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Railway Accessibility and Property Values around Stations in Italy: HPM–SUR Evidence on Residential and Commercial Prices and Rents

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Abstract

This dissertation develops a station-level, policy-oriented econometric framework to quantify how railway accessibility, and urban context are capitalized into real-estate outcomes in Italy. Using a 2023 cross-sectional dataset of 985 stations, it estimates hedonic models for four segments (residential purchase/rent and commercial purchase/rent) and applies hybrid log–level Seemingly Unrelated Regression (SUR) to compare purchase and rental capitalization and test cross-equation differences.

Composite indicators capture rail centrality, long-distance supply, multimodal integration, and residential attractiveness. Results show that GDP per capita and tourism context are strongly associated with higher prices and rents. Accessibility is consistently valued, but through different channels: purchase prices respond more to structural connectivity, while rents respond more to day-to-day usability, especially service intensity and multimodal convenience. Car-oriented catchments are penalized in residential markets, whereas shared mobility and active-access provisions generate measurable uplifts.

To support implementation, SUR estimates are translated into decision-ready policy scenarios for Local station contexts, reporting baseline predictions and lever-based deltas in €/sqm and €/sqm/year (also scaled to € per 100 m^2). The scenario tables enable RFI and Sistemi Urbani to prioritize interventions and design value-capture strategies, while emphasizing the need to pair high-uplift interventions with affordability safeguards to avoid gentrification.

Keywords: hedonic modelling; Seemingly Unrelated Regression (SUR); railway stations; accessibility; purchase prices and rents; multimodal integration; policy scenarios; land value capture.

Abstract Italiano

Questa tesi sviluppa un framework econometrico, a scala di stazione e orientato alle politiche pubbliche, per quantificare come accessibilità ferroviaria, posizionamento nella rete e contesto urbano si capitalizzino nei risultati del mercato immobiliare in Italia. Utilizzando un dataset nazionale cross-section (2023) su 985 stazioni, l'analisi stima modelli edonici per quattro segmenti (acquisto/locazione residenziale e acquisto/locazione commerciale) e applica sistemi Seemingly Unrelated Regression (SUR) in specificazione ibrida log–level per confrontare la capitalizzazione tra acquisto e locazione e testare differenze tra equazioni.

Indicatori compositi rappresentano centralità ferroviaria, offerta a lunga percorrenza, integrazione multimodale e attrattività residenziale. I risultati mostrano che PIL pro capite e contesto turistico sono fortemente associati a prezzi e canoni più elevati. L'accessibilità è valorizzata in modo sistematico, ma attraverso canali distinti: i prezzi di acquisto rispondono maggiormente alla connettività strutturale, mentre i canoni riflettono soprattutto l'usabilità quotidiana, in particolare l'intensità del servizio e la convenienza multimodale. I contesti car-oriented risultano penalizzati nei mercati residenziali, mentre soluzioni di mobilità condivisa e di accessibilità attiva generano uplift misurabili.

A supporto dell'implementazione, le stime SUR sono tradotte in scenari di policy per contesti di stazioni Local, riportando livelli baseline e variazioni (delta) in €/mq e €/mq/anno (e scalando gli impatti in € per 100 m^2). Le tabelle di scenario consentono a RFI e Sistemi Urbani di prioritizzare interventi e definire strategie di value capture, evidenziando la necessità di accompagnare gli interventi ad alto uplift con misure di tutela dell'accessibilità economica per evitare fenomeni di gentrificazione.

Parole chiave: modellazione edonica; Seemingly Unrelated Regression (SUR); stazioni ferroviarie; accessibilità; prezzi e canoni; integrazione multimodale; scenari di policy; land value capture.

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Introduction

The impact of transport infrastructure on real-estate values is a key component of land value–capture policies, which are emerging as an innovative form of infrastructure funding [1]. Accessibility improvements (e.g., via the opening of a new station, or via the enhancement of services provided) can generate a wide array of benefits to transport and non-transport users. Direct impacts are mainly reflected by changes in generalized transport costs for users, while indirect effects are those transmitted to external systems and to both transport and non-transport users. The arising of these indirect effects, known as Wider Economic Impacts (WEIs), occurs because the transport system, being an imperfect market, cannot capitalize the full benefit (or cost) of investment (or divestment) in infrastructure and services; thus, part of the change is absorbed by external systems such as the labour market and the real-estate market, affecting job opportunities, wages, agglomeration, prices, and location choices [2].

Real-estate markets are therefore a common focus of WEIs studies, as proximity to high-quality transit and urban amenities is often associated with higher property values [3]. However, the magnitude, and sometimes the direction, of capitalization effects can vary widely across contexts, market segments, and tenure forms. Beyond residential housing, station areas also host retail and service activities whose values depend on customer footfall, accessibility and agglomeration economies, making commercial property markets an additional channel through which WEIs may materialize.

Across studies, explanatory variables adopted in hedonic price modelling generally fall into four categories: (i) property characteristics, (ii) land-use features, (iii) accessibility to transport and urban amenities, and (iv) socioeconomic context characteristics. Table 1 summarizes the variables most frequently used in the literature, with accessibility-related measures, particularly rail services, major road networks and public transport facilities, consistently emerging as key contributors to price formation [4]. Empirical evidence supports a positive relationship between railway accessibility and housing prices: Chen et al. [5] find that housing prices increase as the distance between residential properties and high-speed railway stations decreases, while Bao and Mok [6] show price increases after the opening of the Guangzhou–Shenzhen–Hong Kong express rail link.

In addition to accessibility-related variables, economic and social indicators, such as GDP per capita and income levels, are often included in model specifications, underscoring their contextual role in shaping market responses. Di Ruocco [7,8] further highlights that population size, income per capita, and employment rates contribute significantly to higher residential property prices in areas located near transit stations. Similar mechanisms can apply to commercial markets, where local income and tourism influence retail demand and willingness to pay for centrally located space.

Table 1: Variable Taxonomy from the Hedonic Real-Estate Literature: Built Form, Land Use, Accessibility, and Socioeconomic Context

Variable category	Variable	Sources
Property characteristics	Area size, floor area, lot size, gross building, # stories	[3,4,9–22]
	Central air conditioning and facilities (garage, view, pool)	[3,4,9,11,12,15,20,23]
	House age; building grade	[4,9,10,12–15,17–20,23–26]
	# rooms; # bedrooms; # bathrooms; # stories	[3,4,9,10,12–14,19,20,22,23,25,27]
Land use features	Greening ratio; % covered by trees; air/noise pollution	[15,19,23]
	Street frontage	[3,24,26]
	Road characteristics (width; # intersections) Parking facilities	[20,23,24,26]
	Zoning: commercial; residential	[13,19,21,24,26,28]
	Land-use pattern: mixed use	[4,13,19,21,23]
Accessibility to transport and urban amenities	Distance to HSR station/ Walking distance along street network to railway station	[3,4,10–12,14–16,19–23,25–29]
	Distance to main road	[10,14,17,19,27]
	Distance to light railway line	[9–12,14–17,20,23,27]
	Distance from highway	[12,13,15,18,19,23,26,27,29]
	Distance from highway exit	[12,15]

	Distance to bus/metro stop; BRT	[3,4,9,11–14,16–20,23,27]
	Distance to city center / CBD	[3,4,9,12–15,17,18,22,24–29]
	Distance to school	[12,13,18–20,28]
	Distance to park	[5,7,30–37]
	Distance to cultural attractions	[13,20]
	Distance to river / located at the beach	[3,4]
	Distance to hospital / medical center	[13,17,19]
	Located in provincial capital / city center	[3,4,12,19]
	Job accessibility	[3,17]
	Nearest study station	[4,13,16,18,20,28]
Socioeconomic context	% housing units occupied by renters / homeowners	[9,12,13,25,29]
	% college-educated	[4,12,16]
	Population density; population growth rate	[3,4,9,15,17,25]
	Income; median income	[4,9,10,12,16,17,25,26,38]
	Employment density	[3,13,17,23,29,38]
	Violent/property crime rate; crime density	[4,9,16,20,25,29,38]
	Race/ethnicity (% White, Asian, Black; minority %)	[3,10,12,13,16,17,27,29]
	Tax rate	[16]

Despite extensive international research, macro-scale analyses of railway stations' impacts remain limited in Italy. Challenges include fragmented institutional data, inconsistent datasets, and limited nationwide coverage, leading to reliance on localized case studies. By contrast, countries such as Germany benefit from integrated, georeferenced housing and socioeconomic datasets, enabling robust and systematic analyses [39]. In the Italian context, recent evidence by Di Ruocco et al. [40] for a set of high-speed-rail cities suggests that residential properties near major stations can exhibit measurable price premiums, but comprehensive assessments that also cover ordinary stations, rental markets and commercial segments are still scarce.

To address this gap, this thesis models the influence of railway stations on surrounding real-estate values through a national dataset of 985 Italian railway stations, combining station-level information on railway and multimodal services, municipal socioeconomic features, and local land-use and accessibility measures. Four Multiple Linear Regression (MLR) models are estimated, residential price, residential rent, commercial purchase price and commercial rent, integrating both observed variables and latent constructs. A further Seemingly Unrelated Regression (SUR) framework is used to directly compare the capitalization of shared determinants between purchase and rental markets within each sector, testing whether the same attribute is valued differently by buyers versus tenants.

The remainder of the thesis is structured as follows: Section 1 describes the dataset and modelling strategy, including the construction of latent variables and the model estimation workflow. Section 3 presents results for the four MLR models and the joint SUR comparisons between purchase prices and rents. The final sections discuss policy-relevant implications for station-area development and provide concluding remarks, limitations and directions for future research.

Methods and Data

Section 1 is organized as follows: the dataset used for model estimation is described in sub-section 1.1; the representativeness of the dataset with respect to "station population" is discussed in sub-section 1.2, while the methodological approach is introduced in sub-section 1.3.

