between distance to the CBD and distance to the subway. This is attributed to the specific topography of Dnipro's transit network, where the subway line is concentrated almost entirely within the center. To prevent variance inflation, the subway variable was excluded from Dnipro model. Similar logic was applied to cities with unique suburban distributions to ensure that each local OLS model remained statistically stable.

4.5.4 Stage 4: Ordinary Least Square Regression Models and Decomposition of R^2

To establish a global baseline for rental market determinants across the five metropolitan areas, this study utilizes an OLS regression framework. While the subsequent spatial analysis (GWR) focuses on local variations for only one FUA, the OLS models provide the foundational "average" price elasticities. Such approach allows for a standardized comparison of the five FUAs.

A primary objective of the OLS phase was to ensure that results the remain indicative and comparable across heterogeneous urban contexts (Kyiv, Lviv, Odesa, Dnipro, and Kharkiv). To achieve this, a core of structural variables was maintained across all city-level models. Where city-specific features differed (e.g., the presence of a subway), they were treated as modular extensions rather than global requirements.

To mitigate the risk of omitted variable bias and to account for unobserved heterogeneity, the OLS models incorporate two sets of fixed effects:

- Spatial fixed effects: District-level dummy variables were introduced to capture neighborhood-specific characteristics that are not explicitly measured by distance metrics, such as local prestige or safety perceptions clusters.
- Temporal fixed effects: Periodic indicators for each scrape cycle were included to control for the global trend of the market across the six-month study period.

Standard errors were estimated using the HC3 robust covariance estimator to ensure valid inference in the presence of the heteroscedasticity.

Following the estimation of the OLS parameters, the study quantifies the relative importance of each predictor. Given the high dimensionality of the model (including spatial and temporal dummies), a standard Shapley R^2 decomposition was computationally prohibitive.

Instead, I utilized Owen Value decomposition – a grouped variable importance approach (Huettner & Sunder (2012)). This methodology allows for the total explained variance (R^2) to be partitioned into several theoretically distinct "Blocks":

1. Centrality: distance to the CBD
2. Access to social infrastructure: Distance to hospitals; kindergartens
3. Natural amenities: distance to the shoreline; greenery
4. Living area of flats: area
5. Floor structure: floority; floor ratio
6. Resilience amenities: generator, distance to shelters, pet-friendly status
7. Type of housing: residential complex status
8. Urban mobility #1: distance to bus stops
9. Urban mobility #2: distance to tram stops
10. Urban mobility #3: distance to subway stops (Kyiv and Kharkiv only)
11. Attack index: KDE of attacks (Kyiv, Odesa and Kharkiv only)
12. Spatial fixed effects: (district fixed effects)
13. Temporal fixed effects: (time fixed effects)

By using Owen grouping, the research can meaningfully identify the relative contribution of the resilience or attack index dimension compared to classical urban drivers. This allows to observe a hierarchical view of what truly drives rental value.

4.5.5 Stage 5: Spatiotemporal Dynamics: Case Study of Odesa via GWR

While the OLS models provide a robust global average of market drivers, they are fundamentally constrained by the assumption of spatial stationarity – a premise that a single coefficient can represent the entire metropolitan area. To investigate the local variations this study adopts the Geographically Weighted Regression (GWR) framework that was introduced by Fotheringham, Brunsdon, and Charlton in 2002.

Given a high dimensionality of the spatial output (which generates a unique set of coefficients for every grid cell), a full GWR analysis for all five metropolitan areas was deemed unfeasible within the scope of this thesis. Instead, Odesa was selected as the primary case study for high-resolution spatial modeling. Odesa presents an interesting urban structure for spatial analysis:

- Less monocentric urban fabric: Unlike the majority of cities, Odesa's economic activity and prestige peaks are spread along the Black Sea coastline. This creates interesting, non-linear price gradients that traditional OLS is unable to capture.
- Attack variable: Odesa provides a significant variance in the attack intensity metric. This feature allows to identify how specific missile strikes shift neighborhood-level rental preferences.
- Computational efficiency: The smaller scale of Odesa relative to Kyiv allows for a more accessible analysis.
- Less explored market: Compared to Kyiv, Odesa remains relatively understudied in the urban economics, meaning that a detailed analysis will contribute novel empirical evidence to a market.
- Kyiv as a future extension: Kyiv, as the dominant and most data-rich metropolitan area, warrants a dedicated high-resolution spatial analysis of its own. More granular data (including the data on energy efficiency or attacks) exist only for Kyiv, making it a very compelling candidate for a follow-up study.

Prior to the GWR estimation, the necessity of a spatial model was empirically verified using the Global Moran's I test on the residuals of the Odesa OLS model. A significant positive Moran's I (I = 0.4933) indicated that "errors" of the global model are spatially clustered. This clustering confirms that the OLS model suffers from the spatial autocorrelation (Anselin, 1988).

The empirical results prove that location is a structural feature of the data that requires a local kernel-based approach like GWR to resolve. Formally, the GWR model is specified as:

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

where:

- y_i is a log price per square meter at location i with coordinates (u_i, v_i).
- $\beta_k(u_i, v_i)$ is locally estimated coefficient for variable k in that location.
- ε_i is a local error term.

Local coefficients are estimated via weighted least squares, where each observation receives a weight determined by its proximity to the estimation point. This study uses a bisquare kernel function, which is the common choice in GWR literature:

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{b_i}\right)^2\right]^2 \qquad if\ d_{ij} < b_i, \qquad w_{ij} = 0\ otherwise$$

where:

- d_{ij} is the Euclidean distance between observation i and observation j.
- b_i is the bandwidth at location i.

The bisquare kernel has several properties that make it preferable to other popular alternatives like Gaussian kernel. Firstly, it is more computationally efficient, since observations that go beyond bandwidth boundary get exactly zero weight. Moreover, this approach prevents really distance observations from exerting false influence on estimates. Finally, smooth quadratic decay produces continuous and stable coefficient surfaces, avoiding sharp discontinuities that uniform kernel would introduce.

All coordinates were projected into UTM Zone 36N (EPSG:32636) to ensure that kernel distances are computed in meters. An adaptive bandwidth specification was adopted, where the kernel radius is not fixed in meters but instead expands or contracts to encompass a fixed number of k nearest neighbours. This is important for Odesa, where listing density varies substantially between the dense center and the sparse periphery, since a fixed bandwidth would either oversmooth in center or produce unstable estimates in suburbia.

The optimal number of neighbors k was determined by minimizing the corrected Akaike Information Criterion (AICc), according to Hurvich et al (2002) as adapted for the GWR. The minimization was conducted via golden section search algorithm, which efficiently identifies the AICc minimum without testing every possible value of k.

At each observation location, local t-statistics were computed for every coefficient to assess whether the local estimate is statistically distinguishable from zero. A significance threshold of $|t| > 1.645$ ($p < 0.1$) was applied, which reflects the desire to detect spatially varying effects that may be weaker in data-sparse areas. Final GWR model was implemented in Python using the mgwr library.

4.5.6 Stage 6: Robustness Check via Quantile Regression

Quantile regression (QR) extends the classical OLS framework by estimating conditional quantiles of the dependent variable rather than its conditional mean. This allows the marginal effect of each predictor to vary across the conditional distribution of rental prices. In this study, quantile regression serves as a robustness check for Odesa case study. QR complements GWR and OLS results by examining whether the identified findings are also consistent across different market segments.

Three quantiles were estimated: Q10 (budget segment), Q50 (median segment), and Q90 (luxury segment). They were chosen to maximise contrast and provide a stricter test of distributional robustness. The model specification is identical to the OLS benchmark to ensure comparability. Standard errors were estimated using the robust variance-covariance matrix, which is consistent with the HC3. Model fit is assessed via the pseudo-R^2 statistic, which is analogous to, but not directly comparable with the OLS R^2. QR was estimated in Python using statsmodel.

5 RESULTS

5.1 Ordinary Least Square Regression Models

Five OLS regression models were estimated for each FUA. Heteroscedasticity-robust HC3 standard errors were used. After, Owen Value grouped R^2 decomposition was applied to each model. Table 3 presents OLS coefficient estimates across five cities. For conciseness, full tables with spatial and temporal fixed effect coefficients are included in Annex B. Table 4 summarises the corresponding decomposition results. Detailed interpretation of both follows in the dedicated subsections below.

