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Understanding the value of retail accessibility in private housing markets: A study from Turin, Italy

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ABSTRACT

Numerous urban studies have explored the relationship between urban amenities and real estate value. However, a notable gap exists in the literature concerning the specific impact of retail activities on housing values, particularly within European contexts. This study addresses this gap by examining the relationship between housing values and accessibility to different retail typologies, expanding the research stream to a European city by applying the Geographically Weighted Regression (GWR) model. The results indicate that accessibility to shopping retailers, bars and restaurants has a positive effect. In contrast, accessibility to convenience retailers and traditional markets has a negative impact. No significant relationship is observed between housing values and accessibility to supermarket retailers. Furthermore, this study shows that retail accessibility typologies impact differs in different urban areas. These findings provide useful implications for planners and policymakers, highlighting the need for strategic support for the retail sector in safeguarding and enhancing the investments of investors and families.

1. Introduction

Amenities, defined as location-specific assets, contribute significantly to the attractiveness of cities or regions (Öner, 2017). Numerous studies have highlighted the positive impact of amenities on the regional economy, population, and income growth (Brueckner et al., 1999; Glaeser et al., 2001; Partridge et al., 2010). In post-industrial cities, urban amenities are crucial economic assets to transition from urban production to consumption (Clark et al., 2002). In recent years, recognition of the value of clustered amenities has increased, including shopping, entertainment, and education. The significance of amenity clusters is evident to homeowners and city governments, as demonstrated by the housing market and public policies (Hidalgo et al., 2020; Li et al., 2019).

Brick-and-mortar retailers are important amenities that play significant economic and social roles in urban settlements. They enhance the city's social fabric and offer entrepreneurial and employment opportunities (Glaeser et al., 2001). Their presence benefits residents and tourists, contributing to creating more liveable neighbourhoods. Retailers play a significant role in achieving the objectives of urban policies such as Smart Growth and New Urbanism, promoting community cohesion, economic development, and environmental sustainability by enhancing urban spaces (Knaap & Talen, 2005).

This study investigates the relationship between housing values and accessibility to different retail typologies, expanding the research stream to a European city and applying the Geographically Weighted Regression (GWR). The study aligns with Öner's (2017) and Ballantyne et al.'s (2023) observations on the crucial role of retailers as urban amenities that impact economic prosperity, desirability, and spatial interactions in neighbourhoods. The impact of retailers as amenities on housing value has received less attention in the literature, which tends to prioritise public goods (Jang & Kang, 2015) or investigates the role of retail in broader policies such as mixed land use. These policies aim to enhance retail accessibility, optimise land use, stimulate the local economy, reduce polluting trips, and address retail deserts (Glaeser et al., 2001; Lang & LeFurgy, 2003; Schuetz et al., 2012).

This study examined the relationship between housing values and retail accessibility across the study area using the Hedonic Price Model (HPM) with a database of 2157 apartments. Accessibility indices for different retail typologies were computed for each apartment, based on data from over 17,000 retailers. Additionally, the GWR was used to investigate the spatial relationship, a novel approach in this research

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field to address the common problem of spatial heterogeneity.

The findings support the inclusion of retail accessibility in urban policies. Retail accessibility enhances economic development and community cohesion (Sevtsuk, 2014; Jacobs, 1961) and impacts housing value positively. This study provides valuable insights for urban planners, policymakers, and real estate professionals seeking to understand the complex relationship between retail accessibility and housing market dynamics.

The study contributes to existing research in this field in three ways: First, it incorporates a classification system of retail types, including shopping, convenience, supermarkets, bars and restaurants, and traditional markets. This classification framework is designed to capture the diverse retail dynamics in urban environments and their potential impact on housing value. Second, it applies GWR for the first time in this research stream, thereby enriching our understanding of the spatial dynamics that shape the relationship between retail activities and housing value. Finally, it expands the research to include a European city: Turin, Italy.

The remainder of the paper is organised as follows: the next section provides a brief review of the topic; Section 3 includes contributions and hypotheses; Section 4 illustrates the methods; and Section 5 describes the data and context of the study. The results and discussion of the findings are presented in Section 6. Finally, Section 7 concludes the paper.

2. Background of the study

2.1. Research streams

Several studies employ the HPM as the benchmark methodology to explore real estate values (Rosen, 1974). The existing body of research underscores a positive relationship between housing values and amenities such as educational facilities, religious buildings, urban parks, transport accessibility, and mixed land use (Carroll et al., 1996; Koster & Rouwendal, 2012; Seo et al., 2014; Wang et al., 2015; Wen et al., 2014; Wu et al., 2017; Bottero et al., 2022). The literature also considers local facilities that may threaten housing value, defined as disamenities, such as incinerators, waste facilities, cell phone towers, landfills, and landscape-spoiling infrastructure (Casado et al., 2017; Groothuis & Miller, 1994; Bond & Squires, 2007; Nelson et al., 1992; Sander & Polasky, 2009).

Empirical studies on retailer accessibility as an amenity affecting housing value can be categorised into two streams.

The first stream focuses on the impact of retail activities on housing values, using the HPM. Song and Sohn (2007) investigated how Hillsboro's (Oregon) single-family housing market valued retail accessibility. Jang and Kang (2015) studied the relationship between the presence of supermarkets and condominium housing submarkets in Seoul, Korea, categorising supermarkets by size. They observed varied effects of accessibility to retailers in different city areas, contingent on supermarket type. Kang (2018) advanced this research by introducing an accessibility index that integrated Urban Network Analysis (UNA) and urban morphology. Chiang et al. (2015) investigated the connection between housing values and convenience retailers by employing quantile regression to depict the impact of their availability and density in Taipei, Taiwan's housing market. Öner (2017) explored the national-level relationship between housing values and retail accessibility in Sweden by differentiating city municipalities (positively correlated) from rural municipalities by aggregating housing values at the municipality level. Studies in the second stream include accessibility to retailers as a variable in a broader set of characteristics that affect housing value. Some studies include retailer accessibility as a variable in mixed land use (Cervero & Duncan, 2004; Matthews & Turnbull, 2007; Koster & Rouwendal, 2012) and a measure of new urbanism (Song & Knaap, 2003). These analyses occur at various geographical scales, including neighbourhoods (Li & Brown, 1980), cities (Koster & Rouwendal, 2012), and regions (Franklin & Waddell, 2003).

Urban economic theory provides two main explanations for the link between accessibility to retailers and housing value (Li & Brown, 1980; Pivo & Fisher, 2011). The first, known as 'proximity effects', suggests that convenient access to retail services increases housing values by reducing the time and effort required for consumers to obtain goods and services. This decrease in search costs - such as time spent travelling to shops - enhances convenience and overall quality of life for residents, making the area more attractive to potential buyers. The second explanation, 'disamenity effects', refers to the negative impacts on housing values resulting from externalities associated with retail activities, such as noise, litter, and congestion (Yang et al., 2016). Despite these potential drawbacks, the overall evidence indicates that the positive aspects of proximity - such as reduced travel time and increased convenience - generally outweigh the negative impacts, leading to higher housing values.

This study aims to contribute to the first research stream by examining how retail accessibility influences housing values using both the HPM and GWR. This approach seeks to fill existing gaps in the literature and provide valuable insights about the nuanced relationship between retail accessibility and housing values.

2.2. Retail classification

According to the literature on the retail industry, the dynamics of the sector vary depending on the types of stores. Stores can be classified into different types based on the breadth of their categories and products, search costs, and competitive forces.

Copeland (1923) classified retailers as shopping and convenience retailers. Shopping retailers usually focus on specific categories, such as fashion products, and offer a limited range of items despite the availability of numerous potential brands and products. Consumers prefer locations, allowing them to compare prices and assortments from various competing retailers, resulting in agglomeration forces that concentrate these retailers in specific areas of the city. Such agglomerations enhance consumer attractiveness and offset heightened competition (Ingene, 1984). On the contrary, convenience retailers such as newsstands and pharmacies minimize consumers' search costs by choosing the most convenient location for consumers. According to Dudey (1990), these retailers are uniformly distributed throughout the city. Supermarkets, a distinct subindustry, consolidate various product categories under one roof, further reducing consumer search costs. Customers can easily find weekly essentials such as food, personal care, and home care products in supermarkets. Customers often develop shopping habits and visit the same supermarket repeatedly. Bars and restaurants are often clustered in areas where consumers gather at nighttime. In these cases, consumers tend to value the presence of other consumers; thus, retailers tend to cluster (Eaton & Lipsey, 1975; Scitovsky, 2013). Finally, traditional markets differ from brick-and-mortar stores because retailers do not have physical stores and can relocate daily. The areas in which traditional markets are located are selected by local authorities. Traditional markets are two-sided markets chosen by both retailers and consumers.

3. Research hypotheses and contributions

3.1. Hypotheses

A positive relationship is expected between accessibility to the retail sector and housing values, as summarised in Table 1. Retailers are often considered amenities that enhance the liveability of neighbourhoods, as demonstrated in previous studies, and such preference for easy access to retail stores is reflected in housing values (Song & Sohn, 2007; Öner, 2017).

This study posits that the distinct dynamics of retail sub-industries have varying impacts on housing values. The market dynamics of the

Table 1
Hypotheses of the relationship between housing values and retail accessibility.

Retail typlogy	Overall relationship	1st-4th quartile relationship
Retailers	Positive	
Shopping retailers	Positive	↗
Bars and restaurants	Positive	↘
Convenience retailers	Negative	↘
Supermarket retailers	Positive	↘
Traditional markets	Negative	↘

five retail subindustries differ, including their externalities on the surrounding space. A positive relationship between housing values and accessibility to shopping retailers is likely owing to the benefits they bring to the area (Zukin & Kosta, 2004; Chapple & Jacobus, 2009). Furthermore, the concentration of these shops is expected to enhance the positive externalities generated. Therefore, properties with a high concentration of shopping retailers are likely to command a premium on their price. The presence of bars and restaurants is a significant feature of liveable neighbourhoods (Sevtsuk, 2014). Thus we expect the value of houses to grow with accessibility to these retailers. However, bar and restaurant retailers also generate negative externalities such as night-time noise and potentially unpleasant odours (Schuetz et al., 2012). Therefore, this positive relationship is expected to decline in areas with high concentrations of bar and restaurant retailers, as the negative externalities from these retailers may offset the benefits of increased liveliness. A positive relationship between housing values and supermarket accessibility is anticipated, consistent with previous studies (Chiang et al., 2015; Jang & Kang, 2015; Kang, 2018). Contrastingly, higher accessibility to convenience retailers and traditional markets is expected to negatively impact housing values owing to the negative externalities they generate. High concentrations of such retailers carrying a relatively standard set of items rarely add any benefit, leading to a hypothesised negative relationship in such areas without significant improvement in access (i.e. reduced search costs) to these retailers. However, in underserved areas, wherein these retailers are sparse, an additional store is likely to improve accessibility and reduce search costs, which can affect housing values positively, lowering search costs to outweigh negative externalities.

3.2. Contributions

This study makes three key contributions to the field. The first is an investigation of Turin, Italy, a European city. Previous research was focused on two Asian cities (Chiang et al., 2015; Jang & Kang, 2015; Kang, 2018) and one American city (Song & Sohn, 2007). The inclusion of Turin in this research stream is interesting for two reasons.

- European cities, characterised by mixed-use spaces (Anas et al., 1998) are significant to this research stream. A comparison of European cities with those in Asia and the United States reveals notable differences, starting from the historical periods during which they were established and evolved. These differences are reflected in various aspects of urban design, including urban form, population density, and the level of mixed-use spaces (Chen et al., 2020). In particular, European cities represent an intermediate case in terms of population density (European cities are 1.5–6.5 less dense than Asian cities and twice denser than American ones) (Chen et al., 2020), with implications for accessibility and pollution (Zhao, 2010). Furthermore, urban planning differs significantly between continents. In Europe, the absence of a rigid zoning system, typical of the United States, results in more fluid and complex local dynamics (Hirt, 2012; Schmidt & Buehler, 2007). A further distinctive feature of European cities is the greater cultural and social mix, evident not only in urban activities but also in population composition and culture (Rose et al., 2013). Indeed, European neighbourhoods function as genuine communities, characterised by a distinctive social and culture that sets European cities apart (Ambrosini and Boccagni, 2015).
- Turin's intermediate size, larger than Hillsboro (100,000 inhabitants) but smaller than Seoul and Taipei (10 million and 7 million inhabitants, respectively), adds valuable diversity to this stream of research.

The second contribution of this study lies in the methodology employed. This study uses the HPM to analyse the entire study area and employs GWR to emphasise local dynamics and address spatial heterogeneity issues without predefining the spatial structure. Although GWR has been commonly used alongside HPM (e.g. Liu & Strobl, 2023; Zhang et al., 2020), our study introduces its application in the research stream to investigate the relationship between accessibility to retailers and housing values. Unlike other studies that examine the entire study area or partition it into predefined submarkets or administrative boundaries, our approach employs GWR to explore the local connection between retail activities and housing values over space.