The Dataset

The cross-sectional dataset provides a comprehensive representation of railway stations and their surrounding contexts in Italy, at year 2023. It includes 985 railway stations, corresponding to approximately 43% of the total stations managed by Rete Ferroviaria Italiana (RFI), the national railway infrastructure manager. Each observation in the dataset refers to a single station and its surroundings, described through a set of variables related to three main categories:

- Railway services and multimodal accessibility,
- Socio-economic context (at the municipal level),
- Land-use features.

The data extraction process involved clipping an area with a 1 km radius from every station, with the purpose of approximating a 15-minutes pedestrian isochrone that defines in order to define the station’s surroundings. Data on land-use features was extracted, as well as on railway and multimodal transport services considering the station itself. Additionally, municipal-level socioeconomic variables, namely GDP per capita and tourist orientation, were extracted from national open-source data sources1.

Residential real estate prices in the stations’ surroundings (variable name: “compr_res”) were instead extracted from the Osservatorio del Mercato Immobiliare (OMI) database2. The extracted values average at around 1,280 €/m², showing a slight overall variability across the dataset (standard deviation accounts to 750.9 €/m²).

Each station features a classification label, as defined by RFI, which reflects the relative importance, size, and functionality of each railway node in the national transport system. Classes range from Main Hubs, the major national or international hubs, to Local stations, serving primarily regional or commuter traffic. Intermediate categories include Hub, Major, Plus, and Local Plus.

Residential property prices vary systematically across station classes. Higher-tier stations (Hub and Major) are associated with higher average prices, while lower-tier stations (Local Plus and Local) exhibit lower prices. This pattern reflects a clear price gradient corresponding to station hierarchy, indicating that proximity to more important stations is linked to higher property values. Additionally, it is worth noting that, as per the multimodal service analysis presented in Figure 1, high-tier stations are located in denser and more populated urban centers, where demand for housing is high, and so are prices.

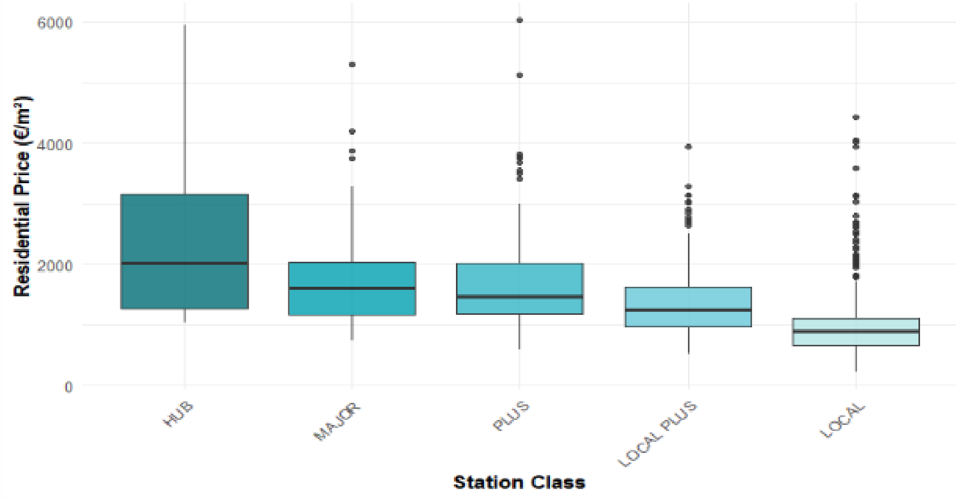

Figure 1: Distribution of Residential Property Prices (€ / sqm) by Station Class

Table 2 provides an overview of the variables describing railway services and multimodal accessibility, extracted for each station in the dataset. The number of daily trains per service type is present; these are: "Regionale" (train_reg), "Regionale Veloce" (train_regv), "InterCity" (train_ic), "Alta Velocità" (train_av). These service types represent the incremental service offer that national and regional railway operators provide at each station, and they are hereby presented in order: from the most basic service ("Regionale", the short-distance, commuter service), to the most exclusive one ("Alta Velocità", the long-distance, high-speed, business travel service).

"Regionale" train frequencies show substantial variation across stations, with a mean of 37, and a maximum of 363, indicating that some stations function as major regional hubs while many serve more limited services. In contrast, "Alta Velocità" (AV) and "InterCity" (IC) trains are less frequent at most stations, with first quartile values of zero, reflecting the concentration of these services at a smaller number of major stations, though maximum values reach 89 AV and 35 IC trains, respectively, for the busiest nodes.

The combined railway service offering that each stations has, together with its placement in the national network, is reflected in the train catchment area attribute, which measures the number of stations reachable within a one-hour threshold. The average catchment area is 17.

Regarding multimodal accessibility, stations can be characterized by the presence of car-sharing and bike-sharing services, along with dedicated parking spaces bikes and for taxis.

Car-sharing services are present at roughly 12.89% of stations, while bike-sharing services and dedicated bike parking are less common, available at 3.45% and 7.61% of stations. Taxi parking is slightly more widespread, present at about 11.88% of stations.

Table 2: Description of the dataset features related to railway services and multimodal accessibility

Variable	Description	Type	Summary Statistics
Train_reg	Daily frequency of "Regionale" trains	num.	Q1 = 15; Mean =37; Q3 = 42; Max = 363
Train_regv	Daily frequency of "Regionale Veloce" trains	num.	Q1 = 0; Mean =3.3; Q3 = 1; Max = 126
Train_ic	Daily frequency of "InterCity" trains	num.	Q1 = 0; Mean = 1.32; Q3 = 0; Max = 35
Train_av	Daily frequency of "Alta Velocità" trains	num.	Q1 = 0; Mean = 0.67; Q3 = 0; Max = 89
catchment_train	Train catchment area (stations reachable within 1h)	num.	Q1 = 7; Mean = 17; SD = 14.7; Q3 = 23
sharing_car	Availability of car-sharing services	Dummy (0/1)	Count(1) = 127; Share = 12.89%
sharing_bike	Availability of bike-sharing services	Dummy (0/1)	Count(1) = 34; Share = 3.45%
parking_bike	Availability of dedicated bike parking spaces	Dummy (0/1)	Count(1) = 75; Share = 7.61%
taxi_parking	Availability of dedicated taxi parking spaces	Dummy (0/1)	Count(1) = 117; Share = 11.88%

As expected, shared mobility services are mostly found at higher-tier stations, reflecting the contemporary urban mobility supply of services. Interestingly, residential prices tend to be higher where these services are available (Figure 2).

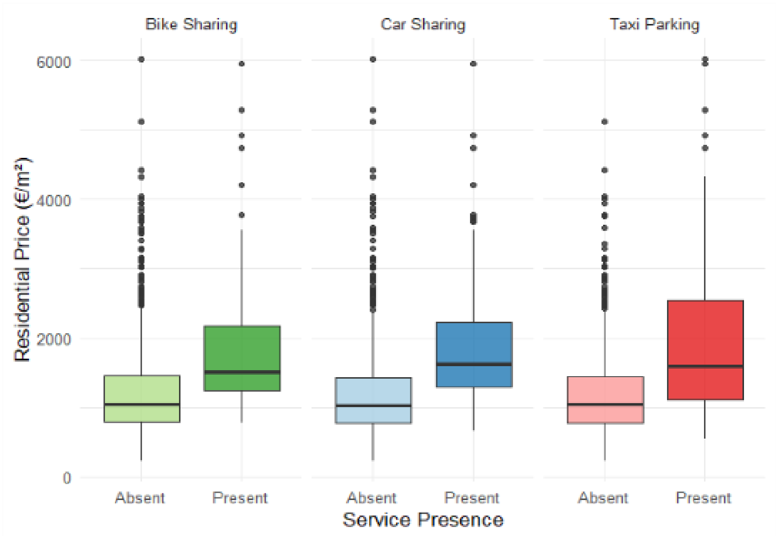

Figure 2: Impact of Multimodal Services and Facilities on Residential Real Estate Values (Distribution).

The socioeconomic context variables are shown in Table 3. They represent municipal-level features, namely GDP per capita and tourist orientation. The latter attribute represents the predominant nature of tourism that a specific municipality experiences. A total of 12 different classes are identified: ranging from big cities and areas with low or no tourist significance, to area with a seaside, cultural, or mountain tourism orientation. The largest share of stations (52%) falls into the "non-touristic" category.

The inclusion of tourist orientation aims to account for the strong heterogeneity in tourism-related attractiveness that characterizes the Italian context. Several railway stations serve municipalities experiencing substantial tourist flows (e.g., Venezia_Santa Lucia, Roma Termini), and distinguishing between touristic and non-touristic contexts was therefore deemed relevant for modelling residential property values. Tourist orientation data were obtained from the Italian National Statistical Institute (ISTAT), which provides a detailed classification of municipalities based on their dominant tourism type. For representativeness and statistical robustness, some of the original ISTAT categories were aggregated into broader classes. While this aggregation reduces the level of detail in capturing tourism characteristics at the municipal level, it allows for a more consistent and robust representation of tourism type across the national dataset.

An additional limitation concerns the absence of detailed information on tourism intensity (e.g., number of visitors or overnight stays) at a spatial resolution suitable for the scope of this analysis. Consequently, the tourism variable captures the predominant type of tourism rather than its magnitude.

Further data limitations were encountered in relation to socioeconomic variables capturing territorial disparities between Northern and Southern Italy. Although regional controls were tested, they did not emerge as statistically significant and were therefore not retained in the final model specification.