Table 3. OLS regression estimates of rental price determinants for 5 FUAs

Variable	Kyiv	Odesa	Lviv	Dnipro	Kharkiv
Log shelter distance	0.0009	-0.001	0.031***	0.01*	0.003
	(0.663)	(0.761)	(0.000)	(0.036)	(0.462)
Pet friendliness	-0.126**	-0.018*	-0.002	-0.007	-0.062***
	(0.008)	(0.019)	(0.780)	(0.389)	(0.000)
Suburbia	-0.365***	-0.22***	-0.022		
	(0.000)	(0.000)	(0.490)		
Generator	0.067***	0.006	0.175***	0.099***	0.090*
	(0.000)	(0.551)	(0.000)	(0.001)	(0.019)
Attack index	-0.034***	-0.016***			0.002
	(0.000)	(0.000)			(0.676)
Floor ratio	-0.034***	0.061***	0.048***	-0.045***	-0.059***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Floority	0.007***	0.04***	0.015***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log distance to kindergartens	0.0036	-0.008	-0.014*	0.018**	-0.004
	(0.247)	(0.209)	(0.017)	(0.002)	(0.563)
Log distance to hospitals	0.0036	-0.017*	0.003	0.014**	-0.024***
	(0.247)	(0.015)	(0.462)	(0.008)	(0.001)

Log distance to the center	-0.165***	-0.037***	-0.155***	-0.137***	-0.169***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log distance to subway	-0.040***				-0.036***
	(0.000)				(0.000)
Log distance to tram stops	0.022***	-0.004	0.021***	0.015**	0.008
	(0.000)	(0.331)	(0.001)	(0.002)	(0.200)
Log distance to bus stops	0.076***	-0.022***	0.008	-0.002	0.027***
	(0.000)	(0.000)	(0.247)	(0.811)	(0.000)
Log area of flats	-0.195***	-0.153***	-0.234***	-0.292***	-0.123***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Residential complex	0.232***	0.156***	0.187***	0.240***	0.197***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Greenery	-0.316***	-0.047*	-0.153**	0.290**	-0.321*
	(0.000)	(0.040)	(0.007)	(0.005)	(0.012)
Greenery (squared)	0.135*		0.252***	-0.309*	0.369**
	(0.011)		(0.000)	(0.020)	(0.010)
Log distance to the shoreline	-0.039***	-0.127***	0.044***	-0.007	-0.014
	(0.000)	(0.000)	(0.000)	(0.163)	(0.065)
N	22,028	8,195	6,248	4,974	4,514
Adjusted R^2	0.527	0.465	0.296	0.436	0.378

p-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Owen Value grouped R^2 decomposition for 5 FUAs

Variable	Kyiv	Odesa	Lviv	Dnipro	Kharkiv
Spatial fixed effects	31.05%	17.06%	5.15%	18.44%	12.67%
Distance to the center	17.75%	2.67%	11.36%	18.76%	21.33%
Residential complex status	14.97%	19.91%	34.20%	29.83%	23.05%
Distance to subway stops	9.82%				6.79%
Floor structure	6.20%	23.07%	11.77%	10.30%	3.02%
Area of listings	3.47%	2.93%	23.46%	11.85%	3.38%
Natural amenities	3.04%	17.43%	3.85%	3.40%	7.73%
Resilience amenities	2.48%	4.67%	4.86%	1.72%	4.77%
Temporal fixed effects	2.22%	8.15%	2.48%	3.49%	3.52%

Table 4 (continued)

Attack index	1.04%	.81%			8.21%
Distance to social infrastructure	2.20%	.73%	1.18%	.85%	3.92%
Distance to bus stops	2.66%	1.34%	.11%	.23%	1.03%
Distance to tram stops	3.10%	1.23%	1.56%	1.13%	.58%

5.1.1 Kyiv

The OLS model for Kyiv achieved an adjusted R^2 of 0.527, which represents the highest explanatory power among 5 OLS models.

The temporal dummies reveal a consistent downward trend in rental prices following the initial sampling period in August 2025 (Annex B). All subsequent scrape cycles show negative and statistically significant coefficients compared to the August baseline (e.g., February 2026: $\beta = -0.099$, $p < 0.001$). This reflects a seasonal spike in August, likely driven by the influx of students moving to big cities for the start of academic year. Statistics from lun.ua also indicates that this is a common pattern – the data also showed a spike in August-September of 2024.

As expected, Pecherskyi raion (the intercept) is the most expensive and prestigious district in the city. All other administrative raions exhibit negative coefficients relative to the Pecherskyi baseline. The steepest discounts are found in the peripheral districts of Desnianskyi ($\beta = -0.591$, $p < 0.001$) and Darnytskyi ($\beta = -0.482$, $p < 0.001$). This reflects an expected "left bank" discount that is present in Kyiv.

One of the most significant predictors in the model is the residential complex status dummy ($\beta = 0.232$, $p < 0.001$). In this analysis this variable serves as a proxy for several unobserved quality traits, such as newer construction materials, allegedly enhanced security and infrastructure, potential presence of generators, which explains the high magnitude of the coefficient.

Interestingly, building height (floority) has a positive impact on price ($\beta = 0.007$, $p < 0.001$), as taller buildings in Kyiv are more likely to be newer. However, the floor_ratio exhibits a negative coefficient ($\beta = -0.034$, $p < 0.001$), suggesting that within a given building, tenants prefer lower floors. This confirms the hypothesized adaptation in the wartime context, where higher floors are perceived as riskier.

The model confirms the dominance of classical urban determinants. Distance to the CBD ($\beta = -0.165$, $p < 0.001$) and distance to the subway ($\beta = -0.040$, $p < 0.001$) both show significant negative elasticities. The closer a listing is to the economic center or a metro station, the higher the price. Similarly, proximity to the water ($\beta = -0.039$, $p < 0.001$) is a valued environmental amenity.

Conversely, proximity to trams ($\beta = 0.022$, $p < 0.001$) and bus stops ($\beta = 0.076$, $p < 0.001$) is associated with lower prices (as distance increases, price increases). This suggests that for surface transit negative externalities exist, such as noise and proximity to high-traffic highways, where bus stops are typically located, outweigh the accessibility benefits.

The presence of a generator increases the price per square meter by approximately 6.9% ($\beta = 0.067$, $p < 0.001$). Simultaneously, the severity of attacks shows a significant negative impact ($\beta = -0.034$, $p < 0.001$), proving that the market responds to the physical and psychological risk of localized conflict events. Furthermore, pet-friendly listings command lower prices ($\beta = -0.012$, $p = 0.008$). This can indicate that owners of luxurious listings are less likely to allow to own animals.

The relationship between greenery and price follows a quadratic, convex dependency. The function reaches its minimum at a value of 1.17, which is outside the possible range (0 to 1) for the index. This indicates that the relationship is decreasing: more expensive listings tend to be in less green areas. This reflects the urban centrality trade-off, where the most valuable real estate is concentrated in the dense city center, while greenery increases as one moves toward the periphery.

The Owen Value decomposition provides a hierarchical view of the market's explanatory power. Spatial fixed effects account for 31.05% of the explained variance, followed by centrality (17.75%), residential complex status (14.97%) and distance to subway stops (9.82%). Resilience and war variables (generator, attacks, shelters) collectively account for approximately 3.5% of the variance. This confirms the analytical framework: while wartime resilience is a critical and significant modifier of value, the fundamental economic structure of Kyiv is still dictated by the classical determinants such as location or construction quality.

5.1.2 Odesa

The OLS model for Odesa provides an adjusted R^2 of 0.465. While slightly lower than the Kyiv model, the results are still significant and reveal several patterns unique to Odesa's urban structure.

As expected, Prymorskyi Raion (the intercept) was found to be the most expensive district in the city. All other administrative districts show negative coefficients, with the steepest discount found in Peresypskyi Raion ($\beta = -0.309$, $p < 0.001$). This finding reflects the concentration of economic activity and proximity to the shoreline within the Prymorskyi center.

In Odesa, proximity to the coastline is an important driver of value, with a high-magnitude negative elasticity ($\beta = -0.127$, $p < 0.001$). This indicates that as the distance from the water increases, rental prices per square meter drop significantly. In fact, the natural block in the Owen Value decomposition (which includes water and greenery) explains 17.43% of the total variance – around five times its importance in other observed cities. This confirms that the Odesa market is oriented toward its sea boundary rather than a single CBD.

Odesa is the only city where a simple linear model was sufficient for greenery, which showed a significant negative relationship ($\beta = -0.047$). The peak of rental value is more anchored to the shoreline or the central area, which are characterized by high-density construction and minimal vegetation. The further a listing moves inland towards potentially greener outskirts, the more the price drops. This demonstrates that greenery is viewed as a peripheral rather than a central amenity in Odesa. Though, this theory will be investigated further in GWR analysis.

Interestingly, the vertical preferences in Odesa differ from those in Kyiv. While floority remains a positive driver ($\beta = 0.014$, $p < 0.001$), likely proxying for newer construction, the floor_ratio also exhibits a positive coefficient ($\beta = 0.040$, $p < 0.001$). This suggests that, despite Odesa being a frequent target for drone and missile attacks, landlords still expect a premium for higher floors within a building. This may be driven by the high value placed on the sea views, which are only accessible from upper floors, potentially outweighing the perceived security risks. Index of attacks, on the other hand, is a significant negative driver ($\beta = -0.016$, $p < 0.001$), confirming that localized war shocks depress rental values in Odesa.

Unlike in Kyiv, where surface transit was associated with negative noise externalities, bus stops in Odesa have a positive impact on price ($\beta = -0.022$, $p < 0.001$). This reflects Odesa's greater reliance on its bus network as a mode of urban mobility.

The Owen Value decomposition reveals a market driven by structural quality and environmental amenity. Floor and residential complex status collectively explain over 43% of the model's power. At 17.43%, environmental factors (primarily water) are the third most important dimension of value. Market trends over time explain 8.15% of the variance, while spatial fixed effects account for 17.06%.

5.1.3 Lviv

The OLS model for Lviv achieved an adjusted R^2 of 0.296. This represents the lowest explanatory power among all metropolitan areas. This suggests that Lviv market is influenced by a high degree of idiosyncratic factors not fully captured by the model, such as the historical value listings, or specific architectural characteristics, like "Austrian-era" buildings.

In Lviv, Halytskyi Raion (represented by the intercept) is the most expensive district, which reflects the premium associated with the historical center. Frankivskyi Raion showed no statistically significant difference from the baseline ($p = 0.527$). All other districts demonstrate significant discounts, with Sykhivskyi ($\beta = -0.055$, $p = 0.004$) being the most affordable relative to the center.