The third contribution is the study of the relationship between housing values and the accessibility of five types of retailers: stores that carry shopping goods, convenience retailers, supermarkets, bars, restaurants and traditional markets. Previous studies have treated all retailers equally (Song & Sohn, 2007; Öner, 2017) or focused on a specific retail sector (Chiang et al., 2015; Jang & Kang, 2015; Kang, 2018). By classifying retailers into these five distinct types, this study provides a more nuanced understanding of how different types of retail accessibility impact housing values, addressing a gap in prior research.

4. Methodological background

This study employed a methodological framework to evaluate the impact of retail proximity on housing market values. Data collection included retail, housing, and control data, setting the stage for in-depth analysis. Retail types were classified, and a tailored gravity-based accessibility index was developed alongside Euclidean distance calculations to quantify the spatial relations between homes and retail and urban amenities. These data were analysed using HPM to understand the influence of retail proximity on housing prices and GWR to address spatial variations. Marginal price estimation highlighted the value of retail access, visualised using mapping techniques. The research concluded with a discussion of the implications, offering insights for urban planners and investors. Fig. 1 illustrates the methodological framework applied to the study.

4.1. A metric for accessibility to retailers

This study employed a gravity-based accessibility index to measure accessibility from houses to the overall retail sector and each retail type. Accessibility indexes were computed using Equation (1):

$$A_{it} = \sum_{j=1}^{N_t} e^{-\gamma d_{ij}} \tag{1}$$

In the Equation, A_{it} is the accessibility index to retail type t for house i, d_{ij} is Euclidean distance between house i and retailer j that belongs to type t in kilometres, γ is the decay parameter, and N_t is the total number of retailers for type t.

The accessibility index measures the retailers' proximity to each

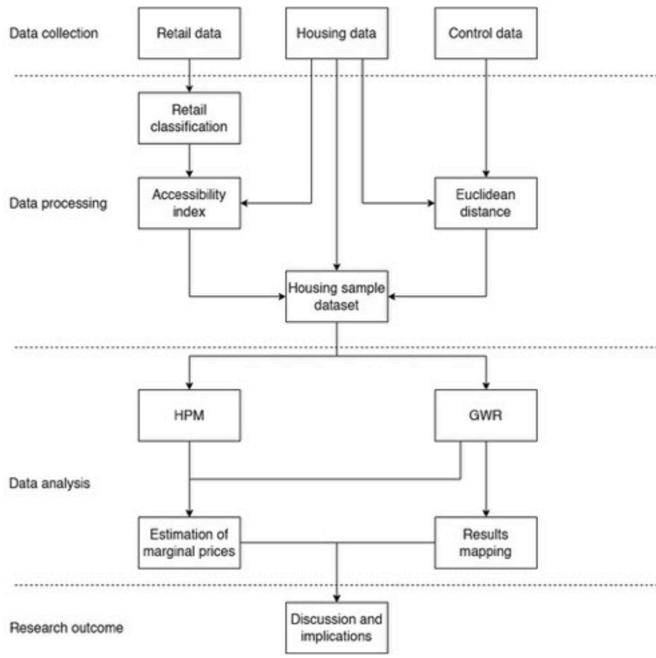

Fig. 1. Methodological framework.

house, with decreasing contributions as the distance and decay parameter increase. Higher decay parameter values discount more the impact of distance on the accessibility index. A sensitivity analysis was conducted to identify the decay parameter with the greatest explanatory power. The HPM was carried out with different values of γ, and the model with the decay parameter $\gamma = 8$ in the accessibility index was found to have the greatest explanatory power of the dependent variable (i.e., $\gamma = 8$ maximizes R^2). Accordingly, this value was selected.

To investigate the sensitivity of the analyses, we computed various accessibility indexes with all 5 values of (4; 8; 12; 16 and 20), built 5 models in parallel and compared the beta coefficients of all five models. The estimated beta coefficients of the accessibility indexes, calculated with different decay parameters, showed no significant variations in either absolute value or sign. Therefore, the selection of the decay parameter has a negligible impact on the reliability and outcomes of the analysis. Fig. 2 shows the impact of varying decay parameter values on the accessibility index from 0 to 1000 m.

Retailers' contributions to the accessibility index using a decay parameter of 8 are negligible, at approximately 500 m from houses (contribution = 0.018). This is a reasonable value since pedestrians usually cover this distance in a 10-min walk and similar distances were

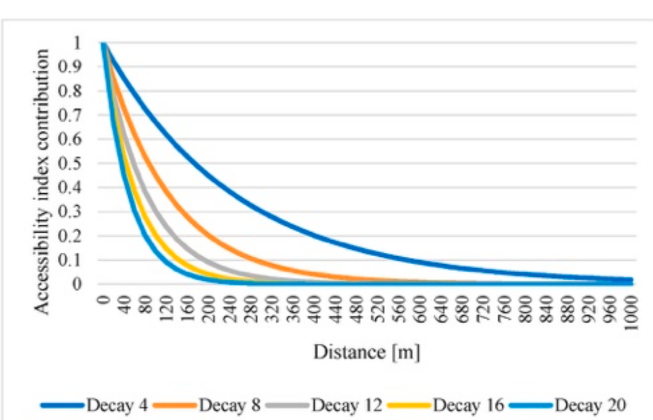

Fig. 2. Contributions to accessibility index of different decay parameters.

used in other studies (e.g., Handy & Niemeier, 1997; Sevtsuk, 2014). The accessibility index describes the retail environment around the houses and reduces the importance of retailers as the distance increases. Previous studies have used this index to measure accessibility to amenities (Hidalgo et al., 2020) and assess accessibility to supermarkets for households (Handy & Niemeier, 1997).

4.2. Hedonic Price Model

In this study, we employed the HPM estimated using Ordinary Least Squares (OLS) to explore the relationship between accessibility to retailers and housing values. The HPM is a well-established method in the literature for quantifying the economic value of various attributes by estimating implicit or 'hedonic' prices based on observed prices and the specific quantities of each attribute (Rosen, 1974). In our analysis, we applied this method to examine the real estate market, focusing on housing attributes. The empirical specification of the Hedonic Pricing Model (HPM) is detailed in Equation (2):

$$P_i = \beta_0 + \beta_1 A_i + \beta_2 H_i + \beta_3 D_i + \beta_4 L_i + \beta_5 T_i + \varepsilon_i \tag{2}$$

where P_i represents the log of house prices for house i; A_i is the vector of accessibility indexes for each set of retailers for house i; and H_i, D_i, L_i, T_i are the housing attributes, demographic attributes, location attributes, and transportation attributes, respectively. The variables β_0 to β_5 are the coefficients to be estimated; β_0 is the estimated constant term, ε_i is the error term, β_1 is the vector of estimated coefficients for each set of accessibility indexes to retail types. A positive coefficient β_1 indicates that houses with greater access to retail activities have higher prices, while those with less access tend to have lower prices. There is no general theoretical agreement on the form (linear, log-linear, log-log) of the HPM. After the statistical analysis (non-linear residual patterns, normal residual distribution, homoscedasticity, linearity assumptions, and influential outliers), a log-mixed regression form (log transformation of price and surface) was chosen.

To address potential multicollinearity issues in the regression model, we calculated the Pearson correlation matrix, Variance Inflation Factor (VIF) values, and applied the eigenvalue method (Appendix A). These are the most used methods for detecting multicollinearity (Shrestha, 2020). The results confirmed that multicollinearity was not a concern in the dataset used for the HPM analysis.

4.3. Geographically Weighted Regression

Traditional HPM using Ordinary Least Squares (OLS) often faces the challenge of spatial non-stationarity due to location effects. Spatial non-stationarity, where relationships between variables vary across locations, complicates the use of a single global model to describe these relationships within a dataset. This issue, characterized by spatial dependence and spatial heterogeneity, can lead to spatial autocorrelation, which conventional global regression models struggle to address effectively (Anselin, 1988; Brunsdon et al., 1996). GWR offers a solution to these limitations by accommodating spatial heterogeneity. GWR is a local regression model that estimates regression coefficients at the local level, allowing for variation in these coefficients across different locations. By developing a series of localized regression equations, one for each point in space where the dependent variable (house price) is observed, GWR captures the spatial variability within the dataset (Fotheringham et al., 2009).

The GWR model operates by estimating regression coefficients at the local level, utilising data points that are geographically proximate to each specific location. This is accomplished by developing a series of localized regression equations: one regression is estimated for each point in space, where the dependent variable is observed (in our case for each point where the price of a house is observed). Such points are called focal points. The GWR model permits the relationships between variables to vary across space, since one set of regression parameters is estimated for each focal point. This is achieved by fitting a regression model for each focal point: at each location, only the neighbouring data points, within a specified spatial range, are considered to estimate parameters. This approach effectively captures the spatial variability present within the dataset (Fotheringham et al., 2009), since subsets of data are considered locally. GWR incorporates a spatial weighting mechanism through the utilisation of spatial kernels, such as Gaussian or Bisquare, which assign weights to neighbouring data points based on their proximity to the focal point. The weight assigned to each point is inversely proportional to the distance from the focal point. The bandwidth represents a critical factor in GWR, determining the width of the neighbourhood considered in the local regression. The bandwidth may be defined in two ways: either as a fixed distance or as a fixed number of neighbouring points. The selection of the appropriate bandwidth may be based on statistical techniques or predefined criteria. The integration of these spatial kernels enables the effective incorporation of geographic information into the regression process, thereby enhancing the model's capacity to address spatial nonstationarity and improving the accuracy of local estimates (Páez et al., 2008). In our study, the GWR model assumes the form illustrated in equation (3):

$$P_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)A_i + \beta_2(u_i, v_i)H_i + \beta_3(u_i, v_i)D_i + \varepsilon_i(u_i, v_i) \tag{3}$$

where P_i represents the log of the price of house *i*; (u_i, v_i) are the spatial coordinates of house *i*, A_i is the vector of accessibility indexes for each set of retailers for house *i*, and H_i, D_i are the housing and demographic attributes for house *i* respectively. β_0 to β_3 are the coefficients to be estimated at location (u_i, v_i); β_0 is the estimated constant term, ε is the error term at location (u_i, v_i), β_1 is the vector of estimated coefficients for each set of accessibility indexes to retail types at location (u_i, v_i). Location, transportation, and Boolean variables for accessibility index quartiles are not included in the GWR model owing to local multicollinearity issues. In the model, a Gaussian kernel with a fixed spatial bandwidth is employed. The optimal value of the bandwidth is determined using the Golden Section Search method, with the optimisation criterion being the Corrected Akaike Information Criterion (AICc). This process involves the iterative narrowing of the range of potential bandwidth values and the evaluation of the model's performance at each step. The bandwidth value that yields the lowest AICc score is selected as the optimal one to compute the GWR model (Oshan et al., 2019).[1]

Table 2 illustrates the descriptive statistics of the number of apartments and retailers within the bandwidth. The data indicate that local regressions are based on a substantial number of nearby apartments, which ensures a robust spatial representation. This enhances the accuracy of the regression models. Appendix B explores the impact of varying bandwidth dimensions on the GWR results. The signs and magnitudes of the estimated coefficients remain consistent, supporting the robustness of the analysis.

Table 2
Descriptive statistics of apartments and retailers in the bandwidth.

Variable	Mean	Std. Dev.	Median
Number of apartments in bandwidth	89.21	37.76	91
Number of shopping retailers in bandwidth	129.59	125.53	99
Number of convenience retailers in bandwidth	363.23	155.39	364
Number of supermarket retailers in bandwidth	4.64	4.66	10
Number of bars and restaurants retailers in bandwidth	193.23	136.29	161
Number of market stalls in bandwidth	59.45	33.21	41

5. Data and context of the study

5.1. Context of the study

The study area covers 109.4 km^2 of the Turin municipality but excludes the hillside area, which is sparsely populated, segregated by the Po River and with hardly any retail activity. Turin, the fourth largest city in Italy, has a population of 836,148 (ISTAT 2023) and serves as the primary economic centre in the northwest, boasting a GDP of 20 billion euros. The city's recent history is intertwined with its industrial origins and the presence of FIAT (Fabbrica Italiana Automobili Torino), the largest Italian car manufacturer. Turin was likened to Detroit as a Fordist single-industry city, producing urban, economic, and social challenges in the 1980s (Bagnasco & Antonelli, 1990; Bolzoni & Semi, 2023). In 2011, Turin's retail sector employed 42,660 individuals across 13,795 locations (Taramino, 2021). This sector significantly contributed to positioning Turin as a key destination for tourism, leisure, and consumption, redefining its identity as a post-industrial city (Bolzoni & Semi, 2023). A large network of traditional markets contributes to the 'Turin model', characterised by numerous market stalls per inhabitant and relations between sellers and consumers (Città di Cittàdi Torino, 1993).

5.2. Data and data sources

This study analysed 2157 dwellings, specifically apartments, which are the predominant housing type in the area, for the second quarter of 2022 (Fig. 3). The data was sourced from www.immobiliare.it, Italy's leading real estate listings platform. The study focused on a three-month period to ensure data comparability and minimize temporal variability related to macroeconomic factors. The dataset included asking prices, geographical coordinates (latitude and longitude), and housing attributes. The asking price is a reliable proxy for housing values (Curto et al., 2012).[2] The control variables included house surface area, presence of an elevator (Boolean), garden availability, number of parking spaces, green-label energy efficiency (ordinal), property type (deluxe, elegant, medium, economic), and house conditions (new/under construction, excellent/renovated, good/habitable, to be renovated). The surface area and price per square meter of the datasets were aligned with 2021 housing data for Turin (Mazzitelli & Moine, 2022).