This feature was added to attempt to model the variety in tourist attraction that a country like Italy has. Indeed, some railway stations serve particularly high flows of tourists per year (e.g., Venezia Santa Lucia, Roma Termini) and thus it was deemed relevant to distinguish stations that are not located in touristic areas and those that are. In the former case, the availability of data from the Italian National Statistical Institute (ISTAT) allowed to obtain a fine-grained characterization of the touristic nature of each municipality, adding detail to the socioeconomic context in which each station is located in.

Table 3: Description of the dataset features related to the socioeconomic context

Variable	Description	Type	Summary statistics
gdp_per_capita	Municipal GDP per capita	Continuous (€/person)	Q1 = 25,651; Mean = 32,865; SD = 9,737.9; Q3 = 37,794
Tourist_Orientation	Tourist orientation	Categorical	Non-touristic: 516 (52%); Seaside: 240 (24%); Cultural: 140 (14%); Big City: 60 (6%); Mountain: 29 (3%)

The land use features (Table 4) describe the local context surrounding each railway station. Catchment areas describe the spatial reach of different transport modes in a relatively given time constraint. The 20 min car catchment area is the largest among modes, averaging 217 km², while bicycle and walking catchment areas (both in 15min thresholds) are much smaller, highlighting the different mobility ranges. Although perceptions of catchment areas related to active mobility have been identified in the literature as relevant (see, for instance [41,42]), it is worth nothing that the dataset contains, in this respect, only objective and directly measured data. Proximity to key urban attraction poles is also considered, namely distances to hospitals and universities. Similarly, public amenities such as services, schools, and commercial activities are counted around each station. Total number of residents and employees is also included.

Table 4: Description of the dataset features related to land-use.

Variable	Description	Type	Summary Statistics

catchment_car	Size of car catchment area in 20 min	Continuous (km^2)	Q1 = 133.6; Mean = 217.1; SD = 102.2; Q3 = 294
catchment_bike	Size of bicycle catchment area in 15 min	Continuous (km^2)	Q1 = 5.7; Mean = 8.4; SD = 3.7; Q3 = 11.1
catchment_walk	Walking catchment area in 15 min	Continuous (km^2)	Q1 = 1.2; Mean = 1.6; SD = 0.5; Q3 = 1.9
bike_lanes	Total bike lane extention	Continuous (km)	Q1 = 0; Mean = 1.2; SD = 2.12; Q3 = 1.62
parking_private	Total parking surface	Continuous (m^2)	Q1 = 573; Mean =1738; SD = 882; Q3 = 2509
dist_to_hospital	Distance to nearest hospital	Continuous (m)	Q1 = 1,411.2; Mean = 6,903.9; SD = 8,830.6; Q3 = 8,455.5
dist_to_edu	Distance to nearest school or educational facility	Continuous (m)	Q1 = 5,537; Mean = 15,986; SD = 13,685; Q3 = 22,907
services	Number of general services around the station	(#)	Q1 = 2; Mean = 16.01; Q3 = 20
commerce	Number of commercial activities near the station	(#)	Q1 = 28; Mean = 165.6; Q3 = 193
school	Number of schools around the station	(#)	Q1 = 1; Mean = 6.18; Q3 = 8
jobs	Estimated number of jobs around the station	(#)	Q1 = 208; Mean = 1,970; Q3 = 2,211
res	Resident population around the station	(#)	Q1 = 841; Mean = 4,761; Q3 = 6,475

edu	Presence of a university	Dummy (0/1)	Count(1) = 37; Share = 3.76%

Comparison Between the Sample and the Population

Table 5 compares the distribution of stations in the sample database with the full RFI network. No Main Hub stations are included due to their very small number in the RFI network (<30), which would imply handling an unrepresentative sample for the purpose of this work.

Table 5: Comparison between the sample dataset (985 observations) and the full RFI network across station classes.

Station Class	Sample Dataset	Sample Dataset [%]	RFI Network (Population)	RFI Network (Population) [%]
Main Hub	0	0%	25	1%
Hub	32	3.25%	53	3%
Major	60	6.09%	114	6%
Plus	120	12.18%	242	12%
Local Plus	259	26.29%	518	25%
Local	514	52.18%	1104	54%

To assess geographic representativeness, Table 6 compares the spatial distribution of stations across Italian macro-areas (North, Center, South) between the sample and the full RFI network. The sample, as per the previous station class comparison, closely mirrors the full network: 51% of stations are in the North, 24% in the Center, and 25% in the South.

Table 6: Geographical comparison between the sample dataset (985 observations) and the full RFI network3.

Macro Area	Sample Dataset	Sample Dataset [%]	RFI Network (Population)	RFI Network (Population) [%]
Center	235	23.9%	561	24.15%
North	504	51.2%	1139	49.03%
South	246	25.0%	623	26.82%

Methodology

Railway stations influence socio-economic and land use dynamics through indirect and partly unobservable mechanisms (e.g., perceived accessibility, residential attractiveness, etc.), which are only partially reflected in observable characteristics (e.g., daily train frequencies, number of commercial services, etc.). To model these complex relationships, latent variable techniques are commonly employed, as they allow abstract and multidimensional constructs to be integrated into quantitative empirical models are often used, allowing for the integration of abstract and qualitative constructs into quantitative analyses.

This study adopts a Multiple Linear Regression (MLR) HPM framework, based on a Multiple Linear Regression (MLR) model that combines both observed and latent variables to estimate the impact of railway stations on residential property prices. Although MLR models may be limited in their ability to identify strict causal relationships, they offer a transparent, easily implementable, and highly replicable methodological approach, making them particularly suitable for empirical analyses aimed at extracting policy-relevant insights. To this Accordingly, several explanatory dimensions are modelled through a combination of observed variables and latent constructs derived from observed indicators using factor analysis techniques. end, several explanatory dimensions are modelled as latent variables derived from observed indicators through factor analysis techniques.

Latent variables are used to represent complex and non-directly observable concepts, such as station accessibility, or residential attractiveness, that are typically measured through multiple correlated indicators. The identification of these latent dimensions follows a two-step procedure.

First, Exploratory Factor Analysis (EFA) is employed to explore the underlying structure of the observed variables and to identify groups of indicators that exhibit common variance, suggesting the presence of shared latent constructs. Subsequently, Confirmatory Factor Analysis (CFA) is used to validate the resulting factor structure by explicitly specifying the relationships between observed indicators and their corresponding latent variables (i.e., the factor loadings).

Once estimated, the latent variables are then incorporated as explanatory features in the MLR model.

The MLR model aims to model housing ,purchase prices by a combination of observed variables and latent factors, reflecting both accessibility features of a railway hub and land use characteristics of its surroundings. The general specification can be expressed as:

$$Pi = \alpha + \sum_{k=1}^{K} \beta k Zik + \sum_{l=1}^{L} \gamma l LVil + \varepsilon i$$

Where:

- $\boldsymbol{Pi}$ is the estimated residential property price (in €/m²) of an area surrounding station i
- $\boldsymbol{\alpha}$ is the intercept
- $\boldsymbol{\beta k}$ and $\boldsymbol{\gamma l}$ are the estimated regression parameters
- $\boldsymbol{Zik}$ represent the observed variables
- $\boldsymbol{LVil}$ represent the latent variables derived from factor analysis
- $\boldsymbol{\varepsilon i}$ is the error term

Confirmatory Factor Analysis (CFA) was employed to identify and validate latent dimensions underlying transport supply, accessibility, and urban context variables. The CFA allowed assessing the internal coherence of each latent construct and the contribution of the observed indicators to the corresponding latent dimension. Table 7 reports the estimated CFA loadings, including both unstandardized and standardized coefficients. Latent variable scales are identified by fixing one loading per construct, and all estimated loadings are statistically significant ($p < 0.01$). Unstandardized loadings reflect the original measurement scale of the observed indicators and are reported for transparency purposes only. Standardized loadings are instead used to interpret the latent constructs and to construct the CFA-based composite latent variables included in the regression model. Model fit statistics from the CFA are reported for diagnostic purposes. As expected, given the large sample size, the chi-square test rejects the null hypothesis of perfect fit. Global fit indices indicate a moderate overall fit (CFI = 0.82; TLI = 0.80; RMSEA = 0.095; SRMR = 0.085), however it is worth mentioning that, in this research, the CFA is not intended as a fully-fledged structural equation model, but as a dimensionality-reduction tool supporting only the construction of latent variables used in the regression analysis.

Table 7: Confirmatory Factor Analysis (CFA) results – Unstandarized and standardized loadings

Latent construct	Observed indicator	Loading (unstandardized)	Loading (standardized)
Residential Attractiveness	res	1.000	0.041
	school	0.551	0.844
	commerce	19.082	0.968
	services	1.955	0.959
	train_reg	1.000	1.001

Railway Centrality & Connectivity	catchment_train	0.282	0.727
Long-distance Railway Supply	train_longhaul[4]	1.000	0.686
	train_regv	1.020	0.549
Sharing Services	taxi_parking	1.000	0.555
	sharing_car	1.201	0.644
	parking_bike	0.800	0.541
	sharing_bike	0.441	0.434
	bike_lanes	7.323	0.618
Distance to Attraction Poles	dist_to_hospital	1.000	0.548
	dist_to_edu	1.922	0.680

Variable Selection and Model Estimation Strategy

The selection of explanatory variables began with a theory-driven approach. Potential predictors were identified based on established theoretical frameworks and prior empirical literature relevant to the dependent variable. This ensured that model specification was conceptually grounded and avoided purely data-driven selection procedures that may lack interpretability.

Variables were included in the initial pool only if a clear theoretical rationale justified their relationship with the dependent variable. This step minimized omitted variable bias while preserving substantive interpretability of the regression coefficients.

Preliminary Data Exploration and Correlation Screening

Following theoretical identification, exploratory data analysis was conducted. Descriptive statistics were examined to assess distributional properties, detect outliers, and identify potential measurement inconsistencies.