A unique finding in Lviv is the positive coefficient for distance to bomb shelters (β = 0.031, $p < 0.001$), which is the opposite of the expected relation. This can be explained by two factors. Firstly, data from the State Emergency Service of Ukraine indicates that shelters are present in nearly every building in Lviv. However, the quality and actual accessibility of these official shelters vary wildly. Secondly, Lviv is geographically further from the frontline and relatively safer than other cities. That is why proximity to shelter may be a secondary concern for tenants compared to other amenities. Conversely, the generator dummy is a powerful and significant driver (β = 0.175, $p < 0.001$), commanding a 19.1% increase.

The model confirms that centrality is important, with a significant negative elasticity for distance to the CBD (β = -0.155, $p < 0.001$). Proximity to kindergartens also acts as a positive amenity (β = -0.013, p = 0.017). Regarding transportation, trams act as a negative externality (β = 0.021, p = 0.001), where being further from a tram stops increases the price.

As for greenery, Lviv exhibits a convex, U-shaped relationship with a mathematical minimum at 0.30. This suggests a bimodal market where the highest prices are found at the extremes of the greenery scale. The first peak is at 0% greenery, that most likely represent prestigious paved historical center. As greenery increases to 30%, prices drop, which potentially represent standard Soviet-era residential zones. However, beyond the 30% threshold, the relationship flips, since prices begin to rise again as listings are located in greener areas.

Similar to Odesa, both floority and floor_ratio have positive and significant impacts. This may suggest that in a relatively safer Lviv the premium for elevated views supersedes safety considerations of tenants. Additionally, the residential complex dummy (β = 0.187, $p < 0.001$) also demonstrated a significant positive effect.

Owen Value decomposition shows the main drivers of value in Lviv. Residential complex status was found to be the single most important factor, explaining 34.20% of the model's power. Area accounts for 23.46% of the variance, a much higher proportion than in other cities. Distance to the center explains 11.36%, which demonstrates that while location matters, the type of building has overtaken the location of the building as the primary driver of value.

5.1.4 Dnipro

The OLS model for Dnipro achieved an adjusted R^2 of 0.436.

In Dnipro, Sobornyi Raion (β = 0.072, $p < 0.001$) and Shevchenkivskyi Raion (β = 0.046, p = 0.001) were identified as the most expensive administrative areas. Conversely, peripheral and industrial districts such as Novokodatskyi (β = -0.089, $p < 0.001$) and Samarskyi (β = -0.072, $p < 0.001$) offer significantly cheaper listings.

Similar to Kyiv, Dnipro exhibits a more pronounce penalty for higher floors. While floority remains positive (β = 0.008, $p < 0.001$), which indicates a preference for newer, taller buildings, the floor ratio is negative (β = -0.045, p = 0.001). This again confirms that within a building tenants prefer lower floors, potentially because higher floors are more associated with security risks.

The model again confirms the importance of centrality, with a significant negative elasticity for distance to the CBD ($\beta = -0.137$, $p < 0.001$). For transportation, the tram network acts as a negative externality ($\beta = 0.015$, $p = 0.002$), where being further from a tram stop increases the price. The generator dummy showed a significant positive impact ($\beta = 0.099$, $p = 0.001$), which suggests that energy autonomy is valued.

The relationship with greenery follows an inverted U-shape, with a positive linear term ($\beta = 0.290$, $p = 0.005$) and a negative quadratic term ($\beta = -0.309$, $p = 0.02$). The function reaches its peak at approximately 0.47 (47% greenery). This indicates an optimal greenery threshold. Rental prices increase as neighborhood greenery increases up to 47% coverage, after which the marginal utility declines. This represents a classic urban trade-off where moderate greenery is a high-value amenity, but excessive greenery may signal a lack of urban connectivity.

Owen Value decomposition reveals the primary contributors of value in Dnipro. Residential complex status explains 29.83% of the model's power – the highest of any other block. Centrality accounts for 18.76%, which means that proximity to the center is still an important determinant. Spatial controls explain 18.44%, followed by area that accounts for 11.85%.

5.1.5 Kharkiv

The OLS model for Kharkiv achieved an adjusted R^2 of 0.378, meaning the model explains approximately 38% of the variance in rental prices per square meter. In Kharkiv, Kyivskyi Raion serves as the reference baseline district. All other districts demonstrate positive coefficient relative to it when controlling for other factors, which indicates that Kyivskyi represents the most affordable district. The largest magnitudes were observed in Industrialnyi ($\beta = 0.201$, $p < 0.001$) and Slobidskyi ($\beta = 0.158$, $p < 0.001$) raions.

The temporal fixed effects for Kharkiv reveal a pattern that is distinct from the other metropolitan areas. Unlike other cities, where the August–September represented the seasonal peak of rental demand, Kharkiv exhibits an opposite trajectory. The earliest scraping period (early August 2025) serves as the reference baseline after which prices trend upward persistently. This monotonic upward shift is confirmed by statistics from lun.ua, which documented one of Kharkiv's most pronounced rental price increase in recent years.

The underlying mechanism driving this demand surge is empirically unresolved, since the existing literature offers no explanation for it so far. However, there are several plausible hypotheses. First, the return of displaced people may have created a new demand. Some tentative empirical support for this dynamic is provided by the IOM's Ukraine Returns Report (Round 21), which documented return flows to regions close to the frontline, including Kharkiv. However, the rate of return was not sufficient enough to explain a significant demand shift. Second, the intensification of military activity in Kharkivska oblast may have driven displacement to the city itself. Third, an increased presence of military personnel in the city may have introduced an increased demand. Regardless, what the temporal coefficients do confirm, is that Kharkiv's rental market in the observed period behaved not as a market on pause, but as one experiencing accelerating demand pressure.

The subway is also an important determinant of value. The negative elasticity for distance to the subway ($\beta = -0.036$, $p < 0.001$) confirms that proximity to subway stations is valuable. In Ukraine subways serve a dual purpose: it is a primary method of efficient transit and the most reliable bomb shelter. Similarly, centrality remains a dominant driver, with a strong negative elasticity for distance to the CBD ($\beta = -0.169$, $p < 0.001$). This indicates that even under the war, economic utility of the urban core continues to influence the market.

Kharkiv shows one of the strongest penalties for high floors in the study. The floor ratio has a significant negative coefficient ($\beta = -0.059$, $p < 0.001$), while floority has a small positive impact ($\beta= 0.007$, $p < 0.001$). This reflects a logical wartime adaptation that was present in Kyiv and Dnipro.

Similar to Lviv, greenery in Kharkiv follows a convex quadratic relationship with a minimum at 0.43. The U-shape of this dependency reflects a market split between the highly valuable (but paved) central business district and prestigious, heavily forested residential zones.

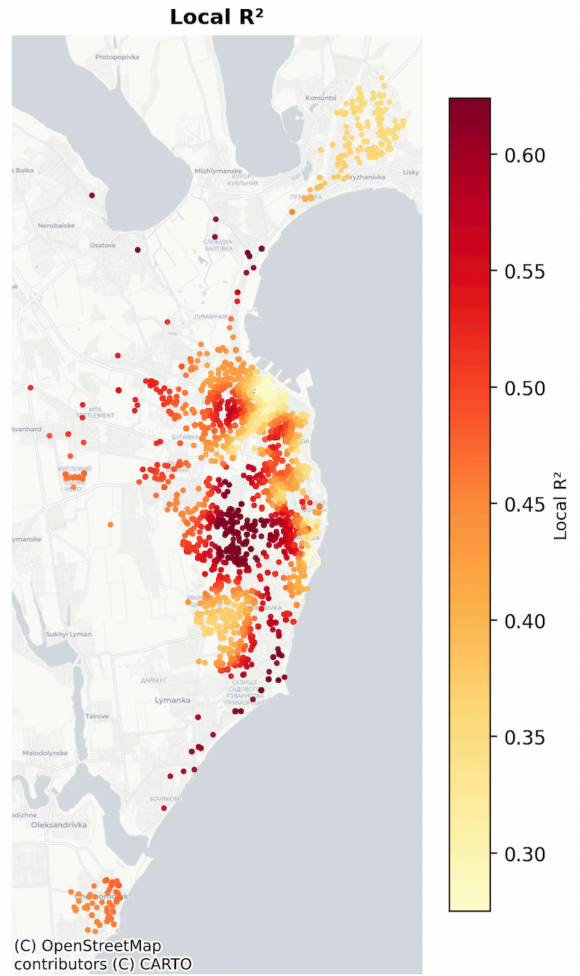
A notable statistical paradox was identified in Kharkiv model: while the attack index was not statistically significant in the final OLS specification ($p = 0.676$), Owen Value decomposition attributed 8.21% of the model’s explained variance to the conflict dimension. This discrepancy suggests a high degree of spatial multicollinearity, where the impact of war events is connected to city's distance variables. Indeed, Pearson correlation between the attack index and distance to the center stands at $r = -0.73$, which indicates that strikes cluster disproportionately in center. While OLS fails to isolate marginal effect of a war severity due to this overlap, R^2 decomposition shows that conflict intensity is a valuable contributor of the Kharkiv rental market (8.21%).

Owen Value decomposition reveals important contributors of value in Kharkiv. Residential complex status (23.05%) and centrality (21.33%) are the main drivers of value. Spatial fixed effects (12.67%), attack index (8.21%) were also found to be valuable determinants.