This study included demographics, location effects, and accessibility to transportation facilities to consider the characteristics of house surroundings. Demographic attributes refer to the population density, foreign residents density, and average gross income per capita. Population and foreign resident data are obtained from the geo-portal of the municipality of Turin (2021 data) and illustrate the population and foreign residents per square kilometre in the 21 neighbourhoods of the study area. The Ministero dell'Economia e Finanze provided the average gross income data (2020) for each of the 31 postal codes. These attributes are assigned to each house based on their neighbourhood and postal codes of their location. The demographic attributes pertain to a different period than the housing data, with a one-year gap for the population and foreign residents and a two-year gap for average gross

[1] The MGWR 2.2 software (Oshan et al., 2019) was used to implement the GWR model. The software offers two spatial kernel options: fixed Gaussian and adaptive bisquare. Both kernels were applied, and no significant disparities in outcomes were found. The GWR outcomes presented in this text were derived using a fixed Gaussian spatial kernel. The bandwidth was determined through the 'Golden Section' setting, optimizing it by minimizing the Corrected Akaike Information Criterion (AICc). The other version is available by the authors upon request.

[2] Models were computed with the asking price and the price per square metre as dependent variables. The beta estimations from both models exhibited comparable signs and magnitudes, thereby indicating consistency between the two approaches.

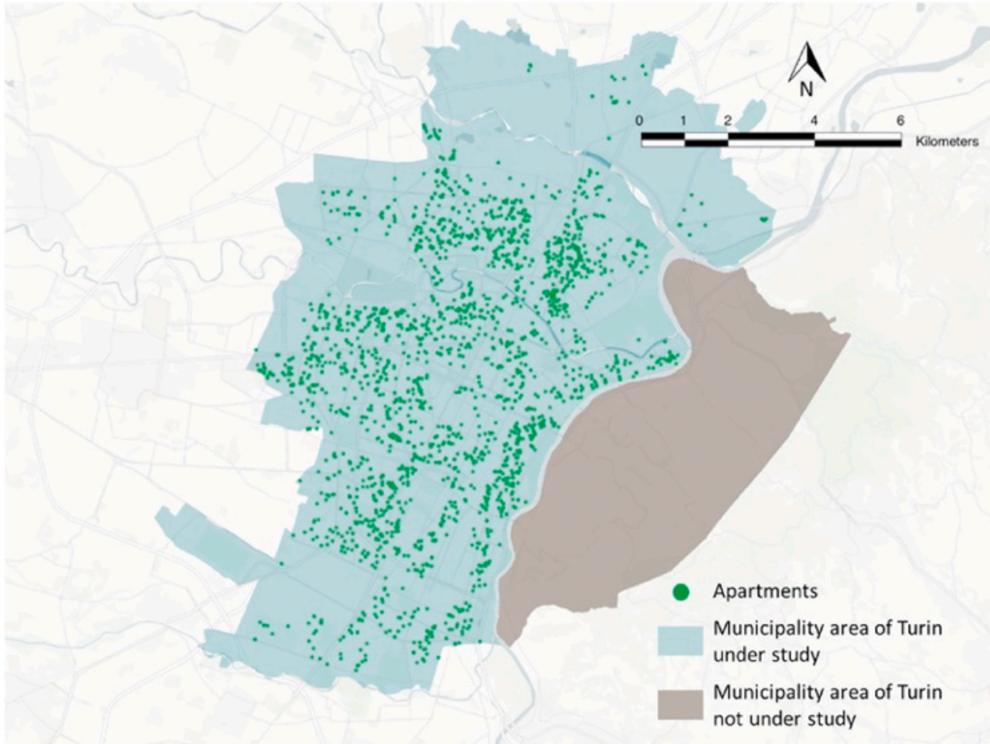

Fig. 3. Spatial distribution of apartments.

income. This is not an issue because these variables change gradually over time.

To account for location effects, our regression analyses assumed that distances to public transportation and to amenities of interest were continuous variables. The minimum Euclidean distance from each of the 2157 houses in the dataset to the city centre, parks, libraries, sports centres, cinemas, nurseries, and schools was computed. To control for the influence of transportation services on housing values, we measured the minimum distances to metro stations, train stations, and bus stops. The latitudes and longitudes of these amenities were obtained from the geoportal of the Turin municipality (2022 data).

Accessibility indices for retailers and traditional markets were

Table 3
Descriptive statistics for variables.

Variable	Description (unit)	Mean	Std. Dev.	Min	Max
price	Apartment asking price (€)	162′133.30	147′814.30	6′900.00	1′950′000.00
log (price)	Log apartment asking price(€)	11.73	0.69	8.84	14.48
sqm price	Asking price per square meter (€/m^2)	1′796.04	851.64	325.65	7′777.78
Retail accessibility					
acc_shopping	Accessibility index to shopping retail	6.77	7.17	0.00	62.99
acc_convenience	Accessibility index to convenience retail	20.30	10.70	0.57	58.67
acc_supermarket	Accessibility index to supermarket retail	0.49	0.42	0.00	2.63
acc_bars_and_restaurants	Accessibility index to bars and restaurants retail	10.44	8.34	0.05	46.41
acc_traditional_market	Accessibility index to traditional market	9.00	24.44	0.00	365.79
Housing attributes					
surface	Housing surface (m^2)	84.46	47.12	15.00	1′200.00
elevator	Presence of elevator	0.71	0.45	0.00	1.00
parking	Parking spaces	0.15	0.40	0.00	2.00
garden	Presence of garden	0.23	0.42	0.00	1.00
Demographic variables					
population	Population of the neighbourhood per square km	11′240.24	5′981.19	2′401.41	23′685.66
foreigners	Foreigners of the neighbourhood per square km	1′927.85	1′418.61	325.72	6′213.84
income	Average postal code income (k€/per person per year)	26.09	9.81	17.91	63.38
Location characteristics					
dis_city_centre	Distance to city centre (m)	3′353.69	1′540.32	115.09	8′177.50
dis_parks	Min distance to parks (m)	636.95	416.93	34.71	2′536.24
dis_library	Min distance to libraries (m)	924.12	518.82	71.25	2′763.46
dis_sport_centres	Min distance to sports centres (m)	289.16	168.60	3.20	1′823.91
dis_cinema	Min distance to cinemas (m)	999.94	739.11	3.99	4′701.66
dis_nursery	Min distance to nurseries (m)	378.83	236.85	7.64	2′178.57
dis_schools	Min distance to schools (m)	192.05	127.60	7.82	2′087.57
Transportation characteristics					
dis_bus_stop	Min distance to bus stops (m)	113.54	71.22	2.80	599.23
dis_metro_station	Min distance to metro stations (m)	1′726.14	1′301.57	23.15	7′294.88
dis_train_station	Min distance to train stations (m)	1′213.62	655.73	23.43	3′938.33

calculated for the same 2157 properties in Turin using municipal data. Retailers in Italy must obtain a licence from the municipality to operate, categorised by ATECO codes indicating sector, goods sold, and geographical coordinates. In Q2 2022, 17,232 licences were active in the area and divided into shopping (3059), convenience (9124), supermarket (232), and bar/restaurant (4817) retailers. Appendix C, D and E present respectively the ATECO code classification, retailers location, and retailers accessibility. Forty traditional markets are in Turin. For each market, we considered its location and the average number of stands, with an average of 99.14 stands per market. Boolean variables denote whether a house's accessibility index falls in the first or fourth quartile. These Boolean variables in the regression can be used to explore non-linear relationships between retail accessibility and housing values. Descriptive statistics for the dependent and independent variables are provided in Table 3.

6. Results and discussion

This section outlines the results from the HPM and the GWR model. We begin by discussing the findings from the HPM, which provides an overview of how factors like housing attributes, demographics, and accessibility to amenities influence housing values on a city-wide scale. We then examine the GWR model results, which reveal how these relationships vary spatially across Turin. By comparing the results from both models, we highlight key patterns and differences, offering a detailed understanding of the factors influencing housing values and their spatial dynamics.

6.1. HPM results

Seven variations of the HPM were run, each incorporating different sets of variables to examine their impact on the prediction model (Table 4). Model (1) explains 76.1% of the variation in housing values based only on housing attributes. Model (2) includes demographic variables improving R^2 to 0.846. Model (3) enhances R^2 to 0.857 adding distance to the city centre. Model (4) incorporates distances from houses to local and transportation amenities, increasing R^2 from 0.857 to 0.873. Model (5) integrates accessibility to the retail sector, not yielding substantial improvement, although the beta coefficient for this variable remains significantly different from 0 ($p < 0.1$). However, Model (6) divides retail accessibility into typologies, enhancing the adjusted R^2 from 0.873 to 0.880, underscoring the association between housing values and retail accessibility contingent on retail typologies. Including different retailer types increases R^2 by 0.007, whereas other locations and transportation amenities contribute to a 0.016-point enhancement in R^2. Model (7) shows a slight improvement, with an adjusted R^2 of 0.882. In all seven models, the f-statistic is significantly nonzero ($p < 0.01$).

The relationships between housing prices and control variables in the seven models align with the results of previous studies (Bottero, Bravi, Dell'Anna, 2018; Jeanty et al., 2010; Ma et al., 2022; Bottero, Bragolusi, Bravi, D'Alpaos, & Dell'Anna, 2023), supporting the data quality and providing robustness to the analyses presented in this study. The estimated accessibility coefficient to retailers in Model (4) confirms previous findings, indicating that greater accessibility to the overall retail sector is associated with higher housing values. This suggests that households perceive spatial accessibility to retail as an amenity (Jang & Kang, 2015; Kang, 2018; Song & Sohn, 2007) and value the opportunity to consume and purchase various goods in conveniently located stores (Rivera-Batiz, 1988).

Since the dependent variable is log-transformed, the estimated beta coefficient represents the percentage change in housing values for each one-unit increase in the independent variable. This interpretation does not apply to surface area, which is also log-transformed; for surface area, the coefficient indicates the percentage change in housing value for a one-percent change in surface area. Focusing on the accessibility index to retailers, a one-point increase in this index is associated with a 0.1% increase in house value in Turin.

To evaluate the relationship strength between the independent and dependent variables in multiple linear regression, the independent variable's beta can be multiplied by its relative standard deviation. This method calculates the effect of one standard deviation change in the independent variable on the dependent variable. One standard deviation change in the accessibility index to the overall retail sector resulted in a 2.4% change in housing values. For instance, for a 300,000€ house, a one standard deviation change in the retail accessibility index would lead to approximately 7,000€ value change. Hence, retail deserts risk creating inhospitable places (Schuetez et al., 2012) and devaluing real estate assets.

Models (6) and (7) show a positive correlation between housing values and accessibility to shopping retailers and bar and restaurant retailers while indicating a negative correlation with convenience stores and traditional markets, supporting our hypotheses. The beta coefficient estimates suggest that a one-unit increase in the shopping retailer accessibility index corresponds to a 1.1% and 0.9% rise in housing values in Models (6) and (7), respectively. Similarly, a one-standard deviation in shopping retailers' accessibility index results in 7.9% and 6.5% changes in housing values in Models (6) and (7), respectively. Concurrently, a one-point increase in the accessibility index of bars and restaurants leads to 0.6% and 0.4% increases in housing values in models (6) and (7), respectively, with a one-standard-deviation change resulting in 5% and 3.3% changes in housing values, respectively. These findings support the hypothesis that increased accessibility to shopping and food establishments is positively correlated with housing value, possibly attributable to urban vibrancy, aesthetics, and street liveliness (Zukin & Kosta, 2004; Chapple & Jacobus, 2009; Sevtsuk, 2014).

Conversely, a one-unit increase in convenience retailers' accessibility index corresponds to a 0.8% and 0.5% decrease in housing values in Models (6) and (7), respectively, with a one-standard-deviation change resulting in an 8.6% and 5.4% decrease in housing values in Models (6) and (7), respectively. Moreover, a one-unit increase in the traditional markets' accessibility index leads to a 0.1% decrease in housing values in Models (6) and (7), with a one standard deviation change in accessibility resulting in a 2.4% change in housing values. The empirical analyses confirm the hypothesis that increased accessibility to convenience retailers and traditional markets affects housing values negatively, suggesting that negative externalities, such as noise and traffic, outweigh the proximity benefits (Yang et al., 2016). Previous studies (Chiang et al., 2015; Jang & Kang, 2015; Kang, 2018) suggested a significant difference in the beta coefficient for accessibility to supermarket retailers. However, our findings indicated no significant deviation from zero. This study presents diverse retail typologies that may explain this disparity between findings and results from previous researches. Additionally, the high concentration of supermarkets in Turin could explain these results. It must be noted that an increase in weekly supply availability does not necessarily improve quality of life or housing values, provided that adequate, convenient options are available.