A correlation matrix was computed to evaluate the bivariate associations between the dependent variable and candidate predictors, as well as among the predictors themselves. Variables exhibiting negligible correlation with the dependent variable and lacking strong theoretical justification were considered for exclusion. However, correlation screening was used only as a preliminary diagnostic tool and not as the sole selection criterion, given that multivariate relationships may differ from simple bivariate associations.

Initial Multiple Linear Regression Estimation

An initial Multiple Linear Regression (MLR) model was estimated using Ordinary Least Squares (OLS). This baseline model included all theoretically justified predictors. The purpose of this step was to evaluate joint explanatory power and assess the statistical significance of individual regression coefficients.

Variables with consistently insignificant coefficients (based on conventional significance thresholds) and limited theoretical support were considered for removal in order to improve model parsimony. Model fit was evaluated using R^2, adjusted R^2, and the F-statistic.

This step ensured that the retained model balanced explanatory capacity with statistical robustness.

Multicollinearity Diagnostics

To ensure stability and reliability of coefficient estimates, multicollinearity diagnostics were conducted. Variance Inflation Factors (VIFs) were calculated for each predictor variable. Variables exceeding acceptable VIF thresholds were carefully examined.

Where high multicollinearity was detected, corrective measures were implemented, including:

- Removing redundant variables,
- Combining conceptually similar variables,
- Re-specifying constructs.

Addressing multicollinearity was essential to avoid inflated standard errors and unstable parameter estimates.

Latent Variable Construction and Model Re-estimation

To better capture underlying theoretical constructs and potentially enhance explanatory power, latent variables were constructed from conceptually related observed indicators. These latent constructs were designed to represent broader dimensions not fully captured by individual variables.

The regression model was then re-estimated using a combination of:

- Latent variables representing aggregated theoretical constructs, and
- Retained observed variables with independent explanatory value.

To better represent the underlying theoretical constructs and reduce dimensionality among conceptually related observed variables, latent variables were constructed and validated using Confirmatory Factor Analysis (CFA).

Unlike exploratory approaches, CFA allows for theory-driven specification of the measurement model by explicitly defining the relationships between observed indicators and their corresponding latent constructs. In this study, each latent variable was specified a priori based on established theoretical foundations and prior empirical research. The measurement model assumed that each observed indicator loads onto its designated latent construct, while measurement errors remain uncorrelated unless theoretically justified.

This re-specification aimed to improve model fit (as reflected in adjusted R^2) while reducing dimensionality and multicollinearity. The comparative performance of models with and without latent constructs was systematically evaluated. Multicollinearity diagnostics were repeated after latent variable inclusion to ensure model stability.

Algorithmic Variable Selection Procedures

To complement the theory-driven approach and enhance model robustness, several algorithmic selection techniques were applied:

Forward Selection

Starting from an empty model, predictors were sequentially added based on predefined statistical criteria (e.g., p-value). This method allowed identification of variables that incrementally improved model fit.

Backward Elimination

Beginning with the full model specification, predictors were sequentially removed if they failed to meet statistical significance criteria. This approach facilitated the identification of redundant variables.

Stepwise Selection

A hybrid approach combining forward inclusion and backward elimination was implemented. Variables could enter or exit the model iteratively based on statistical thresholds, enabling dynamic optimization of model specification.

Best Subset Selection

Where computationally feasible, alternative model combinations were evaluated to identify the specification that optimized explanatory power and model parsimony according to information criteria.

The results of these procedures were compared against the theory-driven specification to ensure consistency and substantive interpretability. Final model selection was based on a combination of:

- Statistical significance,
- Adjusted R^2,
- Information criteria (P values, etc.),
- Multicollinearity diagnostics,
- Theoretical coherence.

MLR Model Results

This chapter presents the empirical results of the Multiple Linear Regression (MLR) models estimated to examine the determinants of property values in station areas. Building on the theoretical framework and the validated latent constructs obtained through Confirmatory Factor Analysis (CFA), the analysis investigates how transport accessibility, socioeconomic conditions, land-use characteristics, and urban centrality influence both residential and commercial real estate markets.

Four regression models are estimated and discussed:

1. Residential property prices
2. Residential rents
3. Commercial property prices
4. Commercial rents

Residential Purchase Price Model

Table 8 reports the multiple linear regression estimates for residential purchase prices in station areas and shows that housing values are systematically associated with a combination of socioeconomic conditions, rail accessibility, urban amenities, tourism pressure, and mobility-related proxies. (Adjusted $R^2 = 0.897$).

Table 8: Residential property price model (Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively).

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
res_attr	1.95E-01	4.90E-02	3.981	7.37E-05	***
long_dist_supply	8.48E+00	2.38E+00	3.563	0.000384	***
rail_centrality	4.15E+00	4.94E-01	8.404	< 2e-16	***
dist_attr_poles	-3.90E-03	1.23E-03	-3.170	0.001573	**
gdp_pc	3.60E-02	1.54E-03	23.341	< 2e-16	***
private_parking	-3.92E-03	9.17E-04	-4.281	2.05E-05	***
private_parking_Local	5.39E-03	2.35E-03	2.295	0.021919	*
sharing_local	6.42E+01	1.95E+01	3.299	0.001005	**

gdp_balneare	1.10E-02	1.44E-03	7.647	4.94E-14	***
gdp_nontour	-5.70E-03	1.16E-03	-4.907	1.09E-06	***
hotels_bnb	6.15E+00	8.70E-01	7.066	3.04E-12	***
car_majorhub	-1.38E+00	3.26E-01	-4.237	2.48E-05	***
catchment_car	-9.18E-01	1.55E-01	-5.912	4.67E-09	***
park_area	5.95E-04	1.90E-04	3.132	0.001791	**
taxi_parking	1.66E+02	5.83E+01	2.839	0.004619	**
X._centrale	1.32E+02	5.44E+01	2.423	0.015559	*
Multiple R-squared: 0.897, Adjusted R-squared: 0.8953					
F-statistic: 527.7 on 16 and 969 DF, p-value: < 2.2e-16					

The strongest structural driver is local income:

GDP per capita (gdp_pc) is positive and highly significant ($\beta = 0.0360$, $p < 2e-16$), indicating that higher purchasing power and stronger local demand are robustly capitalized into residential prices. However, the model also reveals heterogeneity in how income translates into housing values depending on city typology. The interaction gdp_balneare is positive and highly significant ($\beta = 0.0110$, $p < 0.001$), suggesting that in coastal/touristic contexts income growth amplifies real-estate demand—consistent with second-home dynamics and short-term rental investment, whereas gdp_nontour is negative and highly significant ($\beta = -0.00570$, $p < 0.001$), implying that in non-touristic cities the marginal effect of income on housing purchase prices is weaker or even negative, potentially because additional income is absorbed by other consumption or investment channels and housing demand is less speculative.

Rail-related variables display some of the most substantial accessibility premiums in the model. Rail network centrality (rail_centrality) is large and strongly significant ($\beta = 4.15$, $p < 2e-16$), indicating that stations more integrated in the network—offering broader connectivity and lower generalized travel costs—are associated with higher surrounding residential values. Similarly, long-distance supply (long_dist_supply) is positive and significant ($\beta = 8.48$, $p < 0.001$), implying that the presence of high-speed or long-distance services generates an additional premium by expanding access to national labour and activity markets and increasing the attractiveness of nearby residential locations.

Beyond rail, local living conditions and proximity to essential services also matter. Residential attractiveness (res_attr) is positive and significant ($\beta = 0.195$, $p < 0.001$), confirming that a higher concentration of schools, services, and commercial activities increases neighbourhood convenience and is capitalized into higher prices. In contrast, distance from attraction poles (dist_attr_poles) is negative and significant (β = −0.00390, p = 0.0016), showing that greater distance from key facilities such as hospitals and education reduces accessibility and lowers housing desirability. Environmental quality contributes as well: park_area is positive and significant (β = 0.000595, p = 0.0018), indicating a premium associated with proximity to green amenities.

Consistent with broader urban economics, central location (X._centrale) also raises prices (β = 132, p = 0.016), reflecting the concentration of accessibility and services in central areas that remains valuable even after controlling for specific rail and amenity variables. By contrast, car-oriented accessibility and peripheral morphology are penalized in the residential market.

catchment_car is negative and highly significant (β = −0.918, p < 0.001), suggesting that larger car catchments—typically associated with low-density, car-dependent station environments—are linked to lower purchase prices relative to transit-oriented or central contexts. Likewise, car_majorhub is negative and significant (β = −1.38, p < 0.001), consistent with the interpretation that in major hubs car accessibility correlates with congestion and environmental disamenities and reflects interchange functions rather than residential quality. The model also highlights an important context-dependent interpretation for parking. private_parking is negative and significant overall (β = −0.00392, p < 0.001), consistent with parking acting as a proxy for peripheral, car-oriented development, yet the interaction private_parking_Local is positive (β = 0.00539, p = 0.022), implying that in dense local station contexts parking may become a scarcity/quality attribute and therefore commands a premium. Finally, indicators of mobility service intensity and tourism accommodation strongly correlate with higher prices. sharing_local is positive and significant (β = 64.2, p = 0.001), indicating that shared mobility services in local contexts are associated with higher values—likely reflecting both last-mile accessibility improvements and the tendency of providers to concentrate where demand and centrality are high. taxi_parking is also positive and significant (β = 166, p = 0.0046), reinforcing the interpretation that taxi facilities act as a proxy for central, high-activity, highly accessible station areas.

hotels_bnb shows a strong positive association (β = 6.15, p < 0.001), consistent with tourism intensity increasing competition for space and increasing investment demand, thereby pushing up residential purchase prices.