5.2 Geographically Weighted Regression Model

The Geographically Weighted Regression model for Odesa was estimated at the individual listing level using an adaptive bisquare kernel, with statistical significance assessed at the 10% level ($|t| > 1.645$). This threshold is deliberately more permissive than 5% level, so that it could reflect the inherent variance inflation introduced by kernel-weighted local estimation and the exploratory spatial nature of the analysis. Figure 3 presents the spatial distribution of local model fit across Odesa via the GWR R^2 surface.

Figure 3: GWR Local R^2 Surface

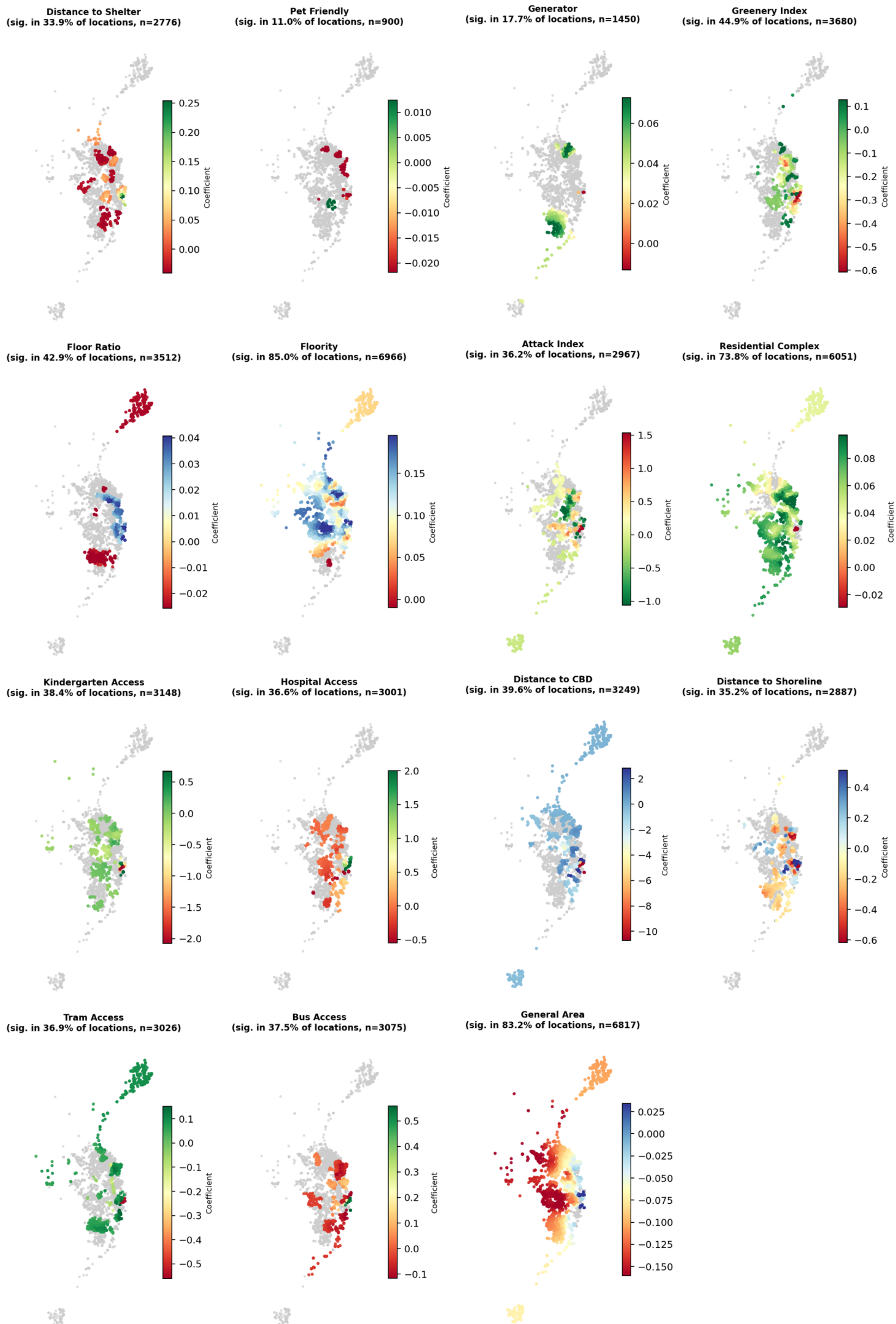


The spatial distribution of local R^2 values confirms meaningful heterogeneity in model fit across the city, with the highest explanatory power (local R^2 in the range of 0.68-0.72) being concentrated in the residential districts of Cheremushky and Selysche OdVO, depicted in dark red on the local R^2 surface. These are relatively homogeneous neighborhoods where rental pricing follows a consistent and predictable spatial logic. By contrast, the lowest local R^2 values of approximately 0.25 were recorded in the historical center and the prestigious coastal district Arcadia, depicted in light yellow. It is important to note that Arcadia is characterized by highly heterogeneous listing composition and combines luxury residential complexes with more ordinary stock in a compact area. This resulted in high within-district variance in both prices and attributes and inflated local standard errors, which reduced model's ability to produce stable coefficient estimates in this zone. Several Arcadia coefficients discussed below should therefore be interpreted with caution, as they likely reflect data noise rather than genuine spatial differentiation.

Figure 4 presents the local coefficient surfaces for substantive variables, with statistically insignificant estimates shown in grey. For conciseness, coefficient surfaces with temporal fixed effects are included in Annex C.

The shoreline distance variable was statistically significant in approximately 35% of locations, confirming the spatially selective nature of coastal amenity pricing already identified in the OLS model. The local coefficient surface reveals a nuanced and geographically structured pattern. Significant negative betas in the range of -0.2 to -0.4 were recorded in the southern districts of Tairovo and Pivdennyi, indicating that proximity to the sea demonstrates a rental premium in these areas, which is consistent with the dominant role of coastal amenity that was shown in global OLS. The southern portion of the central district of Vidrada exhibited the most pronounced negative betas of -0.6 to -0.4. This potentially reflects a particularly high value attributed to first-line sea proximity in this centrally located coastal zone. A cluster of positive betas of approximately 0.4 in the northern portion of Arcadia is noted but, as discussed above, is likely attributable to data noise rather than a genuine reversal of the coastal gradient.

Figure 4. GWR Coefficient Surfaces – Substantive Variables (gray is insignificant at p = 0.1)



The CBD distance variable was significant in approximately 40% of locations and exhibited predominantly negative local betas, which is consistent with classical bid-rent theory and the global OLS finding. The majority of significant locations recorded betas of approximately −1. A notably stronger negative effect of -4 to -3 was identified in a small cluster near the central railway station. Two anomalous clusters were observed in Arcadia: several points with strongly positive betas of approximately +2 situated immediately adjacent to points with extreme negative betas of approximately -10 (highlighted in dark blue and red respectively). Given the magnitude and spatial juxtaposition of these values, these estimates are most plausibly attributed to local multicollinearity and data noise.

The general area variable achieved statistical significance in 83% of locations. The coefficient surface reveals a visually striking and theoretically coherent gradient: betas approach zero (ranging from -0.025 to +0.025) in coastal and near-shoreline locations, increasing in magnitude to approximately -0.15 in inland districts depicted in darker red tones. This gradient indicates that the marginal discount for additional square meter is substantially larger as distance from the sea increases. This finding reinforces the OLS interpretation of Odesa as a shoreline-oriented rather than CBD-oriented market.

The residential complex premium was statistically significant in 73% of locations, with predominantly positive betas across the city. The highest premiums were concentrated in the center closer to the coastal zone (Lanzheron and Vidrada), where betas exceeded 0.08. This demonstrates willingness to pay more for modern residential developments that are close both to the center and the shoreline. Most modest premiums of approximately 0.03 were recorded in the northern district of Kotovskogo, where the stock of newer residential complexes is comparatively limited.

The floority variable demonstrated broadest spatial significance, with statistically significant betas in 85% of locations. The highest local premiums, with betas approaching 0.2, were concentrated in Cheremushky and the northern portion of Arcadia, as well as across much of the historical center. This persistent positive relationship between floority and rental price in a war-affected city is an interesting finding: despite Odesa being one of the most frequently targeted Ukrainian cities during the observed period, high buildings continue to create premiums.

Floor ratio was significant in 43% of locations and exhibited a spatially heterogeneous pattern with clear geographic logic. Listings in coastal and near-luxury districts, starting from the central Lanzheron to Arcadia and Seredniy Fontan, recorded positive betas in the range of 0.02 to 0.04. This indicates the sea-view premium accessible from higher floors. In contrast, listings in the inland northern district of Kotovskogo and in Tairovo recorded significantly negative betas below -0.02, which suggests that in these residential areas, higher floors may be associated with a modest discount for war-related risks.

The generator variable achieved statistical significance in 18% of locations. Significant positive premiums were concentrated in the southern district of Pivdennyi, Tairovo, and the center. The relatively limited spatial significance of the generator in Odesa may indicate that lower listing density in some generator-equipped buildings limed the statistical power of local estimation.

The attack index surface presented quite fragmented and heterogeneous pattern with significance in 36% of locations. Coefficient distribution is concentrated in the central-eastern coastal zone, where both positive and negative betas coexist in close spatial proximity. Positive betas of 0.5 to 1.5 were found in a cluster along the coastal strip. This unexpected finding in coastal zones is likely a symptom of spatial multicollinearity. Attacks in Odesa is are more concentrated along the coastal strip, the same zone that concentrates city's highest-value listings. This potentially supports one of the study's hypotheses that attacks in Ukraine act as a background condition rather than an active pricing factor. Also, negative betas of -0.5 to -1.0 were observed in inland location of district near the railway station and southern center (depicted in deep green). This sporadic spatial pattern of attack coefficients is itself a valuable finding. It suggests that in Odesa (after four years of active war) attacks do not produce a predictable spatial pricing response. Instead, attack severity interacts with local amenities or housing quality in ways that produce highly heterogeneous outcomes.