The beta coefficients of Model (7) support our hypothesis of nonlinear relationships between housing values and accessibility to retailers and traditional markets, except for supermarkets. Houses in areas with high accessibility to shopping retailers experience a 7.6% increase in housing value, while no significant difference is observed for those with low accessibility. These findings support our hypotheses, suggesting that an incremental shopping retailer increases housing values in areas with a high concentration of shopping retailers. The policy implications of these results include incentives and strategic locations for new stores. Houses in the first quartile of accessibility to bars and restaurants show a 4.6% increase in housing values, suggesting a positive impact, particularly in underserved regions (first quartile). However, increased liveliness can be offset by negative factors, such as noise, traffic, and unpleasant odours (Schuetz et al., 2012). Conversely, no

Table 4
Results of hedonic price models (HPM).

Dependant variable:log (price)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
log(surface)	1.115(***)	1.056(***)	1.054(***)	1.059(***)	1.060(***)	1.051(***)	1.053(***)
	(0.020)	(0.016)	(0.015)	(0.015)	(0.015)	(0.014)	(0.014)
elevator	0.205(***)	0.173(***)	0.193(***)	0.197(***)	0.199(***)	0.182(***)	0.179(***)
	(0.017)	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
green labelB	−0.035	0.036	−0.003	0.019	0.018	0.0003	0.0005
	(0.061)	(0.050)	(0.048)	(0.046)	(0.046)	(0.045)	(0.045)
green labelC	−0.071	−0.057	−0.076(*)	−0.051	−0.051	−0.076(*)	−0.075(*)
	(0.056)	(0.045)	(0.044)	(0.042)	(0.042)	(0.041)	(0.041)
green labelD	−0.105(**)	−0.091(**)	−0.103(***)	−0.092(**)	−0.092(**)	−0.117(***)	−0.109(***)
	(0.050)	(0.040)	(0.039)	(0.037)	(0.037)	(0.037)	(0.036)
green labelE	−0.170(***)	−0.147(***)	−0.151(***)	−0.134(***)	−0.133(***)	−0.153(***)	−0.148(***)
	(0.049)	(0.040)	(0.039)	(0.037)	(0.037)	(0.036)	(0.036)
green labelF	−0.236(***)	−0.189(***)	−0.198(***)	−0.176(***)	−0.176(***)	−0.194(***)	−0.188(***)
	(0.050)	(0.040)	(0.039)	(0.037)	(0.037)	(0.036)	(0.036)
green labelG	−0.226(***)	−0.188(***)	−0.201(***)	−0.187(***)	−0.187(***)	−0.197(***)	−0.191(***)
	(0.050)	(0.040)	(0.039)	(0.037)	(0.037)	(0.036)	(0.036)
parking	0.002	0.051(***)	0.068(***)	0.062(***)	0.063(***)	0.062(***)	0.065(***)
	(0.019)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
garden	−0.045(**)	−0.016	0.010	0.019	0.022	0.019	0.017
	(0.019)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
property_typeEconomic	−0.775(***)	−0.484(***)	−0.380(***)	−0.403(***)	−0.400(***)	−0.293(***)	−0.294(***)
	(0.066)	(0.054)	(0.053)	(0.050)	(0.050)	(0.050)	(0.050)
property_typeElegant	−0.331(***)	−0.228(***)	−0.169(***)	−0.203(***)	−0.200(***)	−0.104(**)	−0.108(**)
	(0.063)	(0.051)	(0.049)	(0.047)	(0.047)	(0.047)	(0.046)
property_typeMedium	−0.605(***)	−0.385(***)	−0.294(***)	−0.323(***)	−0.321(***)	−0.208(***)	−0.210(***)
	(0.063)	(0.052)	(0.050)	(0.047)	(0.047)	(0.048)	(0.048)
conditionsGood/Habitable	−0.143(***)	−0.129(***)	−0.127(***)	−0.136(***)	−0.136(***)	−0.132(***)	−0.130(***)
	(0.017)	(0.014)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
conditions New/Under construction	0.181(***)	0.055(*)	0.029	0.054(*)	0.053(*)	0.069(**)	0.074(***)
	(0.039)	(0.032)	(0.030)	(0.029)	(0.029)	(0.028)	(0.028)
conditionsTo renovate	−0.231(***)	−0.254(***)	−0.247(***)	−0.251(***)	−0.250(***)	−0.249(***)	−0.250(***)
	(0.025)	(0.020)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
population		0.00002(***)	0.00001(***)	0.00001(***)	0.00001(***)	0.00001(***)	0.00001(***)
		(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
foreigners		−0.0001(***)	−0.0001(***)	−0.0001(***)	−0.0001(***)	−0.0001(***)	−0.0001(***)
		(0.00000)	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
income		0.012(***)	0.009(***)	0.006(***)	0.006(***)	0.004(***)	0.004(***)
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
dis_city_center			−0.0001(***)	−0.0001(***)	−0.0001(***)	−0.00003(***)	−0.00004(***)
			(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
dis_parks				0.00005(***)	0.00005(***)	0.00004(***)	0.00005(***)
				(0.00001)	(0.00001)	(0.00001)	(0.00001)
dis_bus_stop				0.00001	0.00001	0.00001	−0.00001
				(0.0001)	(0.0001)	(0.0001)	(0.0001)
dis_metro_station				−0.00005(***)	−0.00005(***)	−0.0001(***)	−0.0001(***)
				(0.00001)	(0.00001)	(0.00001)	(0.00001)
dis_train_station				0.0001(***)	0.0001(***)	0.0001(***)	0.0001(***)
				(0.00001)	(0.00001)	(0.00001)	(0.00001)
dis_library				−0.00004(***)	−0.00003(**)	−0.00001	−0.00001
				(0.00001)	(0.00001)	(0.00001)	(0.00001)
dis_sport_centres				−0.0001	−0.0001	−0.00002	−0.00002
				(0.00004)	(0.00004)	(0.00004)	(0.00004)
dis_cinema				−0.0001(***)	−0.0001(***)	−0.0001(***)	−0.0001(***)
				(0.00001)	(0.00001)	(0.00001)	(0.00001)
dis_nursery				0.0001(***)	0.0001(**)	0.0001(**)	0.00005(*)
				(0.00003)	(0.00003)	(0.00003)	(0.00003)
dis_schools				0.00003	0.00004	−0.00002	−0.00001
				(0.0001)	(0.0001)	(0.0001)	(0.0001)
acc_retailers					0.001(*)		
					(0.0003)		
acc_shopping						0.011(***)	0.009(***)
						(0.001)	(0.001)
acc_convenience						−0.008(***)	−0.005(***)
						(0.001)	(0.002)
acc_supermarket						0.019	0.001
						(0.015)	(0.026)
acc_bars_and_restaurants						0.006(***)	0.004(**)
						(0.002)	(0.002)
acc_traditional_market						−0.001(***)	−0.001(**)
						(0.0002)	(0.0003)
shopping_quart_1							−0.017
							(0.020)
shopping_quart_4							0.076(***)
							(0.020)

(*continued on next page*)

Table 4 (*continued*)

Dependant variable:log (price)	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
convenience_quart_1							−0.008
							(0.023)
convenience_quart_4							−0.087(***)
							(0.023)
supermarket_quart_1							−0.003
							(0.016)
supermarket_quart_4							0.017
							(0.021)
bars_and_restaurants_quart_1							0.046(**)
							(0.021)
bars_and_restaurantsquart_4							0.017
							(0.022)
traditional_market_quart_1							0.034(**)
							(0.015)
traditional_market_quart_4							−0.005
							(0.016)
Constant	7.545(***)	7.191(***)	7.537(***)	7.669(***)	7.612(***)	7.539(***)	7.504(***)
	(0.117)	(0.098)	(0.099)	(0.099)	(0.104)	(0.102)	(0.104)
Observations	2157	2157	2157	2157	2157	2157	2157
R^2	0.763	0.847	0.858	0.875	0.875	0.882	0.885
Adjusted R^2	0.761	0.846	0.857	0.873	0.873	0.880	0.882
Residual Std. Error	0.341	0.273	0.263	0.248	0.247	0.241	0.239
F Statistic	430.060(***)	624.476(***)	645.626(***)	512.726(***)	496.181(***)	467.960(***)	368.039(***)

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

statistically significant deviation is observed from zero for houses in the fourth quartile of accessibility to bars or restaurants.

Generally, Turin has adequate convenience retailer coverage, with an average accessibility index of 20. Regression (7) indicates that an increase in access to these retailers is associated with reduced housing values. Houses in the fourth quartile of convenience retailer accessibility experience an additional 8.7% reduction in housing values. This shows that in a well-supplied city, an influx of convenience retailers does not necessarily increase housing values, especially in well-served areas. Accessibility to local markets positively impacts houses in the first quartile (underserved areas). Contrastingly, for houses closer to larger markets, increased accessibility reduces housing values. This confirms the trade-off between accessibility to and the negative externalities of retail activities.

6.2. GWR results

Table 5 displays the GWR results, showing the average parameter values for the 2157 houses analysed in this study. The results reveal a positive correlation between housing values and access to shopping, bars, and restaurant retailers, while a negative correlation is found with convenience retailers and traditional markets. The GWR model enhances Model 7's explanatory power from 0.882 to 0.905 with fewer variables. Therefore, the GWR model helps to capture the spatially varying relationships between variables.

A comparison of HPM with OLS and GWR reveals that the signs of the estimated variables are consistent between the two approaches. However, the absolute values of the estimates differ. While physical characteristics of apartments show similar estimated values in both models, the GWR model provides higher estimates for accessibility to retailers. This difference can be attributed to GWR's ability to capture local spatial variations more effectively by adjusting coefficients according to specific geographic location. Additionally, despite the GWR model excluding location and transportation variables, it exhibits a higher R^2 value compared to OLS. This indicates that GWR offers greater explanatory power by better modelling spatial variations in the relationships between housing values and property characteristics.

Moreover, GWR provides valuable spatial information on these

Table 5
GWR results.

Variable	Mean	Min	1Q	Median	3Q	Max	IQR	SD
Intercept	0.064	−0.809	−0.125	0.133	0.227	1.726	0.352	0.254
log(surface)	0.626	0.360	0.604	0.620	0.651	0.716	0.047	0.036
acc_shopping	0.060	−0.919	0.034	0.094	0.119	2.750	0.085	0.160
acc_convenience	−0.094	−0.415	−0.154	−0.111	−0.036	0.705	0.118	0.114
acc_supermarket	0.012	−0.339	−0.002	0.012	0.035	0.284	0.037	0.040
acc_bar_and_restaurant	0.104	−1.588	0.040	0.095	0.164	1.398	0.124	0.206
acc_traditional_market	−0.006	−0.535	−0.028	−0.004	0.019	0.204	0.047	0.052
elevator	0.109	−0.046	0.090	0.116	0.128	0.170	0.038	0.028
parking	0.036	−0.085	0.023	0.035	0.050	0.106	0.027	0.019
garden	0.020	−0.065	0.001	0.017	0.045	0.142	0.044	0.033
property type	−0.075	−0.171	−0.097	−0.073	−0.053	0.008	0.044	0.035
conditions	−0.145	−0.260	−0.162	−0.144	−0.130	−0.070	0.033	0.028
population	0.083	−0.853	0.028	0.066	0.134	1.312	0.106	0.160
foreigners	−0.010	−1.114	−0.151	−0.088	0.046	1.882	0.197	0.262
income	0.084	−0.207	0.032	0.071	0.127	0.409	0.094	0.080
green_label	−0.071	−0.155	−0.089	−0.068	−0.053	−0.001	0.036	0.028

Number of observations = 2157.
Bandwidth = 0.87 km.
Adjusted R^2 = 0.905.
AICc = 1305.406.
1Q = 1st quartile, Med = median, 3Q = 3rd quartile, IQR = interquartile range, SD = standard deviation.

relationships. The following analyses will explore the spatial distribution of the beta coefficients for accessibility to the five typologies of retailers. This includes examining the quartiles, areas with negative or positive values, and regions where values significantly deviate from the mean beta presented in Table 5.

Fig. 4 shows the quartile of coefficients for retailer accessibility with corresponding p-values. In the city centre, housing values are positively associated with accessibility to shopping (Fig. 4a) and bar/restaurant (Fig. 4b) retailers. Conversely, accessibility to convenience retailers shows a negative relationship in the city centre but a positive one in peripheral areas. Accessibility to supermarket retailers and traditional markets is generally insignificant across most regions, except for a notable negative correlation in the city centre.

Fig. 5 delineates the spatial variability in the impact of different types of retail accessibility on housing prices with the results being statistically significant different from zero at the 95% confidence level. The analysis reveals distinct patterns across the city. Specifically, the beta coefficients for accessibility to shopping retailers (Fig. 5a) are predominantly positive and statistically significant in the city centre. This positive effect diminishes and even turns negative towards the city's periphery, with a notable significant negative cluster in the northwest. A similar trend is observed for accessibility to bars and restaurants (Fig. 5b), where positive impacts are concentrated in central zones, while a small significant negative area is identified in the northeast. Conversely, accessibility to convenience retailers (Fig. 5c) and traditional markets (Fig. 5e) demonstrates a negative relationship in the city centre, which becomes positive towards the outskirts, with some areas showing significant positive effects. For supermarket retailers (Fig. 5d), the coefficients are mainly positive across most of the study area, though negative coefficients are evident in the western and northern regions. These findings underscore the importance of considering spatially varying impacts when assessing the influence of retail accessibility on housing values, highlighting the necessity for localized analyses in urban planning and policy-making.