Overall, Table 8 supports a coherent interpretation in which residential purchase prices near stations reflect a layered capitalization mechanism: macroeconomic strength sets the baseline, rail network connectivity and long-distance access generate substantial premiums, and centrality, amenities, green space, and multimodal service intensity further increase values, while car-dependent and hub-congested contexts are discounted; the significant interaction terms underscore that these relationships are not uniform but vary meaningfully across station and urban typologies.

Residential Rent Model (res_rent)

The second multiple linear regression model estimates the determinants of residential rental values. Table 9 reports the multiple linear regression estimates for residential rental values in station areas and indicates that rents are shaped by a combination of neighbourhood amenities, rail accessibility (both structural and service-based), socioeconomic conditions, tourism pressure, and car-oriented urban form

Table 9: Residential property rent model (Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively).

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
res_attr	7.25E-03	1.90E-03	3.808	0.000149	***
rail_centrality	6.62E-02	2.27E-02	2.915	0.003643	**
train_ic	3.47E-01	1.71E-01	2.023	0.04339	*
dist_attr_poles	-1.60E-04	4.81E-05	-3.326	0.000914	***
gdp_pc	1.23E-03	6.58E-05	18.730	< 2e-16	***
hotels_bnb	1.71E-01	3.44E-02	4.950	8.76E-07	***
sharing_local	3.09E+00	7.57E-01	4.080	4.88E-05	***
gdp_grandecitta	3.68E-04	8.28E-05	4.438	1.01E-05	***
gdp_balneare	4.15E-04	6.07E-05	6.829	1.50E-11	***
gdp_nontour	-2.17E-04	5.03E-05	-4.304	1.85E-05	***
car_majorhub	-3.74E-02	1.21E-02	-3.095	0.002024	**
catchment_car	-2.39E-02	6.20E-03	-3.853	0.000124	***
freq	3.33E+00	5.76E-01	5.775	1.04E-08	***
park_area	2.49E-05	7.59E-06	3.276	0.00109	**
Multiple R-squared: 0.9049, Adjusted R-squared: 0.9035					
F-statistic: 659.8 on 14 and 971 DF, p-value: < 2.2e-16					

The strongest structural driver remains local income: GDP per capita (gdp_pc) is positive and extremely significant ($\beta = 0.00123$, $p < 2e{-16}$; $t = 18.73$), confirming that higher purchasing power and stronger local demand are systematically reflected in higher rents. At the same time, the model highlights pronounced heterogeneity in how income is transmitted into the rental market depending on urban typology. The interaction gdp_grandecitta is positive and highly significant ($\beta = 0.000368$, $p < 0.001$), suggesting that in large metropolitan areas income growth translates more directly into rental willingness-to-pay, consistent with the concentration of students, professionals, and mobile workers who rely on rental housing and value central, well-served locations. Likewise, gdp_balneare is positive and highly significant ($\beta = 0.000415$, $p < 0.001$), indicating that in seaside and touristic cities income effects are amplified by seasonal demand, investment demand tied to tourism, and competition from short-term accommodation. In contrast, gdp_nontour is negative and significant ($\beta = -0.000217$, $p < 0.001$), implying that in non-touristic contexts marginal income growth is associated with a weaker or even negative marginal effect on rents, plausibly reflecting different tenure structures, lower external demand pressures, or demand being absorbed by other consumption/investment channels rather than rental housing.

Beyond macro conditions, local livability and daily-accessibility variables also matter. Residential attractiveness (res_attr) is positive and highly significant ($\beta = 0.00725$, $p < 0.001$), showing that renters pay more in neighbourhoods with higher concentrations of schools, services, and commercial activities, consistent with the importance of everyday convenience for tenants. Conversely, distance to attraction poles (dist_attr_poles) is negative and highly significant ($\beta = -0.000160$, $p < 0.001$), indicating that greater distance from key services such as hospitals and educational facilities reduces rental values, which aligns with the expectation that renters are particularly sensitive to daily accessibility constraints.

Environmental quality contributes positively as well: park_area is positive and significant ($\beta = 0.0000249$, $p = 0.0011$), suggesting a modest but systematic rent premium associated with proximity to green amenities.

Rail accessibility is consistently valued in the rental market, but the pattern of coefficients emphasizes short-term functional accessibility more than long-horizon network positioning. Rail centrality (rail_centrality) is positive and significant ($\beta = 0.0662$, $p = 0.0036$), implying that better-connected stations increase nearby rents by improving access to jobs and urban functions. The presence of InterCity services (train_ic) is also positive ($\beta = 0.347$, $p = 0.043$), suggesting that regional and medium/long-distance connectivity adds rental value, potentially reflecting renters who commute inter-city or value broader mobility options. Most notably, service frequency (freq) shows one of the largest positive effects in the model ($\beta = 3.33$, $p < 0.001$), indicating that renters place a strong premium on frequent services that reduce waiting time, uncertainty, and daily travel frictions; this reinforces the interpretation that tenants prioritize immediate, operational accessibility over purely structural network position.

Tourism intensity and accommodation pressure also strongly affect rents. The coefficient for hotels_bnb is positive and highly significant ($\beta = 0.171$, $p < 0.001$), consistent with tourism-driven competition between long-term rentals and short-term accommodation tightening housing supply and increasing willingness-to-pay in the rental market.

In parallel, sharing_local is positive and highly significant ($\beta = 3.09$, $p < 0.001$), indicating higher rents in local station areas where shared mobility services are present; this likely reflects a combination of improved last-mile accessibility and the tendency of such services to concentrate in central, high-demand neighbourhoods, meaning the variable also proxies urban intensity and service richness. Car-oriented variables show consistently negative associations, mirroring the ownership model and reinforcing the idea that rental demand is weaker in peripheral, car-dependent station environments. catchment_car is negative and highly significant (β = −0.0239, $p < 0.001$), implying that stations characterized by large car catchments—often reflecting low-density, automobile-oriented urban form—are associated with lower rents. Similarly, car_majorhub is negative and significant (β = −0.0374, p = 0.0020), suggesting that in major hubs, car-oriented conditions correlate with disamenities such as congestion, noise, and reduced pedestrian quality, making nearby residential locations less attractive for renters.

Taken together, Table 9 supports a coherent interpretation in which residential rents reflect a layered mechanism: macroeconomic strength sets the baseline demand, tourism and metropolitan contexts amplify (or dampen) income effects, rail accessibility matters strongly—especially through service frequency and practical mobility options—and neighbourhood amenities, green quality, and proximity to essential services further raise willingness-to-pay, while car-dependent and congested hub contexts are systematically discounted in the rental market.

Commercial Purchase Price Model

The multiple linear regression results show that commercial property prices are influenced by a combination of economic strength, accessibility, urban centrality, and service intensity.

Table 10: Commercial property price model (Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively).

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
commerce	3.78E-01	8.79E-02	4.298	1.90E-05	***
train_ic	1.27E+01	3.87E+00	3.275	1.10E-03	**
train_regv	-5.51E+00	1.75E+00	-3.147	1.70E-03	**
train_reg	1.15E+00	5.33E-01	2.157	3.12E-02	*
dist_attr_poles	-3.17E-03	1.10E-03	-2.874	4.14E-03	**
sharing_local	8.20E+01	1.70E+01	4.825	1.62E-06	***
gdp_pc	1.93E-02	1.40E-03	13.846	< 2e-16	***
hotels_bnb	7.04E+00	7.87E-01	8.945	< 2e-16	***
gdp_balneare	3.99E-03	1.29E-03	3.089	2.07E-03	**

gdp_nontour	-7.17E-03	9.98E-04	-7.180	1.38E-12	***
car_majorhub	-9.83E-01	2.72E-01	-3.617	0.000313	***
freq	1.02E+02	1.35E+01	7.552	9.86E-14	***
dist_to_centers	-3.18E-02	1.21E-02	-2.632	0.008616	**
X._centrale	2.40E+02	5.09E+01	4.706	2.90E-06	***
parking_private	-3.41E-03	8.50E-04	-4.009	6.58E-05	***
private_parking_ Local	6.41E-03	2.12E-03	3.024	0.002559	**
Multiple R-squared: 0.8684, Adjusted R-squared: 0.8662					
F-statistic: 399.7 on 16 and 969 DF, p-value: < 2.2e-16					

A core demand-side driver is local economic capacity: GDP per capita (gdp_pc) is positive and extremely significant ($\beta = 0.0193$, $p < 2e-16$; $t = 13.85$), indicating that wealthier local economies—through higher spending potential and stronger market demand—are associated with higher commercial purchase prices. This income effect is not homogeneous across contexts: gdp_balneare is positive and significant ($\beta = 0.00399$, $p = 0.0021$), suggesting that in coastal/touristic areas income growth translates more directly into commercial property demand, consistent with stronger visitor-driven expenditure and secondary demand for retail and services, whereas gdp_nontour is negative and highly significant ($\beta = -0.00717$, $p = 1.38e-12$), implying that in non-touristic contexts marginal income increases are associated with a weaker or negative marginal association with commercial purchase prices, potentially reflecting differences in demand composition, lower visitor flows, or spatial concentration of high-value commercial activity in tourism and core urban hubs rather than in all affluent areas.

Tourism intensity itself exerts a strong independent premium: hotels_bnb is positive and highly significant ($\beta = 7.04$, $p < 2e-16$; $t = 8.95$), indicating that areas with more hotels and short-term accommodation—used here as a proxy for tourism pressure and visitor density—are associated with higher commercial purchase values, consistent with greater footfall, stronger retail turnover potential, and investor expectations of sustained demand. In addition, agglomeration forces within the commercial system are clearly reflected: commerce is positive and highly significant ($\beta = 0.378$, $p < 0.001$), indicating that stations embedded in more commercially active environments command higher purchase prices, consistent with clustering benefits, customer catchment, and complementary demand among businesses.