Distance to bomb shelter achieved significance in 34% of locations, yet the coefficient surface offers limited substantive insight, since local betas were concentrated around zero across all locations. This suggests that proximity to bomb shelters, while theoretically relevant in conflict contexts, does not translate into a measurable rental premium in Odesa.

Pet-friendly listings were statistically significant in only 11% of locations with significant negative betas concentrated almost exclusively in coastal districts. This pattern likely reflects a supply-side dynamic: landlords of high-value coastal apartments are less inclined to permit pets.

Greenery index was significant in 45% of locations and exhibited a broadly negligible positive effect across most of the city, with betas close to zero. The notable exception is Arcadia and a small cluster in the historical center, where betas of -0.4 to -0.6 indicate a negative association. Given that Arcadia is not characterized by abundant greenery, the negative coefficient may reflect that in this zone, green space carries no premium and may proxy for distance from prestigious neighborhood.

Bus access was significant in 38% of locations. Negative betas in the range of -0.1 to 0 were concentrated in Cheremushky, central zone near Lanzheron, and the southern shoreline districts of Seredniy and Velykyi Fontan, which suggests that proximity to bus infrastructure is valued in these districts. Tram access was significant in 37% of locations but produced coefficients tightly centered around zero across the significant surface.

Additionally, the temporal dummy variables that capture price shifts relative to the reference period of 17 August 2025, reveal meaningful spatial heterogeneity in how rental price trajectories evolved over the observation period. Detailed coefficient surfaces for each period are provided in the accompanying maps (Annex C); the discussion here will focus on the most substantively informative period. “February 7, 2026” dummy recorded the highest share of statistically significant locations at 91%. The betas were uniformly negative relative to the August baseline. The most pronounced declines (with betas in the range of -0.10 to -0.09) were concentrated in the southern settlement of Chornomorsk, the historical center, Seredniy Fontan, and Arcadia, which suggests that the winter price correction was sharpest in the city's more prestigious coastal zones and Chornomorsk. More modest but still significant declines of -0.04 to -0.03 were recorded in the inland western districts.

5.3 Robustness Check with Quantile Regression Model

Three quantiles (Q1, Q50, Q90) were estimated for Odesa’s functional urban area with specification, identical to the OLS. Standard errors were estimated using the robust variance-covariance matrix. Table 5 presents the comparison between OLS and QR coefficient estimates in Odesa. For conciseness, the full table with less significant effect coefficients, as well as spatial and temporal fixed effects is included in Annex D.

Table 5. OLS and QR regression estimates of rental price determinants for Odesa

Variable	OLS	Q10	Q50	Q90
Suburbia	-0.22***	-0.147***	-0.208***	-0.214***
	(0.000)	(0.000)	(0.000)	(0.000)
Attack index	-0.016***	-0.017***	-0.015***	-0.019**
	(0.000)	(0.000)	(0.000)	(0.003)
Floor ratio	0.061***	-0.009	0.029**	0.086***
	(0.000)	(0.529)	(0.005)	(0.000)
Floority	0.04***	0.016***	0.013*	0.013***
	(0.000)	(0.000)	(0.012)	(0.000)
Log distance to the center	-0.037***	-0.043***	-0.042***	-0.036**
	(0.000)	(0.000)	(0.000)	(0.002)
Log area of flats	-0.153***	-0.275***	-0.2***	-0.058***
	(0.000)	(0.000)	(0.000)	(0.001)
Residential complex	0.156***	0.12***	0.156***	0.187***
	(0.000)	(0.000)	(0.000)	(0.000)
Greenery	-0.047*	0.106***	-0.024	-0.208***
	(0.040)	(0.000)	(0.357)	(0.000)
Log distance to the shoreline	-0.127***	-0.092***	-0.124***	-0.156***
	(0.000)	(0.000)	(0.000)	(0.000)
Adjusted / Pseudo R^2	0.465	0.300	0.312	0.239

p-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The quantile regression results for Odesa show interesting distributional heterogeneity in the pricing of amenities across budget (Q10), median (Q50) and luxury (Q90) segments. Several findings were identified.

Greenery index shows interesting distributional patterns. At Q10, greenery has a significantly positive coefficient of $\beta = 0.106$ ($p < 0.001$), which may indicate that green surroundings are valued by budget renters. At Q90, however, the coefficient becomes significantly negative with $\beta = -0.208$ ($p < 0.001$), which shows that greenery can be seen as a proxy for distance from the sea, and luxurious coastline districts and is associated with a price discount, as it was hypothesized based on the GWR and OLS results.

Floor ratio also shows an informative distributional pattern. The coefficient is negative and insignificant at Q10, positive and significant at Q50 ($\beta = 0.029$, $p = 0.005$), and most strongly positive at Q90 ($\beta = 0.086$, $p < 0.001$). This confirms that the premium for higher buildings is concentrated in more expensive market segment, which is consistent with the sea-view interpretation from OLS and GWR analyses.

Floority and attack index demonstrate distributional stability. Floority coefficients are positive and significant across all three quantiles at similar magnitudes (0.013 - 0.016), and the attack index is consistently negative across segments (ranging from -0.015 to -0.019). This uniformity is a valuable finding, which shows that higher floors and the conflict penalty are homogeneous across budget and luxury segments. This suggests that these effects are structural features of the Odesa market.

Residential complex status is positive and statistically significant across all quantiles, with coefficient increasing from 0.120 at Q10 to 0.187 at Q90. This gradient indicates that the market premium for residential developments is largest in the luxury segment.

Distance to shoreline produces consistently negative and significant coefficients across all quantiles, but with a pronounced distributional gradient: the magnitude increases from -0.096 at Q10 to -0.168 at Q90. This finding confirms that coastal proximity is valued more intensely by luxury renters than by budget renters. This result is consistent with Odesa's market structure as a shoreline-oriented city, which was demonstrated in OLS and GWR analyses.

Area of listings shows the opposite gradient: a discount for additional square meter is largest at Q10 ($\beta = -0.275$, $p < 0.001$) and diminishes substantially at Q90 ($\beta = -0.058$, $p = 0.001$). This indicates that budget renters face stronger diminishing returns to size, while luxury renters are less sensitive to unit size. This pattern is consistent with GWR coefficient surface, which also demonstrated such opposite gradient.

Overall, quantile regression results confirm the robustness of OLS and GWR findings. The most critical divergence concerns greenery, where the relationship differs not only in magnitude but in direction across market segments.

5.4 Limitations

Despite the high granularity of the dataset, several limitations must be acknowledged.

1. Platform and market selection bias

The data for this study was exclusively retrieved from lun.ua. While it is a popular aggregator in Ukraine, it does not capture the entire market. Also, rental market is characterized by a high degree of informality. A significant portion of listings are often exchanged through personal networks, and are not posted in the Internet. Consequently, this study may over-represent formal segment of the market.

Also, the analyzed prices are asking prices rather than transaction prices. The gap between the asking price and the final negotiated rent can be significant. Moreover, as noted before, the 10-20% link expiration rate suggests that the most desirable listings are removed before they can be scrapped. This could create a bias toward listings with longer market duration.

Additionally, the data is limited only to apartment listings, excluding private houses and other non-apartment residential stock. This may introduce a coverage gap in suburban areas where detached housing takes up a larger share of the market.

2. Geocoding bias

As confirmed by logit model, geocoding success was significantly lower in suburbia. This bias means that the findings are less reliable for this area. Additionally, for listings where only a street name was available, the use of the street center provides an approximation rather than a precise building coordinate.

3. Data source reliability

The study was conducted in a quite volatile environment characterized by inconsistent data reporting. Several data sources, such as data on war events, bomb shelter coverage (and their conditions), data on private hospitals and kindergartens can have coverage gaps or potential inaccuracies that are difficult to fully assess in a constantly changing context.

4. Assumption of Spatial Stationarity in OLS

The OLS models estimated for all five FUAs operate under the assumption of spatial stationarity, that the relationship between variables and price is constant across the entire city. As demonstrated by further GWR case study for Odesa, this assumption is violated in practice. Therefore, OLS coefficients should be interpreted as global average effects.

6 CONCLUSION

This study examined the dynamics of the Ukrainian rental housing market during the 2025-2026 autumn-winter season – a period characterized by infrastructure disruptions and four years of ongoing full-scale war. By analyzing a dataset of almost 46,000 listings across country's 5 largest metropolitan areas, this study investigated how both traditional and ‘resilience’ amenities are valued during prolonged war. The overarching finding of the research is the emergence of spatiotemporal normalization, where the market within cities has largely absorbed war-related risks as background conditions, which allowed classical urban determinants to act as the primary drivers of rental value.

The results provide strong empirical support for the first hypothesis, confirming that conventional amenities remain the dominant predictors of rental prices. Across all observed cities, distance to the center and proximity to major transport networks (particularly the subway in Kyiv and Kharkiv) exhibited significant negative elasticities, meaning that proximity to transportation is highly valued by renters. This dominance was further highlighted by the Owen Value decomposition, which showed that in Kyiv, centrality and spatial fixed effects explained nearly half of the model's variance, when resilience and conflict variables collectively accounted for only about 3.5%. This suggests that the fundamental economic structure of the city, rooted in density and accessibility, remains resilient to external shocks during the state of prolonged war.