Statistical analysis explored the relationship between accessibility to retailers/traditional markets and housing values deviating from the average in specific areas of Turin. The *t*-test was employed at a 95% significance level. Fig. 6 illustrates results for the five retailer types, with green/red points indicating above/below-average relationships.

The association between housing values and shopping retailer accessibility is above average in Turin's city centre (0.089 to 0.300) and below average in a northwestern neighbourhood (−0.421 to −0.038). The hypothesis that a high concentration of shopping retailers positively impacts housing values is supported by the above-average influence in the city centre, attributable to the area's characteristics. The city centre, serving as a cultural and commercial hub, concentrates on shopping retailers, a phenomenon supported by prior studies (Eaton & Lipsey, 1975; Ingene, 1984) generating positive externalities for property owners and consumers (Zukin & Kosta, 2004; Chapple & Jacobus, 2009). The heightened relationship in the city centre implies that an additional shopping store impacts this area substantially, enhancing vibrancy, safety, and aesthetics (Glaeser et al., 2001).

Housing values exhibit an above-average relationship with accessibility to bars and restaurants in central and peripheral southern areas (0.142 to 0.792), contrasting with a below-average relationship in the north and southwest peripheral zones (−1.588 to 0.09). Akin to shopping retailers, bar and restaurant retailers capitalise on agglomeration and create activity clusters that enhance consumer footfall. Sevtsuk (2014) suggested that consumers are attracted to areas with a wide range of options and convenient comparative analysis. Unlike shopping retailers, whose impact on housing values is more pronounced in clusters, the accessibility to bars and restaurants significantly influences neighbourhoods around the city centre. This influence is particularly pronounced in areas with agglomerated activities. Disparities in housing values stem from the equilibrium between the positive proximity and negative disamenities effects. In neighbourhoods adjacent to the city centre, the positive impact of proximity outweighs adverse externalities, such as noise and traffic from bars and restaurants (Schuetz et al., 2012). Conversely, in central neighbourhoods, these effects balance each other, resulting in impacts on housing values that are not above average. These findings confirm that the positive correlation between housing values and accessibility to bars and restaurants diminishes in areas characterised by a high concentration of such establishments.

Accessibility to convenience retailers and traditional markets exhibits an above-average relationship with housing values in peripheral areas (−0.046 to 0.433), but a below-average relationship in the city centre (−0.415 to −0.136). This trend is also observed with traditional markets, which show an above-average relationship in some peripheral areas (0.016 to 0.124) where access to basic supplies is limited, and a below-average relationship in the city centre (−0.535 to −0.022) where a large market (Porta Palazzo) provides abundant supplies but also contribute to noise, odours, and congestion. Enhancing accessibility to convenience retailers and traditional markets in underserved areas such as the periphery may increase housing value. Conversely, increased accessibility to these activities in well-served areas, such as the city centre, may affect housing values detrimentally. These findings confirm our hypothesis that the benefits of proximity and reduced search costs are counterbalanced by the adverse effects of noise and congestion in more densely serviced areas.

7. Conclusions and future developments

This study addresses the gap in the literature concerning the impact of amenities on housing values, focusing on retail activities, essential for economic prosperity, desirability, and social interaction of neighbourhoods. This study expands this research stream by exploring the relationship between housing values and accessibility to various retail activities (shopping, convenience, supermarkets, bars, restaurants, and traditional markets) in Turin, a European city. Using the HPM model at the citywide level and the GWR model at the local level, this study investigates the diverse effects of retail accessibility on housing values capturing spatial heterogeneity.

The findings indicate that retail accessibility has a statistically and economically significant positive effect on housing prices, with notable differences among various retail activities. Shopping retailers, especially in central areas, can collectively contribute to the area's quality. Similarly, bars and restaurants, particularly in semi-peripheral areas, can positively impact, despite potential drawbacks, such as noise, lack of parking, and odours. Traditional markets and convenience retailers benefit underserved areas by providing citizens access to basic products. However, their concentration in well-served areas can reduce the value of houses. Sensitivity analyses were performed to verify the results and identify the appropriate decay factor, revealing that retail activity typically impacts within a radius of approximately 500 m.

These complex relationships have implications for planners and policymakers. Specifically, they highlight the need for policymakers to support the retail industry while safeguarding and developing investors' and families' assets. Encouraging shopping activities in central areas where retailers are clustered and ensuring access to convenience stores and traditional markets in underserved neighborhoods can help avoid retail deserts. However, large retail concentrations may not always reduce search costs for citizens and could even increase negative externalities. While previous studies have concentrated on supermarkets, this study does not provide conclusive evidence of their impact on housing values. Previous studies have focused on supermarkets, but this study does not provide evidence of their impact on housing values.

The findings highlight the necessity for urban planners to develop policies that are tailored to the specific type of retailer and the distinctive characteristics of each urban area. Retailers that generate positive benefits, such as fostering vibrant community spaces, should be supported through incentives such as tax breaks, subsidies or appropriate zoning rules. Such measures have the potential to foster retail

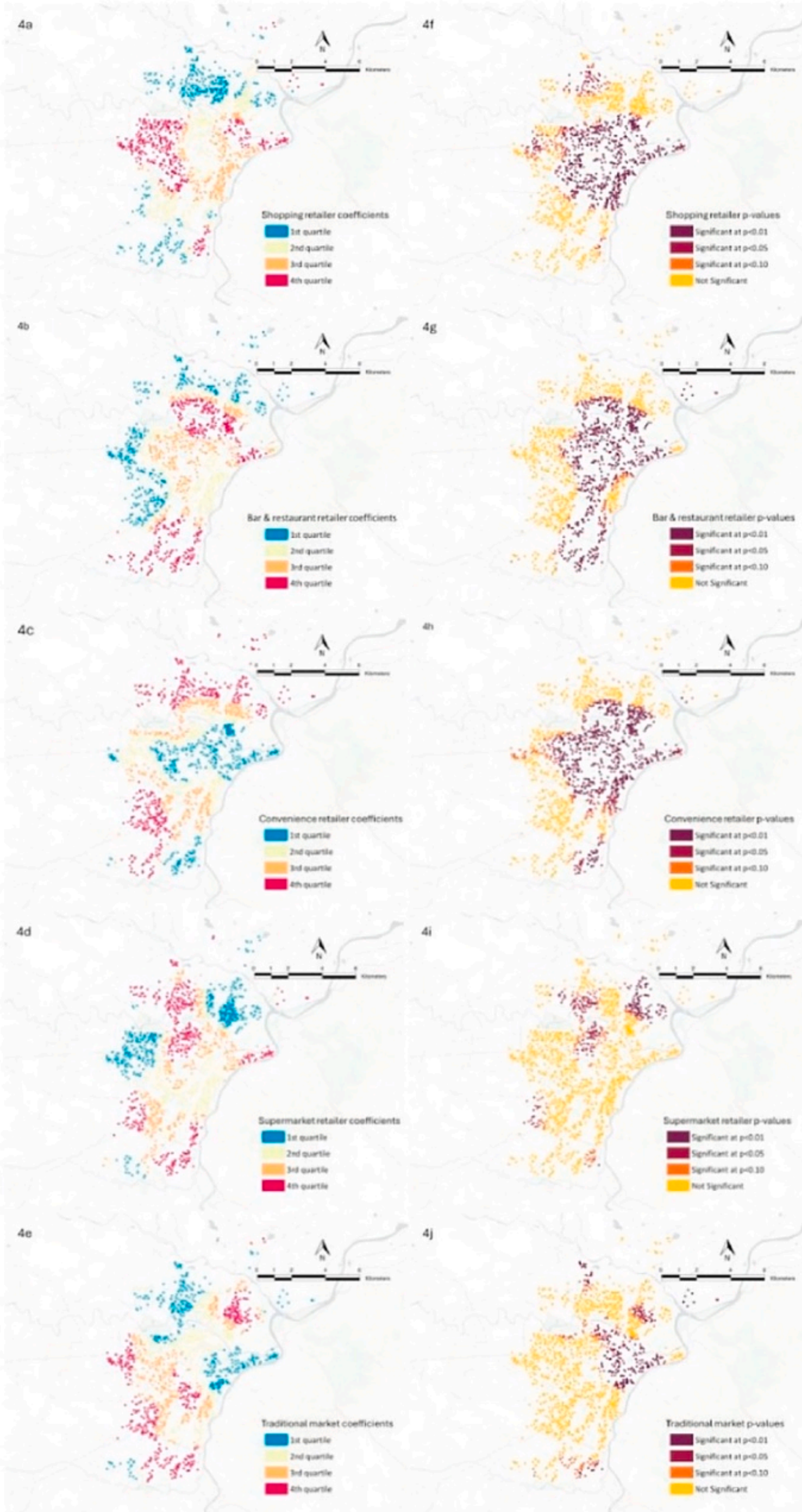

Fig. 4. Local estimates of accessibility to retailers in GWR. Left: coefficients; Right: p-values.

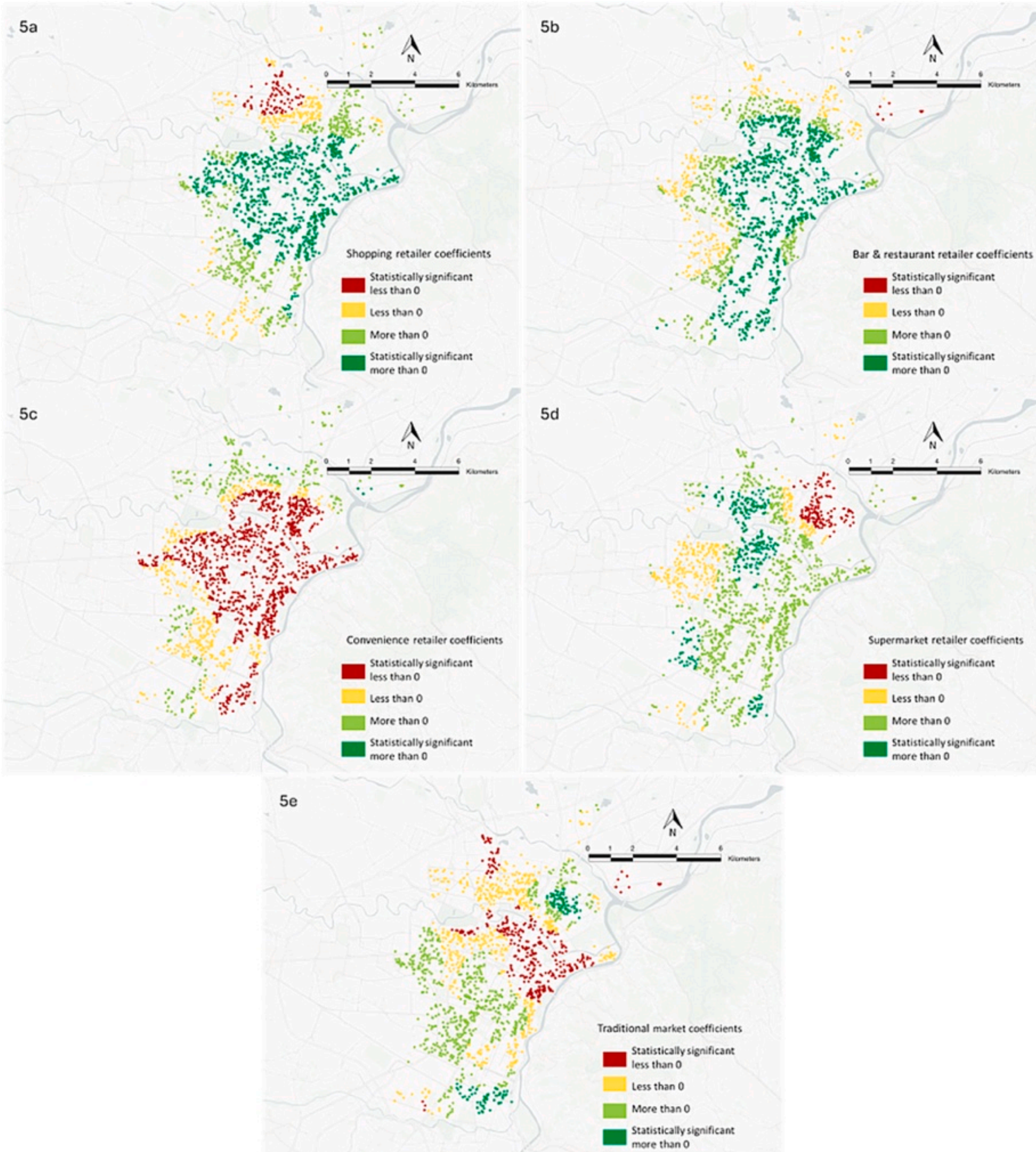

Fig. 5. Local estimates of accessibility to retailers in GWR above or below zero.

environments that contribute to neighbourhood community welfare and enhance housing values. Conversely, it is essential to exercise caution when considering the development of retailers that may have a detrimental impact on housing values, particularly in residential areas where concerns exist regarding noise, traffic, or pollution.