Rail accessibility enters through differentiated service categories and reveals a nuanced pattern that is consistent with station typologies and local market structure. InterCity service availability (train_ic) has a large positive and significant coefficient ($\beta = 12.7$, $p = 0.0011$), suggesting that regional and national connectivity raises the long-term attractiveness of commercial locations by expanding market reach, improving access for visitors and customers, and increasing the strategic value of station areas for higher-order services. Standard regional services (train_reg) are positive though smaller (β = 1.15, $p = 0.031$), consistent with the role of conventional regional trains in supporting daily commuting flows and stable local commercial activity. In contrast, high-speed regional trains (train_regv) are negative and significant (β = −5.51, $p = 0.0017$). Holding overall service intensity (including frequency) and other train categories constant, this suggests that higher RegV presence is associated with lower commercial purchase values, which is plausibly explained by correlation with station archetypes where RegV services are concentrated—e.g., contexts with interchange or corridor functions, more peripheral built form, or less intense local commercial ecosystems—rather than implying that the service itself is intrinsically value-reducing; in other words, the coefficient likely reflects the urban and locational characteristics typically co-occurring with that service pattern once other supply measures are controlled for. Beyond structural connectivity, operational accessibility and multimodal convenience show strong positive effects. Service frequency (freq) is one of the largest positive coefficients and is highly significant (β = 102, p = 9.86e−14), indicating that high-frequency environments—reducing waiting time and improving reliability for workers, customers, and deliveries—are strongly capitalized into commercial purchase values.

Similarly, sharing_local is positive and highly significant (β = 82.0, p = 1.62e−06), implying that station areas with richer shared mobility ecosystems (e.g., bikes, car-sharing, taxis) command higher commercial values, consistent with easier last-mile access, broader customer reach, and higher urban activity intensity; as in many multimodal variables, this effect may reflect both functional accessibility and the tendency for shared services to locate in already high-demand areas. Proximity to major services also matters: dist_attr_poles is negative and significant (β = −0.00317, $p = 0.0041$), indicating that being farther from key attraction poles (such as hospitals and schools) reduces commercial purchase prices, consistent with lower trip generation and reduced local activity potential.

Urban centrality and spatial positioning show clear premiums and discounts. X._centrale is positive and highly significant (β = 240, p = 2.90e−06), confirming a strong central-location premium in commercial purchase markets, consistent with the concentration of employment, consumer flows, multimodal accessibility, and network effects in central areas. Conversely, dist_to_centers is negative and significant (β = −0.0318, $p = 0.0086$), indicating that commercial properties farther from urban centres are less valuable, plausibly due to weaker footfall and reduced accessibility to dense customer bases. Car-related variables reinforce the market penalty for car-dominated station environments, especially in hub contexts. car_majorhub is negative and highly significant (β = −0.983, $p = 0.000313$), suggesting that in major hubs, car dependence is associated with lower commercial purchase values, consistent with congestion, reduced pedestrian quality, and interchange-oriented infrastructure that may weaken retail attractiveness at the micro scale. Parking variables again illustrate context dependence. parking_private is negative and highly significant (β = −0.00341, $p < 0.001$), consistent with private parking acting as a proxy for suburban, car-oriented locations with lower walk-in footfall, whereas private_parking_Local is positive and significant (β = 0.00641, $p = 0.0026$), indicating that in local station contexts private parking can increase commercial value—likely because it improves practical accessibility for customers and employees where parking is scarce or because it supports mixed access modes in those settings.

Taken together, Table 10 indicates that commercial purchase prices capitalize both structural and operational determinants: structural forces such as local income, tourism intensity, urban centrality, and InterCity connectivity establish long-horizon commercial value, while operational accessibility variables such as frequency, shared mobility availability, proximity to attraction poles, and context-appropriate parking increase the day-to-day usability and market reach that support commercial performance. At the same time, the negative coefficients associated with car-dominated hub contexts and peripheral distance measures suggest that commercial property markets discount environments where accessibility is primarily car-based and where pedestrian-oriented activity intensity is weaker, reinforcing a general premium for central, well-served, multimodal station areas.

Commercial Rent Model (com_rent)

The commercial rent model highlights how short-term market dynamics and operational accessibility influence commercial rental values. Table 11 reports the multiple linear regression estimates for commercial rental values in station areas and highlights that commercial rents are primarily driven by short-term market competition and operational accessibility, with demand pressure and footfall-oriented indicators playing a central role.

Table 11: Commercial property Rent model (Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively).

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Significance
long_dist_supply	-3.22E-01	1.38E-01	-2.333	0.01987	*
commerce	2.86E-02	6.05E-03	4.721	2.69E-06	***
gdp_pc	6.16E-04	7.92E-05	7.780	1.85E-14	***
hotels_bnb	4.62E-01	5.68E-02	8.134	1.25E-15	***
gdp_grandecitta	7.12E-04	1.11E-04	6.441	1.86E-10	***
gdp_balneare	6.06E-04	7.99E-05	7.585	7.73E-14	***
dist_to_centers	-1.99E-03	8.46E-04	-2.353	0.01883	*
freq	9.08E+00	8.77E-01	10.356	< 2e-16	***

park_area	5.11E-05	1.21E-05	4.243	2.42E-05	***
parking_private	-1.52E-04	5.91E-05	-2.562	0.01054	*
private_parking_ Local	4.32E-04	1.52E-04	2.842	0.00457	**
Multiple R-squared: 0.8349, Adjusted R-squared: 0.833					
F-statistic: 447.7 on 11 and 974 DF, p-value: < 2.2e-16					

The strongest accessibility-related driver in the model is service frequency (freq), which is positive and extremely significant ($\beta = 9.08$, $p < 2e-16$; $t = 10.36$). This indicates that commercial tenants place a strong premium on locations where transport services are frequent, reflecting lower waiting time, higher reliability, and greater day-to-day accessibility for customers, employees, and deliveries.

In parallel, the positive and highly significant coefficient for commerce ($\beta = 0.0286$, $p < 0.001$) confirms that rents are higher where commercial activity is already concentrated, consistent with agglomeration and competition effects: dense commercial ecosystems signal strong customer flows and increase willingness-to-pay for space.

Socioeconomic strength further reinforces this demand channel. GDP per capita (gdp_pc) is positive and highly significant ($\beta = 0.000616$, $p = 1.85e-14$), indicating that wealthier local economies support higher commercial rents through greater spending power and stronger local demand. This income mechanism is amplified in specific urban contexts: **gdp_grandecitta** is positive and highly significant ($\beta = 0.000712$, $p = 1.86e-10$), suggesting that large metropolitan areas generate stronger commercial rental pressure due to larger markets, higher economic density, and intensified competition for central retail and service space. Likewise, gdp_balneare is positive and highly significant ($\beta = 0.000606$, $p = 7.73e-14$), implying that in coastal/touristic cities income growth is associated with stronger rent premiums, consistent with visitor-driven expenditure and seasonal peaks in demand.

Tourism intensity itself exerts a particularly strong effect: hotels_bnb is positive and extremely significant ($\beta = 0.462$, $p = 1.25e-15$), indicating that areas with higher concentrations of hotels and short-term accommodation—proxying tourist presence and transient demand—experience substantially higher commercial rents, consistent with intensified competition for space in visitor-oriented retail and service markets.

Spatial positioning also matters in ways consistent with footfall and centrality logic. dist_to_centers is negative and significant ($\beta = -0.00199$, $p = 0.0188$), indicating that commercial rents decrease as properties move farther from urban centres, where pedestrian flows, accessibility, and demand density tend to be lower.

Environmental quality shows a measurable premium as well: park_area is positive and highly significant ($\beta = 0.0000511$, $p = 2.42e-05$), suggesting that proximity to parks and green space can slightly increase commercial rents, plausibly through improvements in the attractiveness of the urban environment, higher pedestrian activity, and enhanced streetscape quality that benefits retail and service uses. Car-related variables again demonstrate context dependence. parking_private is negative and significant (β = −0.000152, p = 0.0105), suggesting that standalone private parking is associated with slightly lower rents, consistent with parking acting as a proxy for car-oriented environments where walk-in demand and high street intensity are weaker. However, the interaction private_parking_Local is positive and significant (β = 0.000432, p = 0.0046), implying that in local station contexts, parking provision can increase rents by improving immediate accessibility for customers and staff—particularly where parking is scarce or where mixed-mode accessibility is critical for commercial viability.

A notable difference between commercial rents and commercial purchase prices concerns the role of higher-order rail connectivity. long_dist_supply is negative and significant (β = −0.322, p = 0.0199), indicating that a greater supply of long-distance rail services is associated with slightly lower commercial rents once other factors are controlled for. This result is consistent with the interpretation that long-distance service provision—driven in part by service patterns such as fast regional trains—may characterize station contexts that are not necessarily dense commercial cores (e.g., corridor or interchange-oriented areas, more peripheral or transit-oriented locations), and therefore does not translate into immediate short-term rental premiums driven by local footfall and market competition. In other words, while long-distance connectivity may support long-horizon attractiveness (and may be capitalized more strongly into asset values), the rental market appears to prioritize local activity intensity and operational accessibility that directly support short-run commercial performance.

Overall, Table 11 suggests that commercial rents are fundamentally shaped by demand pressure (income, tourism, commercial intensity), centrality/footfall factors (distance to centres), and highly practical accessibility (frequency, local parking conditions), with long-distance rail supply playing at most a modest and context-dependent role in the rental market compared to these more immediate drivers.

Comparison of Purchase Prices vs Rents in Residential and Commercial Markets

This chapter investigates whether the determinants of property values differ systematically between ownership and rental markets within both residential and commercial sectors. While the previous chapter estimated separate Multiple Linear Regression (MLR) models for Purchase prices and rents, the present analysis moves beyond isolated estimations to formally compare structural effects across tenure types. Specifically, the chapter evaluates whether identical locational, accessibility, and socioeconomic attributes are capitalized differently into purchase prices and rents. To achieve this, a joint econometric framework is employed, allowing for cross-equation comparison and statistical testing of coefficient equality. This approach provides deeper insight into capitalization dynamics and potential segmentation between investment-driven and use-value-driven property markets.