The study also confirmed the second hypothesis: that resilience amenities and war events have a statistically significant but secondary influence on prices. Features like power generators act as a positive bonus rather than primary driver of choice. Nevertheless, their impact was notable in specific contexts; for example, the presence of a generator increased price per square meter by approximately 7% in Kyiv and nearly 20% in Lviv. Additionally, a distinct "wartime adaptation" was observed in vertical preferences. Kyiv, Dnipro, and Kharkiv showed a clear penalty for higher floors due to safety risks, while Odesa and Lviv maintained premiums for upper floors, where the value of scenic views appeared to supersede security concerns.

Beyond confirming the global OLS findings at the local level, the GWR analysis revealed several spatially interesting patterns that the global model was unable to detect. Most notable were the difference of the floor ratio coefficient between prestigious coastal districts, where higher relative floor position creates a significant premium; and between inland areas, where higher position carries a significant discount. Among other valuable findings was a spatial gradient in area discount, where coastal luxury listings exhibit minimal diminishing returns to size, while such discount increases progressively toward inland districts; and heterogeneous response of rental prices to war attacks.

Ultimately, this research illustrates that the "invisible hand of geography" continues to organize urban space even during the war. While conflict violence has introduced new layers of risk, the structural resilience of Ukrainian cities ensures that traditional economic logic continues to dictate the price of housing.

This study carries several practical implications for urban governance. The spatial heterogeneity documented through GWR suggests that city-wide housing interventions, which are dependent on city averages, risk misallocating resources in a market where the pricing logic differs within the city. Local governments would benefit from incorporating spatially explicit market diagnostics into housing policy design. Additionally, the coefficient surfaces distributions produced by this study offer a potential analytical template for reconstruction prioritization. It can help identify districts, where targeted investment in infrastructure would result in greater restoration of residential value.

Several ideas for future research emerge from this study. Most immediately, the GWR analysis conducted for Odesa could be extended to the remaining areas. Kyiv presents the most interesting case for spatial modelling given its biggest market size and large variety of data that is not available for other cities. A dedicated GTWR analysis with temporal kernel dimension could become an important extension of this study. Finally, as longer time series of rental data become available, panel-based spatial models could add value to the future analysis.

7 REFERENCES

1. Andrienko, D., Goriunov, D., Grudova, V., Markuts, J., Marshalok, T., Neyter, R., Piddubnyi, I., Studennikova, I., & Topolskov, D. (2025, February). Report on damages to infrastructure from the destruction caused by Russia's military aggression against Ukraine as of November 2024. KSE Institute. https://kse.ua/wp-content/uploads/2025/02/KSE_Damages_Report-November-2024---ENG.pdf

2. Khelashvili, A., Verbytskyi, I., Bobrova, A., & Miloserdov, V. (2025, January 6). Housing and residential conditions of Ukrainians: Survey results. CEDOS. https://cedos.org.ua/en/researches/housing-and-residential-conditions-of-ukrainians-survey-results/

3. Bobrova, A., Onyshchuk, Y., Kabanets, Y., & Zembitskyi, S. (2025, October 24). Rental housing in Ukraine: Current state and challenges. CEDOS. https://cedos.org.ua/en/researches/rental-housing-in-ukraine-current-state-and-challenges/

4. Goodman, A. C. (1998). Andrew Court and the invention of hedonic price analysis. *Journal of Urban Economics*, 44(2), 291–298. https://doi.org/10.1006/juec.1997.2071

5. Colwell, P. F., & Dilmore, G. (1999). Who was first? An examination of an early hedonic study. *Land Economics*, 75(4), 620–626. https://www.jstor.org/stable/3147000

6. Malpezzi, S. (2002). Hedonic pricing models: A selective and applied review. In K. Gibb & A. O'Sullivan (Eds.), Housing economics and public policy (pp. 67–89). Blackwell. https://doi.org/10.1002/9780470690680.ch5

7. Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy*, 82(1), 34–55. http://www.jstor.org/stable/1830899

8. Sirmans, G. S., Macpherson, D. A., & Zietz, E. N. (2005). The Composition of Hedonic Pricing Models. *Journal of Real Estate Literature*, 13(1), 3–43. http://www.jstor.org/stable/44103506

9. Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2), 132–157. https://doi.org/10.1086/259131

10. Terzi, M. (2025). Transformation of housing preferences in Ukraine under the impact of war: Guidelines for residential strategies [Master's thesis, Kyiv School of Economics]. Faculty of Social and Humanitarian Studies.

11. Ricciato, F., Wirthmann, A., & Hahn, M. (2020). Trusted smart statistics: How new data will change official statistics. *Data & Policy*, 2, Article e7. https://doi.org/10.1017/dap.2020.7

12. LUN UA LLC. (n.d.). LUN — real estate search in Ukraine [Database]. LUN. https://lun.ua

13. Boeing, G., & Waddell, P. (2017). New insights into rental housing markets across the United States: Web scraping and analyzing Craigslist rental listings. *Journal of Planning Education and Research*, 37(4). https://doi.org/10.1177/0739456X16664789

14. Bricongne, J.-C., Meunier, B., & Pouget, S. (2021). Web scraping housing prices in real-time: The Covid-19 crisis in the UK. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3916196

15. Harten, J. G., Kim, A. M., & Brazier, J. C. (2020). Real and fake data in Shanghai's informal rental housing market: Groundtruthing data scraped from the internet. *Urban Studies*, 1–15. https://doi.org/10.1177/0042098020918196

16. Souza, T. G. D., Fonseca, F. D. R., Fernandes, V. D. O., & Pedrassoli, J. C. (2021). Exploratory spatial analysis of housing prices obtained from web scraping technique. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B4, 135–140. https://doi.org/10.5194/isprs-archives-XLIII-B4-2021-135-2021

17. Üzümcü, A. C., & Eligüzel, N. (2023). Predictive analysis using web scraping for the real estate market in Gaziantep. *Bitlis Eren University Journal of Science*, 12(1), 17–24. https://doi.org/10.17798/bitlisfen.1155725

18. Chapelle, G., & Eyméoud, J. B. (2022). Can big data increase our knowledge of local rental markets? A dataset on the rental sector in France. PLOS ONE. https://doi.org/10.1371/journal.pone.0260405

19. Antonov, O., & Laktionova, O. (2020). Evaluation of real estate market value in Ukraine using web-scraping. *Galician Economic Visnyk of TNTU*. https://doi.org/10.33108/galicianvisnyk_tntu2020.02.035

20. Meyberg, C., Rendtel, U., & Leerhoff, H. (2024). Flat rent price prediction in Berlin with web scraping. *AStA Wirtschafts- und Sozialstatistisches Archiv*, 18, 245–278. https://doi.org/10.1007/s11943-024-00340-6

21. Groiss, M., & Syrichas, N. (2025). Monetary policy, property prices and rents: Evidence from local housing markets [Working paper]. University of Duisburg-Essen; Free University Berlin.

22. Hess, C., & Chasins, S. E. (2022). Informing housing policy through web automation: Lessons for designing programming tools for domain experts. CHI EA '22: CHI Conference on Human Factors in Computing Systems Extended Abstracts, Article 32, 1–9. https://doi.org/10.1145/3491101.3503575

23. Moulton, J. G., Sanders, N. J., & Wentland, S. A. (2024). Toxic assets: How the housing market responds to environmental information shocks. *Land Economics*, 100(1), 66–88. https://doi.org/10.3368/le.100.1.102122-0089R

24. Palumbo, L. (2023). Web scraping data for socio-economic research [Doctoral thesis, Università degli Studi della Tuscia di Viterbo].

25. Hrabynskyi, I., Prykhodko, I., Halanets, V., Prokopyshyn-Rashkevych, L., Adamovsky, A., & Zhygalo, I. (2022). The impact of the Russian-Ukrainian war on the development of the primary residential real estate market in Ukraine: Results of a cluster analysis. *Economic Affairs, 67(4s).* https://doi.org/10.46852/0424-2513.4s.2022.17

26. Husakov, Y. (2024). Hedonic price model of commercial real estate lease in Ukraine [Master's thesis, Kyiv School of Economics].

27. Wiersma, S., Just, T., & Heinrich, M. (2022). Segmenting German housing markets using principal component and cluster analyses. *International Journal of Housing Markets and Analysis,* 15(3), 548–578. https://doi.org/10.1108/IJHMA-01-2021-0006

28. Skovajsa, Š. (2023). Review of clustering methods used in data-driven housing market segmentation. *Real Estate Management and Valuation*, 31(3), 67–74. https://doi.org/10.2478/remav-2023-0022

29. Yazdani, M. (2021). Machine learning, deep learning, and hedonic methods for real estate price prediction [Preprint]. arXiv. https://doi.org/10.48550/arXiv.2110.07151

30. Huang, B., Wu, B., & Barry, M. (2010). Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. *International Journal of Geographical Information Science,* 24(3), 383–401. https://doi.org/10.1080/13658810802672469

31. Zhang, S., Wang, L., & Lu, F. (2019). Exploring housing rent by mixed geographically weighted regression: A case study in Nanjing. *ISPRS International Journal of Geo-Information,* 8(10), Article 431. https://doi.org/10.3390/ijgi8100431

32. Tomal, M. (2020). Modelling housing rents using spatial autoregressive geographically weighted regression: A case study in Cracow, Poland. *ISPRS International Journal of Geo-Information,* 9(6), Article 346. https://doi.org/10.3390/ijgi9060346

33. Cellmer, R., Cichulska, A., & Bełej, M. (2020). Spatial analysis of housing prices and market activity with the geographically weighted regression. *ISPRS International Journal of Geo-Information,* 9(6), Article 380. https://doi.org/10.3390/ijgi9060380

34. Wu, C., Ren, F., Hu, W., & Du, Q. (2019). Multiscale geographically and temporally weighted regression: Exploring the spatiotemporal determinants of housing prices. *International Journal of Geographical Information Science*, 33(3), 1–23. https://doi.org/10.1080/13658816.2018.1545158

35. Anselin, L. (1988). Spatial econometrics: Methods and models (Studies in Operational Regional Science, Vol. 4). Kluwer Academic Publishers.