Also, urban planners might want to consider the current accessibility to specific retail types in each area of the city. In underserved areas a convenience store or a bar provide citizens with convenience and support the value to existing houses, whereas in an area with many convenience stores or bars adding an extra store does not generate any relevant incremental convenience, but creates additional negative externalities thus leading to lower housing values. Public policies (incentives, taxes and zoning rules) should be deployed accordingly.

For private investors, these insights highlight the importance of understanding the nuanced effects of various retailers on real estate values. Such knowledge can guide informed investment decisions that benefit both urban development and housing values, which are crucial economic resources for many households.

Future research should address the limitations of this study by incorporating road networks to capture perceived proximity between houses and stores, thereby refining the accessibility index. Additionally, exploring the relationship between housing values and retail accessibility over time through panel datasets could provide further insights. Integrating machine learning techniques for price predictions and Natural Language Processing (NLP) to analyse textual data from residential listings about retailers could further enhance understanding and predictive accuracy (Bottero et al., 2024; Su et al., 2021). Expanding this analysis to other cities - both within Italy and beyond, including

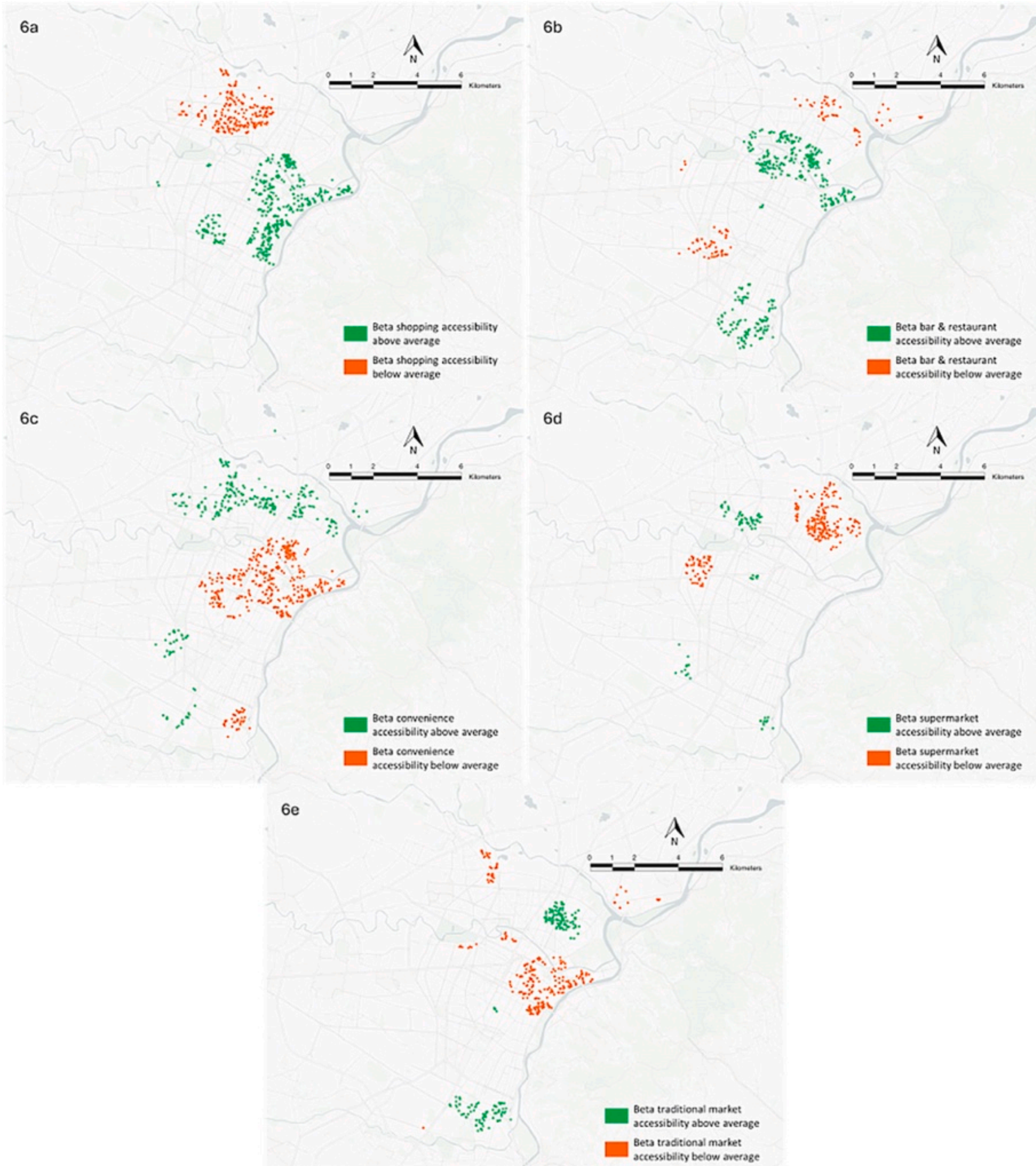

Fig. 6. Local estimates of accessibility to retailers in GWR above average (green) and below average (red).

European, African, and Australian cities - could yield additional valuable findings.

CRediT authorship contribution statement

Marco Del Nibletto: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Giulio Zotteri:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marta Bottero:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Federico Dell'Anna:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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APPENDIX A

The correlation matrix, VIF values and the eigenvalue method have been computed to test the presence of multicollinearity issues. These three methods are the most commonly employed for testing for multicollinearity (Shrestha, 2020). The absolute values of the correlation matrix are below the recognised threshold value of 0.8, above which collinearity is likely to exist (Shrestha, 2020). Models 1 to 6 exhibit no multicollinearity issues, with all VIF values below the threshold of 10 (Shresta, 2020). However, in Model 7, the VIF of accessibility to convenience slightly surpasses the threshold, attributed to the inclusion of Boolean variables indicating accessibility index quartiles. The eigenvalue method was employed to calculate the condition index, which was used to assess the degree of multicollinearity among the predictor variables. This index, derived from the eigenvalue matrix of the independent variables, serves to quantify the extent to which the variance of the estimated regression coefficients is inflated as a consequence of multicollinearity. Once more, the values obtained are below the threshold value of 15, indicating a low level of multicollinearity (Shrestha, 2020).

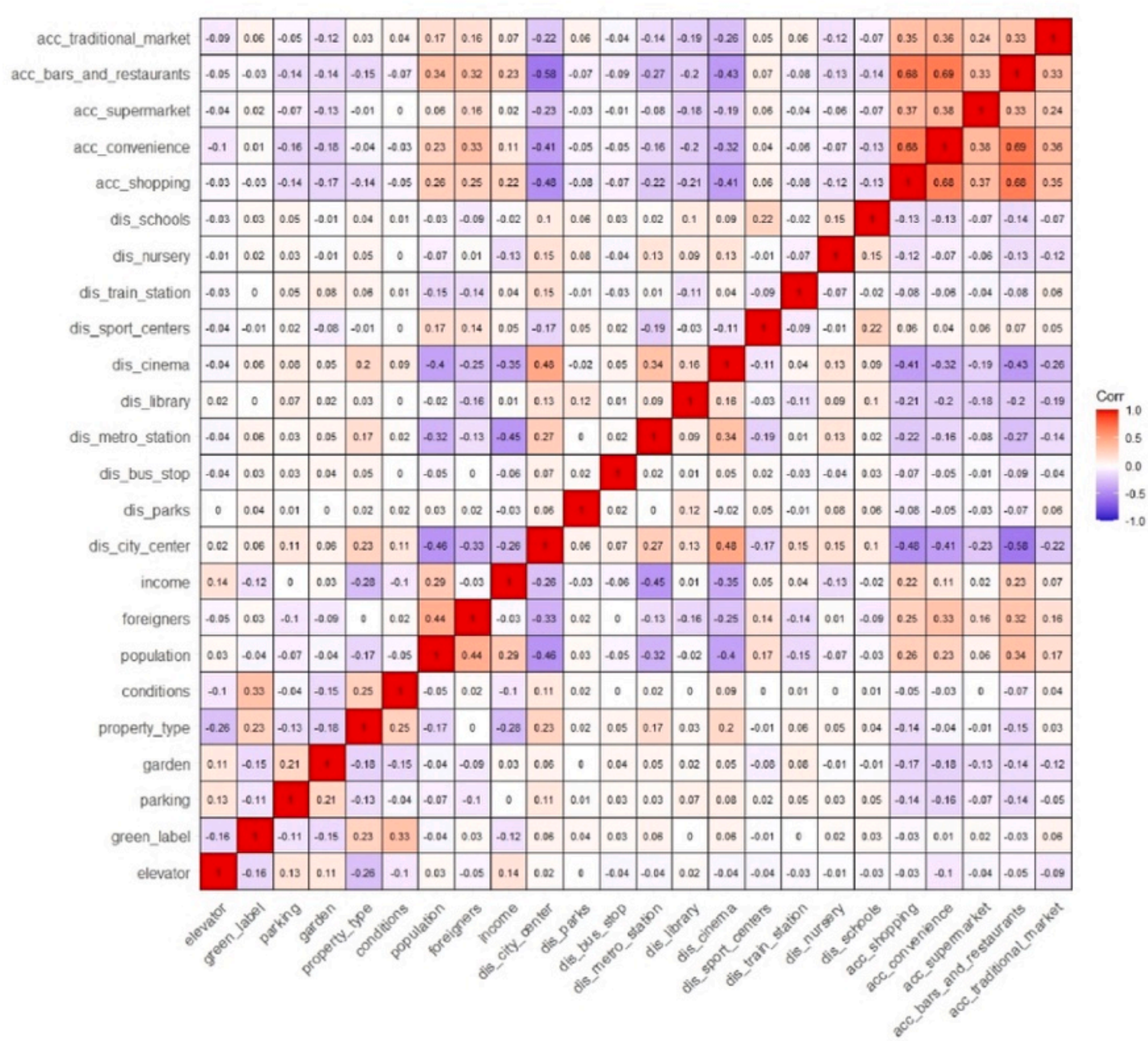
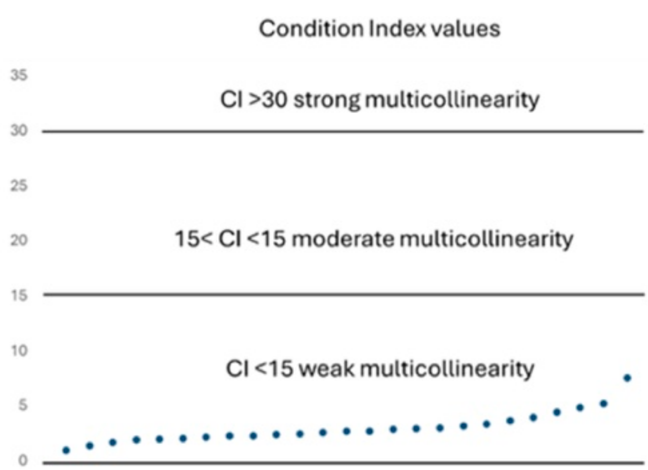


Fig. 5 and Fig. 6.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
log(surface)	1.194	1.212	1.212	1.232	1.232	1.238	1.255
elevator	1.133	1.142	1.159	1.168	1.171	1.192	1.201
green label	2.184	2.298	2.315	2.501	2.510	2.585	2.705
parking	1.107	1.131	1.141	1.160	1.163	1.164	1.172
garden	1.163	1.173	1.197	1.216	1.239	1.254	1.295
property_type	1.354	1.521	1.595	1.627	1.634	1.783	1.826
conditions	2.065	2.124	2.136	2.200	2.202	2.238	2.308
population		1.367	1.696	2.110	2.144	2.302	2.415
foreigners		1.285	1.449	1.829	1.831	2.103	2.167
income		1.502	1.708	1.912	1.929	2.086	2.134
dis_city_center			2.191	3.068	4.067	4.677	4.989
dis_parks				1.253	1.258	1.274	1.356
dis_bus_stop				1.061	1.062	1.065	1.095
dis_metro_station				2.047	2.048	2.062	2.213
dis_train_station				1.239	1.243	1.260	1.279
dis_library				1.417	1.506	1.618	1.726
dis_sport_centres				1.556	1.566	1.588	1.616
dis_cinema				2.728	2.745	2.819	2.951
dis_nursery				1.419	1.434	1.438	1.518
dis_schools				1.615	1.618	1.634	1.658
acc_retailers					2.373		
acc_shopping						3.753	4.199
acc_convenience						4.414	10.618
acc_supermarket						1.472	4.550
acc_bars_and_restaurants						6.592	8.259
acc_traditional_market						1.191	1.496
shopping_quart_1							2.846
shopping_quart_4							2.755
convenience_quart_1							3.664
convenience_quart_4							3.887
supermarket_quart_1							1.865
supermarket_quart_4							3.243
bars_and_restaurants_quart_1							3.029
bars_and_restaurantsquart_4							3.322
traditional_market_quart_1							1.571
traditional_market_quart_4							1.751



APPENDIX B

Appendix B presents the mean values of the estimated coefficients for the explanatory variables using the GWR model with varying bandwidths, starting with an optimal bandwidth of 870 m and extending to a bandwidth of 5000 m. The coefficients of the housing variables, such as log(surface), presence of elevator, garden, and parking, remained relatively stable as the bandwidth changed, indicating a uniform influence on the values of the properties. Accessibility to the retailer variables demonstrates a more pronounced alteration in the coefficients as bandwidth is modified. In particular, the coefficients associated with these variables tended to increase in absolute value with increasing bandwidth, except for accessibility to bars and restaurants, which showed a slight decrease after peaking at intermediate bandwidths. Still, the signs and the relative magnitude of these variables are basically unchanged. Thus, the analyses prove to be rather robust. The coefficients of population, foreigners, and income exhibit considerable variation as bandwidth increases. In particular, the coefficient for foreigners becomes increasingly negative as bandwidth increases. This may reflect broader spatial dynamics, whereby the concentration of the foreign population is perceived differently at the local level than at a larger scale. Furthermore, the adjusted R^2 decreased as bandwidth increased, indicating a reduction in the explanatory power of the model. GWR with a smaller bandwidth captures local variations better, resulting in higher accuracy in predicting real estate prices than models with larger bandwidths.