To analyze the determinants of residential purchase prices and rents simultaneously, we employ a Seemingly Unrelated Regression (SUR) framework. The SUR approach allows us to estimate multiple equations jointly, accounting for potential correlations between the error terms of purchase and rental markets. This joint estimation increases efficiency compared to separate ordinary least squares regressions and provides a rigorous framework to compare structural effects across tenure types.

Residential Log-SUR Model

The SUR approach estimates multiple equations simultaneously, improving efficiency over separate ordinary least squares (OLS) regressions when residuals are correlated. Formally, the system is specified as:

$$\ln(\text{Price}_i) = \beta_1 \ln\left(X_{1,i}\right) + \beta_2 D_i + \epsilon_{1,i}$$

$$\ln(\text{Rent}_i) = \beta_1 \ln\left(X_{1,i}\right) + \beta_2 D_i + \epsilon_{2,i}$$

Where:

- Yi = dependent variable (either residential purchase price or rent)
- $\ln(X1, i)$= strictly positive continuous regressors in logarithmic form (elasticities)
- Di = dummy or level variables (semi-elasticities)
- $\beta 1, \beta 2$ = coefficients to be estimated
- ϵi = error term, potentially correlated across SUR equations

Given the nature of the variables, a hybrid log-level specification is adopted. Strictly positive continuous variables, such as GDP per capita, residential attractiveness, and distances to services, are log-transformed to directly estimate elasticities, allowing a percentage change interpretation. Binary or level variables, such as private parking or the presence of transport services, are kept in levels to estimate semi-elasticities, which can be interpreted as the approximate percentage effect on the dependent variable using the formula $\%\Delta Y=100*(e\beta-1)$. Formally, the model can be expressed as:

$$\ln(Yi) = \beta 1 \ln(X1, i) + \beta 2Di + \epsilon i$$

This specification ensures that the model captures both elasticities for continuous variables and semi-elasticities for dummies, providing a robust basis for subsequent comparison of structural impacts across ownership and rental markets. The SUR estimation in log form allows us to jointly analyze residential purchase prices and rents, accounting for potential correlations in their error terms across the two equations. Continuous strictly positive variables were log-transformed, providing elasticities, while dummy or level variables were kept in levels, producing semi-elasticities.

Wald Test

To formally assess whether the effects of shared explanatory variables differ between the residential purchase and rent markets, we applied Wald tests for equality of coefficients within the Seemingly Unrelated Regression (SUR) framework. The SUR approach allows for simultaneous estimation of correlated equations, accounting for potential cross-equation error covariance, which improves efficiency and provides consistent standard errors when the dependent variables (purchase prices and rents) are likely related. For each shared variable Xj, the Wald test evaluates the null hypothesis:

$$H0: \beta Xj \Pr i ce = \beta XjRent$$

Rejection of the null indicates that the same attribute has a structurally different impact on purchase prices and rents, justifying separate consideration of the two markets. This test is particularly important for variables like income, accessibility, and amenities, where the sensitivity of buyers and renters to the same local conditions may vary.

Interpretation of Residential Purchase Price vs Rent(Log-SUR Results

This section interprets the hybrid log–level Seemingly Unrelated Regressions (SUR) estimated for residential purchase prices and residential rents. The SUR framework is adopted for two reasons. First, it allows the price and rent equations to be estimated jointly while accounting for cross-equation correlation in unobserved factors (e.g., neighbourhood quality shocks affecting both markets). Second, it enables formal cross-market coefficient comparisons, assessed through Wald tests, which cannot be performed reliably using separate regressions alone.

Because the dependent variables are expressed in logarithms, the interpretation of coefficients depends on the functional form of the regressor. For regressors that are also in logarithms (e.g., ln_res_attr, ln_gdp_pc, ln_dist_attr_poles, ln_catchment_car), coefficients are elasticities: a 1% increase in the regressor is associated with an approximate β% change in the outcome, ceteris paribus. For regressors in levels (e.g., rail_centrality, sharing_local, hotels_bnb, park_area_m2), coefficients are semi-elasticities, indicating the proportional change in purchase price or rent associated with a one-unit increase in the regressor. To ensure interpretability, cross-market comparisons are conducted only for the subset of variables that are mutually significant across both equations (Table 12 and Figure 3).

Table 12: Log-SUR Results for Residential Purchase Price vs Rent

Variable	PurchasePrice_Beta	Purchase Price Price_SE	Purchase Price Price_t	Purchase Price Price_p	Purchase Price_Signif	Rent_Beta	Rent_SE	Rent_t	Rent_p	Rent_Signif
ln_res_attr	0.101452	0.009865	10.284	0	***	0.073871	0.010299	7.172	1.51E-12	***
long_dist_supply	0.002654	0.001092	2.43	0.015273	*	NA	NA	NA	NA	NA
rail_centrality	0.001905	0.000303	6.286	5.02E-10	***	0.001113	0.000328	3.399	7.06E-04	***

ln_dist_attr_poles	-0.086744	0.011514	-7.534	1.17E-13	***	-0.123233	0.011481	-10.734	0	***
ln_gdp_pc	0.758884	0.015438	49.157	0	***	0.476473	0.015514	30.713	0	***
private_parking	-0.000002	0.000000392	-4.958	8.48E-07	***	NA	NA	NA	NA	NA
private_parking_Local	0.000000121	0.000001	0.121	0.903		NA	NA	NA	NA	NA
sharing_local	0.054193	0.012627	4.292	1.96E-05	***	0.074859	0.012649	5.918	4.58E-09	***
gdp_balneare	0.00001	0.000000849	11.83	0	***	0.00001	0.000000921	11.299	0	***
hotels_bnb	0.00266	0.000538	4.948	8.90E-07	***	0.001979	0.000541	3.658	2.68E-04	***
car_majorhub	-0.000468	0.000197	-2.376	0.017696	*	-0.000095	0.000191	-0.499	0.618	
ln_catchment_car	-0.143253	0.018484	-7.75	2.40E-14	***	-0.114015	0.018688	-6.101	1.55E-09	***
park_area_m2	0.000000269	0.000000125	2.149	0.03189	*	0.000000173	0.000000127	1.368	0.171703	

train_ic	NA	NA	NA	NA	NA	-0.00147	0.001912	-0.769	0.442	
gdp_grandecitta	NA	NA	NA	NA	NA	0.000004	0.000001	4.668	3.49E-06	***
gdp_nontour	NA	NA	NA	NA	NA	0.000001	0.00000491	2.781	0.005524	**
ln_freq	NA	NA	NA	NA	NA	0.082941	0.016565	5.007	6.62E-07	***

Table 12 reports coefficient estimates and significance for both outcomes. Several determinants are statistically significant in both markets and exhibit economically meaningful differences in magnitude:

Residential attractiveness (ln_res_attr) is positive and significant in both equations, with an elasticity of 0.101 for purchase prices and 0.074 for rents. This indicates that improvements in the land-use and amenity mix around stations are capitalized into both values, but more strongly into asset purchase prices than into annual rents.

Local income (ln_gdp_pc) has the largest estimated elasticities and is highly significant in both equations (0.759 for purchase prices; 0.476 for rents). This pattern is consistent with a strong capitalization channel: higher purchasing power and stronger local economic conditions translate more intensively into capital values than into rental payments.

Distance to attraction poles (ln_dist_attr_poles) is negative and significant in both markets (−0.087 for purchase prices; −0.123 for rents). The larger magnitude for rents suggests that tenants are more sensitive to proximity to essential destinations such as healthcare and education, plausibly reflecting shorter time horizons and greater sensitivity to day-to-day access costs.

Car-oriented accessibility (ln_catchment_car) is negative and significant in both equations (−0.143 for purchase prices; −0.114 for rents), implying that more car-dependent station contexts are associated with lower residential values. This supports the interpretation that stations embedded in highly car-oriented catchments may face weaker local walkability and lower perceived accessibility benefits, even if car access is high.

Local sharing services (sharing_local) is positive and significant in both equations (0.054 for purchase prices; 0.075 for rents). The larger semi-elasticity for rents suggests that shared-mobility and last-mile facilities (bike sharing, car sharing, taxi stand, bike parking, bike lanes) are valued more strongly by tenants, consistent with a "daily usability" mechanism.

Other variables, such as gdp_balneare, hotels_bnb, and park_area_m2, are also positive and significant in at least one equation, but their cross-market interpretation requires care because units and governance feasibility differ. Importantly, some regressors are market-specific (e.g., private parking affects purchase prices only; frequency affects rents only), and thus they are not directly comparable across equations.

Table 13: Wald test among mutual variables, Residential Purchase Price vs Rent.

Variable	F_stat	p_value	Decision
ln_res_attr	14.1158	1.77E-04	Reject H0 (Different)
rail_centrality	10.6439	1.12E-03	Reject H0 (Different)
ln_dist_attr_poles	22.4171	2.36E-06	Reject H0 (Different)
ln_gdp_pc	758.893	0	Reject H0 (Different)
sharing_local	6.0204	0.01423	Reject H0 (Different)
gdp_balneare	0.3083	0.5788	Fail to Reject H0 (Equal)
hotels_bnb	3.6393	0.05659	Fail to Reject H0 (Equal)
car_majorhub	6.8779	0.008798	Reject H0 (Different)
ln_catchment_car	5.6147	0.01791	Reject H0 (Different)
park_area_m2	1.2882	0.2565	Fail to Reject H0 (Equal)

Table 13 provides Wald tests for coefficient equality on the mutually significant variables. The tests show that the differences observed above are not merely descriptive: for ln_res_attr, rail_centrality, ln_dist_attr_poles, ln_gdp_pc, sharing_local, car_majorhub, and ln_catchment_car, the null hypothesis of equality is rejected, confirming structural differences in how the same station-area attribute is priced in the purchase and rental markets. In contrast, for gdp_balneare, hotels_bnb, and park_area_m2, the equality hypothesis is not rejected (at conventional levels), suggesting broadly similar capitalization across tenure markets for those factors.