36. Hoxha, V. (2024). Comparative analysis of machine learning models in predicting housing prices: A case study of Prishtina's real estate market. *International Journal of Housing Markets and Analysis,* 18(3), 694–711. DOI: 10.1108/IJHMA-09-2023-0120

37. Fotheringham, A. S., Brunsdon, C., & Charlton, M. (2002). Geographically weighted regression: The analysis of spatially varying relationships. Wiley.

38. Fotheringham, A. S., Yang, W., & Kang, W. (2017). Multiscale geographically weighted regression (MGWR). *Annals of the American Association of Geographers*, 107(6), 1247–1265. https://doi.org/10.1080/24694452.2017.1352480

39. Openshaw, S. (1984). The modifiable areal unit problem: Concepts and techniques in modern geography 38. Geobooks.

40. OECD/European Commission. (2020). Cities in the world: A new perspective on urbanisation (OECD Urban Studies). *OECD Publishing*. https://doi.org/10.1787/d0efcbda-en

41. Schiavina, M., Moreno-Monroy, A., Maffenini, L., & Veneri, P. (2019). GHSL-OECD functional urban areas 2019 (EUR 30001 EN). Publications Office of the European Union. https://doi.org/10.2760/67415

42. Besley, T., & Mueller, H. (2012). Estimating the peace dividend: The impact of violence on house prices in Northern Ireland. *American Economic Review*, 102(2), 810–833. https://doi.org/10.1257/aer.102.2.810

43. Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review*, 93(1), 113–132. https://doi.org/10.1257/000282803321455188

44. Linden, L., & Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from Megan's Laws. *American Economic Review*, 98(3), 1103–1127. https://doi.org/10.1257/aer.98.3.1103

45. Davis, D. R., & Weinstein, D. E. (2002). Bones, bombs, and break points: The geography of economic activity. *American Economic Review*, 92(5), 1269–1289. https://doi.org/10.1257/000282802762024502

46. Brakman, S., Garretsen, H., & Schramm, M. (2004). The strategic bombing of German cities during World War II and its impact on city growth. *Journal of Economic Geography*, 4(2), 201–218. https://doi.org/10.1093/jnlecg/lbh031

47. Glaeser, E. L., & Shapiro, J. M. (2002). Cities and warfare: The impact of terrorism on urban form. *Journal of Urban Economics*, 51(2), 205–224. https://doi.org/10.1006/juec.2001.2262

48. Alonso, W. (1964). Location and land use: Toward a general theory of land rent. *Harvard University Press*. https://doi.org/10.4159/harvard.9780674730854

49. National Bank of Ukraine. (n.d.). Official exchange rates. https://bank.gov.ua/en/markets/exchangerates

50. Goldberg, D. W., Wilson, J. P., & Knoblock, C. A. (2007). From text to geographic coordinates: The current state of geocoding. *URISA Journal*, 19(1), 33–46.

51. Schiavina, M., Moreno-Monroy, A., Maffenini, L., & Veneri, P. (2019). GHS-FUA R2019A – GHS functional urban areas, derived from GHS-UCDB R2019A (2015), R2019A [Dataset]. European Commission, Joint Research Centre. https://doi.org/10.2905/347F0337-F2DA-4592-87B3-E25975EC2C95

52. Moreno-Monroy, A., Schiavina, M., & Veneri, P. (2021). Metropolitan areas in the world: Delineation and population trends. *Journal of Urban Economics*, 125, Article 103242. https://doi.org/10.1016/j.jue.2020.103242

53. Luttik, J. (2000). The value of trees, water and open space as reflected by house prices in the Netherlands. *Landscape and Urban Planning*, 48(3–4), 161–167. https://doi.org/10.1016/S0169-2046(00)00039-6

54. OpenStreetMap Foundation. (n.d.). OpenStreetMap [Geographic database]. Retrieved March 2026, from https://www.openstreetmap.org

55. Schiavina, M., Freire, S., Carioli, A., MacManus, K., Jacobs-Crisioni, C., Claassens, J., Hilferink, M., & Dijkstra, L. (2025). GHS-WUP-POP R2025A – GHS-WUP population spatial raster dataset, derived from GHS-POP (R2023) and projected using the CRISP model, multitemporal (1975–2100) [Dataset]. European Commission, Joint Research Centre. https://doi.org/10.2905/adba95af-db56-4569-acd3-9513201eba30

56. Jacobs-Crisioni, C., et al. (2025). Population projections by degree of urbanisation for the UN World Urbanization Prospects: Introducing the CRISP model. Publications Office of the European Union. https://doi.org/10.2760/7163875

57. State Emergency Service of Ukraine (DSNS). (n.d.). Electronic register of civil protection shelters [Dataset]. Retrieved March 7, 2026, from https://shelters.dsns.gov.ua

58. Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. Nature, 540, 418–422. https://doi.org/10.1038/nature20584

59. Pekel, J.-F., Cottam, A., Gorelick, N., & Belward, A. S. (2026). Global Surface Water Explorer dataset [Dataset]. European Commission, Joint Research Centre (JRC). Retrieved April 18, 2026, from https://global-surface-water.appspot.com

60. Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N. E., Xu, P., Ramoino, F., & Arino, O. (2022). ESA WorldCover 10 m 2021 v200 [Dataset]. https://doi.org/10.5281/zenodo.7254221

61. Bellingcat. (2026). Civilian harm in Ukraine [Interactive map]. Retrieved March 10, 2026, from https://ukraine.bellingcat.com

62. Raleigh, C., Kishi, R., & Linke, A. (2023). Political instability patterns are obscured by conflict dataset scope conditions, sources, and coding choices. *Humanities and Social Sciences Communications*, 10, Article 74. https://doi.org/10.1057/s41599-023-01559-4

63. Armed Conflict Location & Event Data Project (ACLED). (2026). ACLED data [Dataset]. Retrieved March 5, 2026, from https://www.acleddata.com

64. Harris, R., Singleton, A., Grose, D., Brunsdon, C., & Longley, P. (2010). Grid-enabling geographically weighted regression: A case study of participation in higher education in England. *Transactions in GIS,* 14(1), 43–61. https://doi.org/10.1111/j.1467-9671.2009.01181.x

65. Huettner, F., & Sunder, M. (2012). Axiomatic arguments for decomposing goodness of fit according to Shapley and Owen values. *Electronic Journal of Statistics*, 6, 1239–1250. https://doi.org/10.1214/12-EJS710

66. International Organization for Migration. (2025). Ukraine returns report — Round 21 (Displacement Tracking Matrix). IOM. https://dtm.iom.int/sites/g/files/tmzbdl1461/files/reports/IOM_UKR_Returns_Report_GPS_R21_October_2025_1.pdf

67. Hurvich, C. M., Simonoff, J. S., & Tsai, C.-L. (1998). Smoothing parameter selection in nonparametric regression using an improved Akaike information criterion. *Journal of the Royal Statistical Society: Series B (Statistical Methodology),* 60(2), 271–293. https://doi.org/10.1111/1467-9868.00125

ANNEX A

Table A presents logit coefficient estimates, odds ratios and marginal effects

Variable	Coefficient	p-value	Odds ratio	Marginal effect
Clean price	<0.0001***	0.000	0.999	<0.0001
Area of listings	0.004***	0.000	1.004	0.0005
Residential complex	-0.194***	0.000	0.824	-0.025
Posted by owner	-0.018	0.874	0.982	-0.002
Number of rooms	0.067**	0.007	1.069	0.008
Odesa	-1.176***	0.000	0.308	-0.149
Dnipro	-1.275***	0.000	0.279	-0.161
Lviv	-0.442***	0.000	0.643	-0.056
Kharkiv	-1.136***	0.000	0.321	-0.144
Suburbia	-2.251***	0.000	0.105	-0.285
Pet-friendliness	0.143***	0.000	1.154	0.018
Floority	-0.016***	0.000	0.984	-0.002
Generator	-0.324***	0.000	0.984	-0.041
N	55,446			
Pseudo R^2	0.0993			