Variable	Average Estimated Beta					
Intercept	0.064	0.062	0.033	0.016	0.010	0.007
log(surface)	0.626	0.626	0.618	0.615	0.613	0.613
acc_shopping	0.060	0.067	0.098	0.105	0.107	0.109
acc_convenience	−0.094	−0.102	−0.123	−0.128	−0.128	−0.127
acc_supermarket	0.012	0.013	0.021	0.026	0.027	0.028
acc_bar_and_restaurant	0.104	0.120	0.137	0.131	0.127	0.125
acc_traditional_market	−0.006	−0.008	−0.014	−0.016	−0.016	−0.017
elevator	0.109	0.109	0.110	0.112	0.113	0.113
parking	0.036	0.037	0.039	0.040	0.041	0.041
garden	0.020	0.021	0.015	0.008	0.006	0.005
property type	−0.075	−0.079	−0.099	−0.104	−0.105	−0.105
conditions	−0.145	−0.145	−0.140	−0.135	−0.133	−0.133
population	0.083	0.099	0.155	0.167	0.172	0.175
foreigners	−0.010	−0.038	−0.133	−0.162	−0.170	−0.172
income	0.084	0.092	0.098	0.097	0.098	0.099
green_label	−0.071	−0.071	−0.068	−0.068	−0.069	−0.069
Adjusted R^2	0.905	0.902	0.888	0.878	0.872	0.868
Bandwidth	0.87 km (Optimal)	1 km	2 km	3 km	4 km	5 km

Number of observations = 2157.

APPENDIX C

Classification of ATECO Codes to Shopping Retailers.

Shopping retailer's ATECO codes
182, 1822, 18221, 18222, 1823, 1824, 18241, 18242, 18243, 18302, 362, 3621, 3622, 36221, 36222, 52121, 5241, 52411, 52412, 5242, 52421, 52422, 52423, 52424, 52425, 5243, 52431, 52432, 5244, 52441, 52442, 52444, 52453, 52463, 52483, 52485, 524851, 524852, 524853, 524854, 52486, 524861, 524862, 524863, 524868, 52488, 52489, 5248C, 524800, 525, 52502, 52503, 52622, 526221, 526222, 52623, 52624, 526262, 526265, 5271, 5273

Classification of ATECO Codes to Convenience Retailers.

Convenience retailer's ATECO codes
1581, 15811, 15812, 158121, 158122, 1582, 1586, 158601, 158602, 502, 50201, 50202, 50203, 50204, 503, 503001, 503002, 504, 50401, 504011, 504012, 50402, 504021, 504022, 50403, 5211, 52114, 52115, 522, 5221, 5222, 5223, 5224, 52241, 52242, 5226, 52271, 52272, 52273, 52274, 523, 5231, 5232, 5233, 52331, 52332, 52443, 5245, 52451, 52452, 5246, 52461, 52462, 5247, 52471, 52472, 52473, 52481, 52482, 52484, 524865, 524866, 524867, 52487, 5248A, 5248000, 52480000, 52501, 52621, 526211, 526212, 526213, 526214, 526261, 526266, 526267, 526268, 526269, 527, 5272, 527201, 527202, 527203, 527403, 527404, 64202, 72, 723002, 723003, 723004, 724, 725, 726, 74812,

Classification of ATECO Codes to Supermarket Retailers.

Supermarket retailer's ATECO codes
52111, 52112, 52113

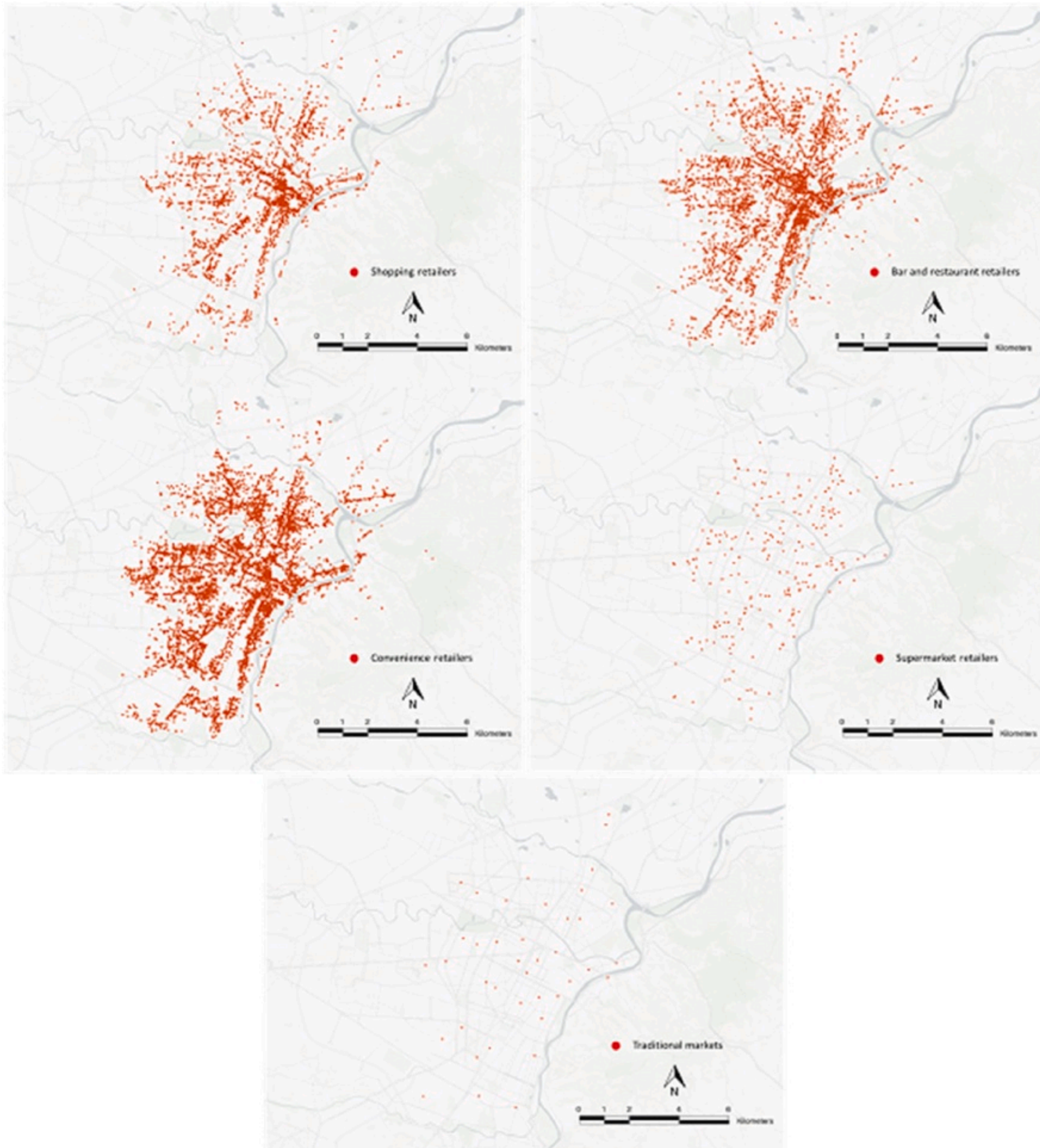
Classification of ATECO Codes to Bars & Restaurants Retailers.

Bars & restaurants retailer's ATECO codes
5225, 553, 55301, 55302, 554, 554002

Additional information on ATECO codes is available at: https://www.istat.it/it/files//2022/03/Volume-integrale-ATECO-2002.pdf.

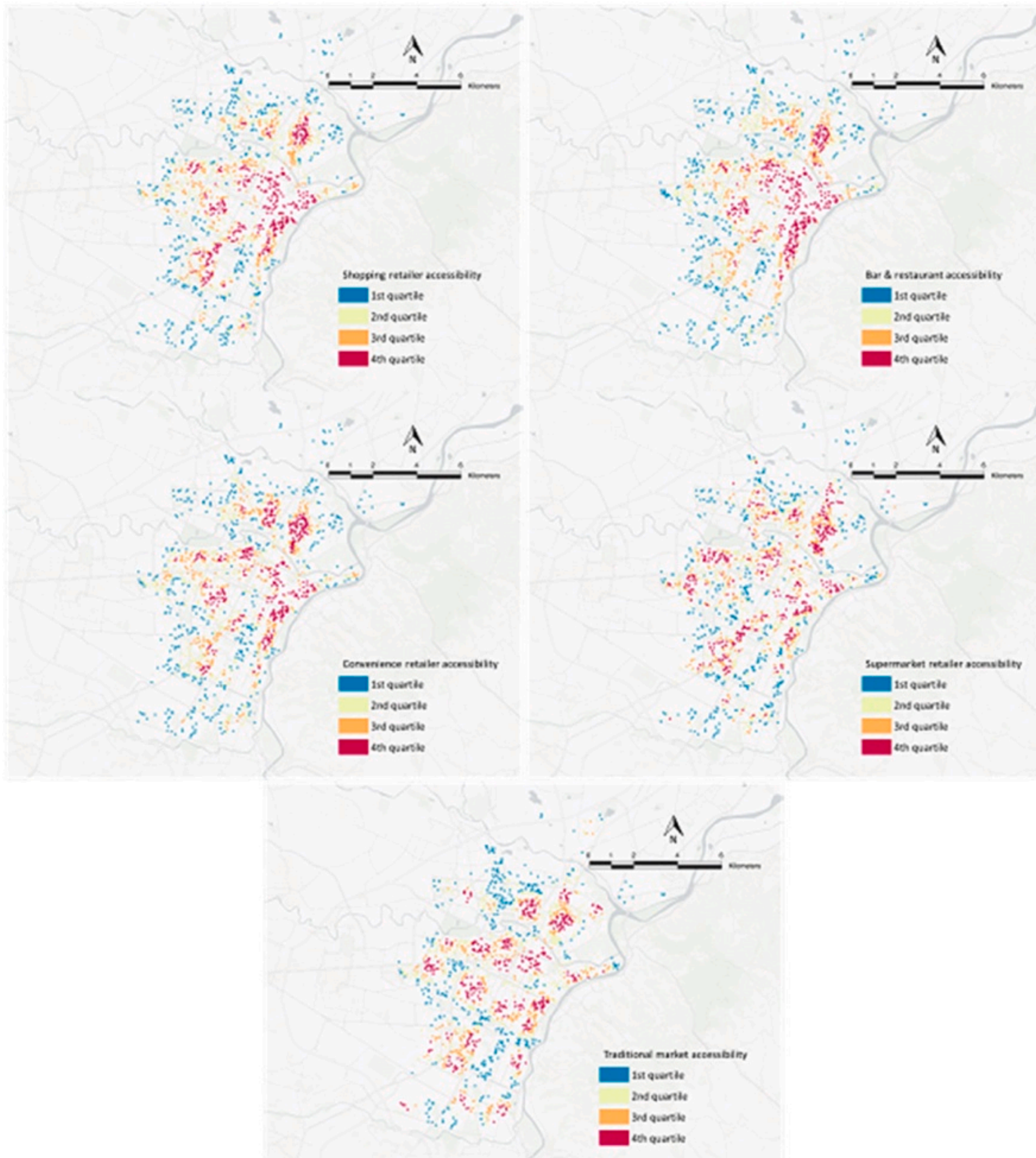
APPENDIX D

Spatial distribution of retailer's location for typology.



APPENDIX E

Spatial distribution of accessibility to retailers for typology.



References

Ambrosini, M., & Boccagni, P. (2015). Urban multiculturalism beyond the 'backlash': New discourses and different practices in immigrant policies across European cities. *Journal of Intercultural Studies, 36*(1), 35–53.