$^{*} p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$

ANNEX B

Table B presents spatial and time controls in OLS across 5 FUAs

Variable	Kyiv	Odesa	Lviv	Dnipro	Kharkiv
2025-08-28	0.002	-0.013	0.033*	0.014	0.002
	(0.781)	(0.344)	(0.011)	(0.301)	(0.911)
2025-09-21	-0.008	-0.073***	0.053***	0.009	0.046***
	(0.321)	(0.000)	(0.000)	(0.491)	(0.001)
2025-09-25	-0.357***	-0.113***	0.044**	-0.009	0.397*
	(0.000)	(0.000)	(0.005)	(0.530)	(0.028)
2025-11-02	-0.062***	-0.154***	-0.009	-0.054***	0.017
	(0.000)	(0.000)	(0.607)	(0.001)	(0.356)
2025-12-04	-0.093***	-0.156***	-0.023	-0.065***	0.027
	(0.000)	(0.000)	(0.097)	(0.000)	(0.072)
2026-01-25	-0.089***				
	(0.000)				
2026-02-03			0.004		
			(0.752)		
2026-02-07		-0.176***			0.097***
		(0.000)			(0.000)
2026-02-22	-0.099***	-0.174	0.024	-0.083***	0.104***
	(0.000)	(0.000)	(0.088)	(0.000)	(0.000)
Darnytskyi Raion Kyiv	-0.482***				
	(0.000)				
Desnjanskyi Raion Kyiv	-0.591***				
	(0.000)				
Dniprovskyi Raion Kyiv	-0.476***				
	(0.000)				
Holosiyvskyi Raion Kyiv	-0.173***				
	(0.000)				
Obolonskyi Raion Kyiv	-0.358***				
	(0.000)				
Podilskyi Raion Kyiv	-0.233***				
	(0.000)				
Shevchenkivskyi Raion Kyiv	-0.044***				
	(0.000)				

Table B (continued)

Solomianskyi Raion Kyiv	-0.265***			
	(0.000)			
Sviatoshynskyi Raion Kyiv	-0.353***			
	(0.000)			
Khadzhybeiskyi Raion Odesa		-0.057***		
		(0.000)		
Kyivskyi Raion Odesa		-0.055***		
		(0.000)		
Peresypskyi Raion Odesa		-0.309***		
		(0.000)		
Frankivskyi Raion Lviv			0.011	
			(0.527)	
Lychakivskyi Raion Lviv			-0.046**	
			(0.004)	
Shevchenkivskyi Raion Lviv			-0.040**	
			(0.007)	
Sykhivskyi Raion Lviv			-0.055**	
			(0.004)	
Zaliznychnyi Raion Lviv			-0.041*	
			(0.016)	
Chechelivskyi Raion Dnipro				-0.068***
				(0.000)
Industrialnyi Raion Dnipro				-0.010
				(0.627)
Novokodatskyi Raion Dnipro				-0.088***
				(0.000)
Nyzhnodniprovskyi Raion Dnipro				-0.013
				(0.533)
Samarskyi Raion Dnipro				-0.072*
				(0.05)
Shevchenkivskyi Raion Dnipro				0.046***
				(0.000)
Sobornyi Raion Dnipro				0.072***
				(0.000)

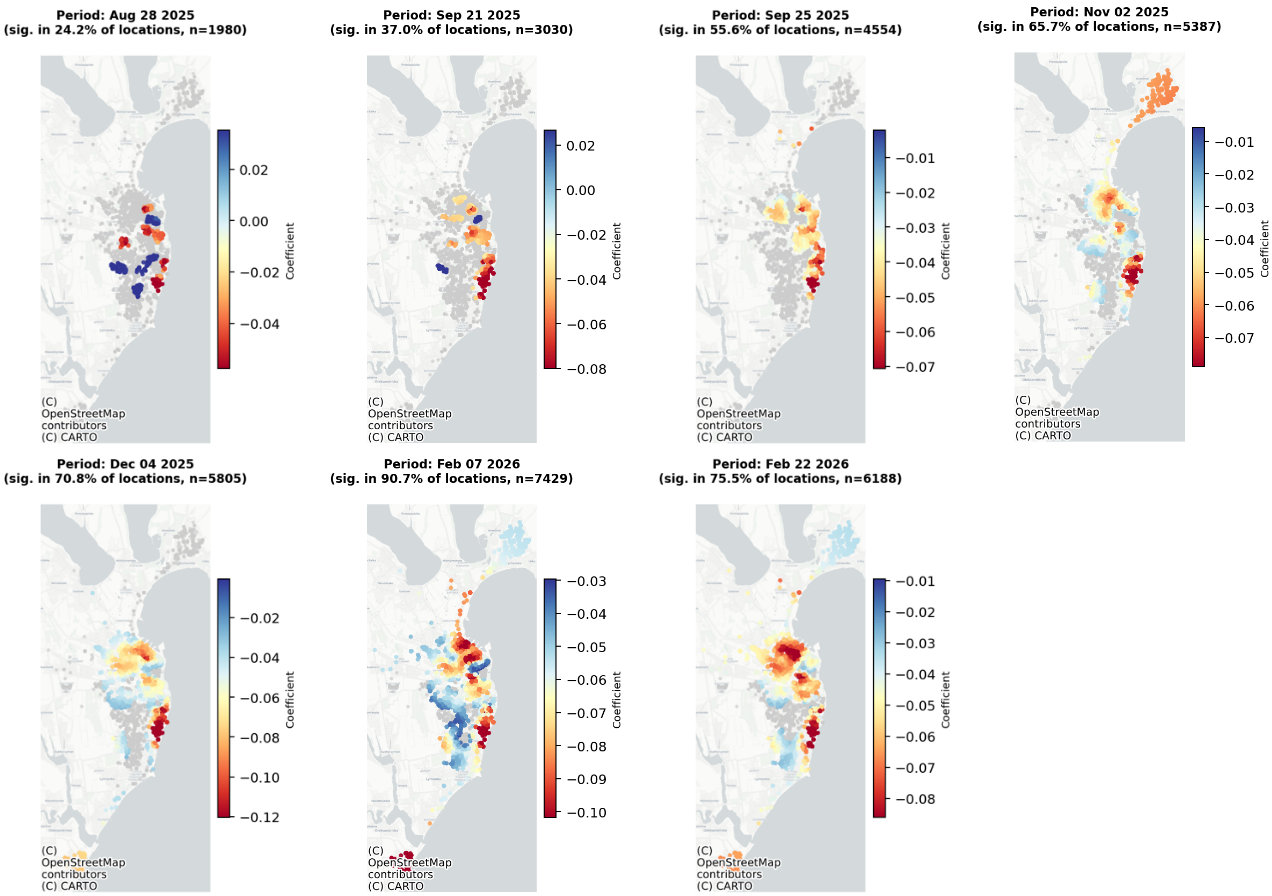
Table B (continued)

Industialnyi Raion Kharkiv					0.201***
					(0.000)
Kholodnogirskyi Raion Kharkiv					0.121***
					(0.000)
Nemyshljanskyi Raion Kharkiv					0.121***
					(0.000)
Novobavarskyi Raion Kharkiv					0.058*
					(0.034)
Osnovianskyi Raion Kharkiv					0.137***
					(0.000)
Saltivskyi Raion Kharkiv					0.052***
					(0.000)
Shevchenkivskyi Raion Kharkiv					0.070***
					(0.000)
Slobidskyi Raion Kharkiv					0.158***
					(0.000)
N	22,028	8,195	6,248	4,974	4,514
Adjusted R^2	0.527	0.465	0.296	0.436	0.378

p-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

ANNEX C

Figure C present GWR coefficient surfaces for temporal fixed effects (gray = insignificant at p<0.1)



ANNEX D

Table D presents the remaining coefficients, spatial and temporal fixed effects in QR in Odesa FUA.

Variable	OLS	Q10	Q50	Q90
Pet friendliness	-0.018*	-0.147***	-0.003	-0.034*
	(0.019)	(0.000)	(0.721)	(0.013)
Generator	0.006	0.022*	0.007	-0.002
	(0.551)	(0.048)	(0.473)	(0.914)
Log distance to kindergartens	-0.008	-0.003	0.008	0.012
	(0.209)	(0.751)	(0.228)	(0.316)
Log distance to hospitals	-0.017*	0.010	-0.007	-0.054***
	(0.015)	(0.231)	(0.300)	(0.000)
Log distance to tram stops	-0.004	-0.007	0.002	-0.013
	(0.331)	(0.262)	(0.773)	(0.120)
Log distance to bus stops	-0.022***	-0.014	-0.035***	-0.0003
	(0.000)	(0.055)	(0.000)	(0.979)
Log distance to shelters	-0.153***	-0.009	-0.0004	0.005
	(0.000)	(0.076)	(0.926)	(0.492)
Khadzhybeiskyi Raion	-0.057***	-0.056**	-0.087***	-0.033
	(0.000)	(0.002)	(0.000)	(0.234)
Kyivskyi Raion	-0.055***	-0.066***	-0.071***	-0.043
	(0.000)	(0.000)	(0.000)	(0.072)
Peresypskyi Raion	-0.309***	-0.241***	-0.284***	-0.382***
	(0.000)	(0.000)	(0.000)	(0.000)
2025-08-28	-0.013	-0.002	-0.018	0.016
	(0.344)	(0.903)	(0.235)	(0.521)
2025-09-21	-0.073***	-0.057***	-0.076***	0.046
	(0.000)	(0.001)	(0.000)	(0.063)
2025-09-25	-0.113***	-0.069***	-0.106***	-0.108***
	(0.000)	(0.000)	(0.000)	(0.000)
2025-11-02	-0.154***	-0.133***	-0.166***	-0.121***
	(0.000)	(0.000)	(0.000)	(0.000)
2025-12-04	-0.156***	-0.149***	-0.164***	-0.123***
	(0.000)	(0.000)	(0.000)	(0.000)
2026-02-07	-0.176***	-0.186***	-0.189***	-0.149***
	(0.000)	(0.000)	(0.000)	(0.000)

Table D (continued)

2026-02-22	-0.174***	-0.186***	-0.189***	-0.131***
	(0.000)	(0.000)	(0.000)	(0.000)
R^2 / Pseudo R^2	0.465	0.300	0.312	0.234

p-values in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$