Anas, A., Arnott, R., & Small, K. A. (1998). Urban spatial structure. *Journal of Economic Literature, 36*(3), 1426–1464.

Anselin, L. (1988). *Spatial econometrics: Methods and models* (Vol. 4). Springer Science & Business Media.

Bagnasco, A., & Antonelli, C. (1990). *La città dopo Ford: il caso di Torino* (No Title).

Ballantyne, P., Singleton, A., Dolega, L., & Macdonald, J. (2023). Integrating the who, what, and where of US retail center geographies. *Annals of the American Association of Geographers, 113*(2), 488–510.

Bolzoni, M., & Semi, G. (2023). Adaptive urbanism in ordinary cities: Gentrification and temporalities in Turin (1993–2021). *Cities, 134*, Article 104144.

Bond, S., & Squires, L. (2007). Using GIS to measure the impact of distance to cell phone towers on house prices in Florida. In *Draft, thirteenth pacific-rim real estate society conference, perth, western Australia*.

Bottero, M., Bragolusi, P., Bravi, M., D'Alpaos, C., & Dell'Anna, F. (2023). The value of urban parks in the city of Turin: An application of the geographically weighted regression. *Valori e Valutazioni, 34*, 71–87.

Bottero, M., Bravi, M., Dell'Anna, F., & Mondini, G. (2018). Valuing buildings energy efficiency through hedonic prices method: Are spatial effects relevant? *Valori e valutazioni*, (21).

Bottero, M., Caprioli, C., Foth, M., Mitchell, P., Rittenbruch, M., & Santangelo, M. (2022). Urban parks, value uplift and green gentrification: An application of the spatial hedonic model in the city of Brisbane. *Urban Forestry & Urban Greening, 74*, 127618.

Bottero, M., Dell'Anna, F., Monaci, S., & Persico, S. (2024). Geo-NLP insights: Unveiling residential real estate trends through textual analysis. In *International conference on computational science and its applications* (pp. 163–175). Cham: Springer Nature Switzerland.

Brueckner, J. K., Thisse, J. F., & Zenou, Y. (1999). Why is central Paris rich and downtown Detroit poor?: An amenity-based theory. *European Economic Review, 43*(1), 91–107.

Brunsdon, C., Fotheringham, A. S., & Charlton, M. E. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis, 28*(4), 281–298.

Carroll, T. M., Clauretie, T. M., & Jensen, J. (1996). Living next to godliness: Residential property values and churches. *The Journal of Real Estate Finance and Economics, 12*, 319–330.

Casado, M. R., Serafini, J., Glen, J., & Angus, A. (2017). Monetising the impacts of waste incinerators sited on brownfield land using the hedonic pricing method. *Waste Management, 61*, 608–616.

Cervero, R., & Duncan, M. (2004). Neighbourhood composition and residential land prices: Does exclusion raise or lower values? *Urban Studies, 41*(2), 299–315.

Chapple, K., & Jacobus, R. (2009). Retail trade as a route to neighborhood revitalization. *Urban and Regional Policy and its Effects, 2*(2), 19–68.

Chen, T. L., Chiu, H. W., & Lin, Y. F. (2020). How do east and southeast asian cities differ from western cities? A systematic review of the urban form characteristics. *Sustainability, 12*(6), 2423.

Chiang, Y. H., Peng, T. C., & Chang, C. O. (2015). The nonlinear effect of convenience stores on residential property prices: A case study of Taipei, taiwan. *Habitat International, 46*, 82–90.

Città di Torino. (1993). Assessorato all'urbanistica. http://geoportale.comune.torino.it/web/sites/default/files/mediafiles/Relazione_Illustrativa_volume_II_0.pdf.

Clark, T. N., Lloyd, R., Wong, K. K., & Jain, P. (2002). Amenities drive urban growth. *Journal of Urban Affairs, 24*(5), 493–515.

Copeland, M. T. (1923). Relation of consumers' buying habits to marketing methods. *Harvard Business Review, 1*(2), 282–289.

Curto, R. A., Fregonara, E., & Semeraro, P. (2012). Prezzi di offerta vs prezzi di mercato: un'analisi empirica. Asking Prices vs Market Prices: An Empirical Analysis. *Territorio Italia, 12*(1), 53–72.

Dudey, M. (1990). Competition by choice: The effect of consumer search on firm location decisions. *The American Economic Review, 80*(5), 1092–1104.

Eaton, B. C., & Lipsey, R. G. (1975). The principle of minimum differentiation reconsidered: Some new developments in the theory of spatial competition. *The Review of Economic Studies, 42*(1), 27–49.

Fotheringham, A. S., Brunsdon, C., & Charlton, M. E. (2009). Geographically weighted regression. *The Sage handbook of spatial analysis, 1*, 243–254.

Franklin, J. P., & Waddell, P. (2003). A hedonic regression of home prices in King County, Washington, using activity-specific accessibility measures. In *Proceedings of the transportation research board 82nd annual meeting* (Washington, DC).

Glaeser, E. L., Kolko, J., & Saiz, A. (2001). Consumer city. *Journal of Economic Geography, 1*(1), 27–50.

Groothuis, P. A., & Miller, G. (1994). Locating hazardous waste facilities: The influence of NIMBY beliefs. *The American Journal of Economics and Sociology, 53*(3), 335–346.

Handy, S. L., & Niemeier, D. A. (1997). Measuring accessibility: An exploration of issues and alternatives. *Environment and Planning A, 29*(7), 1175–1194.

Hidalgo, C. A., Castañer, E., & Sevtsuk, A. (2020). The amenity mix of urban neighborhoods. *Habitat International, 106*, Article 102205.

Hirt, S. (2012). Mixed use by default: How the Europeans (don't) zone. *Journal of Planning Literature, 27*(4), 375–393.

Ingene, C. A. (1984). Structural determinants of market potential. *Journal of Retailing, 60*(1), 37–64.

Jacobs, J. (1961). *Death and life of great American cities*. New York: Random House.

Jang, M., & Kang, C. D. (2015). Retail accessibility and proximity effects on housing prices in Seoul, Korea: A retail type and housing submarket approach. *Habitat International, 49*, 516–528.

Jeanty, P. W., Partridge, M., & Irwin, E. (2010). Estimation of a spatial simultaneous equation model of population migration and housing price dynamics. *Regional Science and Urban Economics, 40*(5), 343–352.

Kang, C. D. (2018). Valuing spatial access to types of retail and effects on the housing price in Seoul, Korea. *Journal of Urban Planning and Development, 144*(2), Article 05018007.

Knaap, G., & Talen, E. (2005). New urbanism and smart growth: A few words from the academy. *International Regional Science Review, 28*(2), 107–118.

Koster, H. R., & Rouwendal, J. (2012). The impact of mixed land use on residential property values. *Journal of Regional Science, 52*(5), 733–761.

Lang, R. E., & LeFurgy, J. (2003). Edgeless cities: Examining the noncentered metropolis. *Housing Policy Debate, 14*(3), 427–460.

Li, M. M., & Brown, H. J. (1980). Micro-neighbourhood externalities and hedonic housing prices. *Land Economics, 56*(2), 125–141.

Li, H., Wei, Y. D., & Wu, Y. (2019). Urban amenity, human capital and employment distribution in Shanghai. *Habitat International, 91*, Article 102025.

Liu, N., & Strobl, J. (2023). Impact of neighbourhood features on housing resale prices in Zhuhai (China) based on an (M) GWR model. *Big Earth Data, 7*(1), 146–169.

Ma, S., Li, T., & Yang, Y. (2022). Housing price appreciation effects of elevator installation in old residential areas: Empirical evidence based on a multiperiod DID model. *Advances in Civil Engineering, 2022*.

Matthews, J. W., & Turnbull, G. K. (2007). Neighbourhood street layout and property value: The interaction of accessibility and land use mix. *The Journal of Real Estate Finance and Economics, 35*, 111–141.

Mazzitelli, F., & Moine, B. (2022). Statistiche regionali Il mercato immobiliare residenziale. https://www.agenziaentrate.gov.it/portale/documents/20143/4504990/SR2022_Piemonte.pdf/e9ba4e4b-8375-61e9-ad85-26f38922344e#:~:text=La.

Nelson, A. C., Genereux, J., & Genereux, M. (1992). Price effects of landfills on house values. *Land Economics, 68*(4), 359–365.

Öner, Ö. (2017). Retail city: The relationship between place attractiveness and accessibility to shops. *Spatial Economic Analysis, 12*(1), 72–91.

Oshan, T. M., Li, Z., Kang, W., Wolf, L. J., & Fotheringham, A. S. (2019). Mgwr: A Python implementation of multiscale geographically weighted regression for investigating process spatial heterogeneity and scale. *ISPRS International Journal of Geo-Information, 8*(6), 269.

Páez, A., Long, F., & Farber, S. (2008). Moving window approaches for hedonic price estimation: An empirical comparison of modelling techniques. *Urban Studies, 45*(8), 1565–1581.

Partridge, M. D., Rickman, D. S., Ali, K., & Olfert, M. R. (2010). Recent spatial growth dynamics in wages and housing costs: Proximity to urban production externalities and consumer amenities. *Regional Science and Urban Economics, 40*(6), 440–452.

Pivo, G., & Fisher, J. D. (2011). The walkability premium in commercial real estate investments. *Real Estate Economics, 39*(2), 185–219.

Rivera-Batiz, F. L. (1988). Increasing returns, monopolistic competition, and agglomeration economies in consumption and production. *Regional Science and Urban Economics, 18*(1), 125–153.

Rose, D., Germain, A., Bacqué, M. H., Bridge, G., Fijalkow, Y., & Slater, T. (2013). 'Social mix'and neighbourhood revitalization in a transatlantic perspective: Comparing local policy discourses and expectations in Paris (France), Bristol (UK) and Montréal (Canada). *International Journal of Urban and Regional Research, 37*(2), 430–450.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34–55.

Sander, H. A., & Polasky, S. (2009). The value of views and open space: Estimates from a hedonic pricing model for Ramsey County, Minnesota, USA. *Land Use Policy, 26*(3), 837–845.

Schmidt, S., & Buehler, R. (2007). The planning process in the us and Germany: A comparative analysis. *International Planning Studies, 12*(1), 55–75.

Schuetz, J., Kolko, J., & Meltzer, R. (2012). Are poor neighborhoods "retail deserts". *Regional Science and Urban Economics, 42*(1–2), 269–285.

Scitovsky, T. (2013). *Welfare & competition* (Vol. 103). Routledge.

Seo, K., Golub, A., & Kuby, M. (2014). Combined impacts of highways and light rail transit on residential property values: A spatial hedonic price model for Phoenix, Arizona. *Journal of Transport Geography, 41*, 53–62.

Sevtsuk, A. (2014). Location and agglomeration: The distribution of retail and food businesses in dense urban environments. *Journal of Planning Education and Research, 34*(4), 374–393.

Shrestha, N. (2020). Detecting multicollinearity in regression analysis. *American Journal of Applied Mathematics and Statistics, 8*(2), 39–42.

Song, Y., & Knaap, G. J. (2003). New urbanism and housing values: A disaggregate assessment. *Journal of Urban Economics, 54*(2), 218–238.

Song, Y., & Sohn, J. (2007). Valuing spatial accessibility to retailing: A case study of the single family housing market in Hillsboro, Oregon. *Journal of Retailing and Consumer Services, 14*(4), 279–288.

Su, S., He, S., Sun, C., Zhang, H., Hu, L., & Kang, M. (2021). Do landscape amenities impact private housing rental prices? A hierarchical hedonic modeling approach based on semantic and sentimental analysis of online housing advertisements across five Chinese megacities. *Urban Forestry and Urban Greening, 58*, Article 126968.

Taramino, R. (2021). *Consumers, city networks and commercial patterns* [Doctoral thesis (Politecnico di Torino).

Wang, Y., Potoglou, D., Orford, S., & Gong, Y. (2015). Bus stop, property price and land value tax: A multilevel hedonic analysis with quantile calibration. *Land Use Policy, 42*, 381–391.

Wen, H., Zhang, Y., & Zhang, L. (2014). Do educational facilities affect housing price? An empirical study in hangzhou, China. *Habitat International, 42*, 155–163.

Wu, C., Ye, X., Du, Q., & Luo, P. (2017). Spatial effects of accessibility to parks on housing prices in Shenzhen, China. *Habitat International, 63*, 45–54.

Yang, H. J., Song, J., & Choi, M. J. (2016). Measuring the externality effects of commercial land use on residential land value: A case study of Seoul. *Sustainability, 8*(5), 432.

Zhang, L., Zhou, J., & Hui, E. C. M. (2020). Which types of shopping malls affect housing values? From the perspective of spatial accessibility. *Habitat International, 96*, Article 102118.

Zhao, P. (2010). Sustainable urban expansion and transportation in a growing megacity: Consequences of urban sprawl for mobility on the urban fringe of Beijing. *Habitat International, 34*(2), 236–243.

Zukin, S., & Kosta, E. (2004). Bourdieu Off-Broadway: Managing distinction on a shopping block in the east village. *City & Community, 3*(2), 101–114.