This distinction is crucial for interpretation: even when a determinant affects both markets in the same direction, its economic relevance may differ substantially depending on whether it is reflected in capital value (purchase price) or cash-flow (rent).

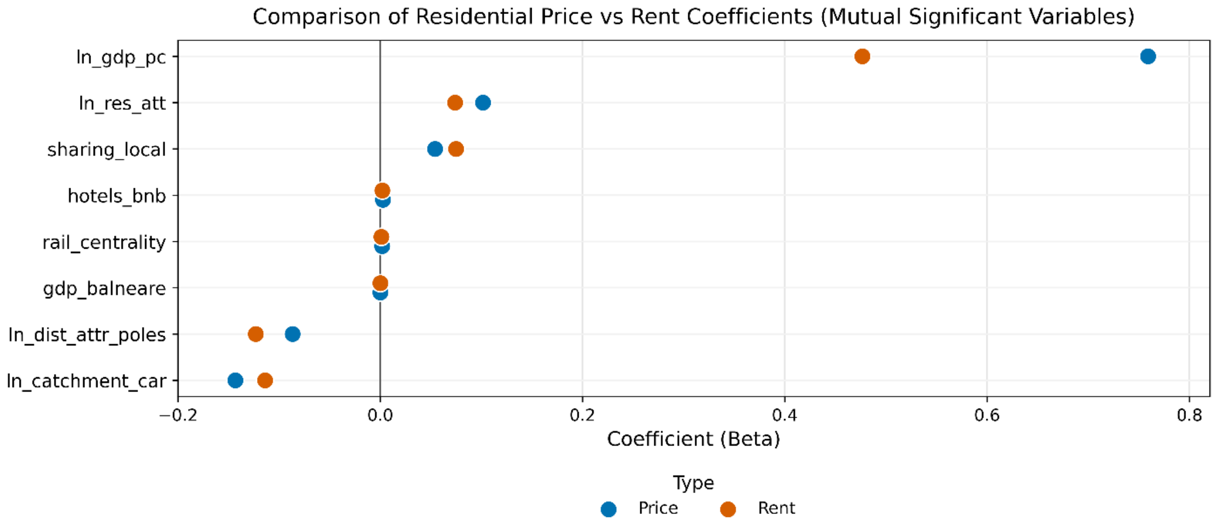

Figure 3: Comparison of Residential Purchase Price vs Rent Coefficients (mutual Significant Variables)

Figure 3 summarizes Table 11 and Table 12 by displaying purchase price and rent coefficients for mutually significant variables on a common scale. Two broad capitalization regimes emerge:

Long-horizon capitalization into asset values
Variables that proxy structural quality and broader economic strength, particularly ln_gdp_pc and ln_res_attr, exhibit larger effects on purchase prices than on rents. This is consistent with the notion that buyers internalize not only current utility but also expected future benefits, resale value, and long-run neighbourhood trajectories. In this regime, the purchase market acts as a forward-looking valuation mechanism.

Short-horizon capitalization into rents (daily usability channel)
Variables tied to day-to-day accessibility and operational convenience, most notably sharing_local and the stronger sensitivity of rents to ln_dist_attr_poles, show comparatively larger effects on rents. This is consistent with tenants valuing immediate mobility options and proximity to essential services, which translate directly into living costs and time savings.

The negative effect of ln_catchment_car in both equations indicates that a station's integration into a car-dominated catchment is not necessarily an advantage for residential value; rather, it may signal weaker pedestrian accessibility and lower perceived station-oriented urbanity, which affects both buyers and renters.

Overall, the hybrid log–level SUR results show that purchase prices and rents respond systematically, and often differently, to the same determinants. For decision-makers, this has a direct operational interpretation:

If the objective is to maximize capital value of nearby residential assets, strategies that strengthen structural attractiveness (amenity mix, services, and broader economic context) are expected to deliver larger price responses.

If the objective is to maximize rental income, interventions that improve station usability and last-mile accessibility (shared mobility supply, micro-accessibility, and reduced effective distance to key poles) are comparatively more effective.

Finally, the joint Wald test over the shared variables strongly rejects equality across markets (Table 14), confirming that price and rent should not be treated as interchangeable outcome measures. Even where determinants are common, the magnitude of their capitalization differs, supporting the thesis approach of analysing purchase and rental markets separately while using SUR and cross-equation tests to quantify these structural differences.

Table 14: Wald test on the shared variables between the residential price and rent equations

Model	Res.Df	Df	F_stat	Pr(>F)	Significance
fit_log	1853	10	4115.8	< 2.2e-16	***

Interpretation of the Commercial Purchase Price vs Rent Log-SUR Results

This section interprets the hybrid log–level SUR estimation for commercial purchase prices and commercial rents. The SUR framework is used to (i) account for correlated unobservables across markets (e.g., local business vitality shocks that affect both sale prices and rents) and (ii) enable formal cross-equation comparisons of how the same station-area determinant capitalizes into capital values versus annual cash flows. As in the residential specification, the dependent variables are in logarithms. Therefore, coefficients on logged regressors (e.g., ln_gdp_pc) are interpreted as elasticities, while coefficients on level regressors (e.g., freq, commerce, hotels_bnb) are semi-elasticities. To preserve comparability, coefficient comparisons are made within the same regressor across the two equations, and equality is assessed using Wald tests for the subset of regressors observed in both equations (Table 15), complemented by a visual comparison for the variables that are statistically significant in both markets (Figure 4).

Table 15: Log-SUR Results for Commercial Purchase Price vs Rent

Variable	Purchase Price Beta	Purchase Price SE	Purchase Price t	Purchase Price p	Purchase Price Signif	Rent Beta	Rent SE	Rent t	Rent p	Rent Signif
commerce	0.0004064	0.0000677	6.005	2.81E-09	***	0.0003709	0.000072	5.15	3.24E-07	***
train_ic	0.001467	0.002176	0.674	0.5003		NA	NA	NA	NA	NA
train_regv	-0.003023	0.001194	-2.533	0.0115	*	NA	NA	NA	NA	NA
train_reg	0.0006351	0.0003009	2.111	0.0351	*	NA	NA	NA	NA	NA
ln_dist_attr_poles	0.002875	0.008494	0.339	0.7351		NA	NA	NA	NA	NA
sharing_local	0.02536	0.009406	2.697	0.00714	**	NA	NA	NA	NA	NA
ln_gdp_pc	0.6237	0.009134	68.29	0	***	0.3468	0.003759	92.26	0	***
hotels_bnb	0.003246	0.000631	5.147	3.28E-07	***	0.002737	0.0006945	3.941	8.78E-05	***

gdp_balneare	5.44E-06	1.00E-06	5.438	7.05E-08	***	8.26E-06	1.02E-06	8.104	1.78E-15	***
gdp_nontour	-3.84E-06	5.49E-07	-7.003	5.06E-12	***	NA	NA	NA	NA	NA
car_majorhub	-0.0004483	0.0001487	-3.014	0.00265	**	NA	NA	NA	NA	NA
freq	0.08508	0.0113	7.528	1.31E-13	***	0.1081	0.01157	9.35	0	***
dist_to_centers	-3.64E-06	1.17E-05	-0.312	0.7555		-8.42E-06	1.29E-05	-0.651	0.5151	
X._centrale	0.07849	0.02803	2.8	0.00523	**	NA	NA	NA	NA	NA
parking_private	-1.93E-06	6.83E-07	-2.829	0.00477	**	-2.27E-07	7.35E-07	-0.308	0.7581	
private_parking_Local	2.39E-06	1.83E-06	1.309	0.1909		2.79E-06	2.01E-06	1.387	0.1657	
long_dist_supply	NA	NA	NA	NA	NA	-0.004043	0.001576	-2.565	0.01048	*
gdp_grandecitta	NA	NA	NA	NA	NA	7.11E-06	1.01E-06	7.041	3.90E-12	***
park_area	NA	NA	NA	NA	NA	2.74E-07	9.88E-08	2.769	0.00575	**

Table 15 reports the estimated coefficients for commercial purchase prices and rents. Three substantive patterns stand out.

- Structural economic context capitalizes more strongly into commercial asset values than into rents. Local income (ln_gdp_pc) is highly significant in both equations, but the elasticity is substantially larger for purchase prices (0.624) than for rents (0.347). This difference is statistically decisive (Table 15). The interpretation is consistent with capitalization theory: commercial transaction prices incorporate expectations about the durability of demand, future rental growth, and longer-horizon risk perceptions, while rents adjust more closely to current operating conditions and contractual frictions.

(1) Operational intensity, proxied by service frequency, matters for both outcomes, but more for rents. Transport frequency (freq) is positive and significant in both equations. However, the rent semi-elasticity (0.108) is larger than the purchase-price semi-elasticity (0.085), and equality is rejected by the Wald test. Economically, this aligns with the role of accessibility in commercial performance: frequency affects footfall potential, reliability, and the effective market size of consumers and workers, which can translate quickly into higher willingness-to-pay for occupancy (rents). The capital value response is also positive, but typically reflects a more gradual re-pricing mechanism through expectations of future rents and vacancy risk.

(2) Place and activity intensity variables show broadly similar capitalization across tenure markets. Commercial intensity (commerce) and accommodation density (hotels_bnb) are positive and significant in both equations, with very similar magnitudes, and the Wald tests fail to reject equality. This suggests that these forms of station-area activity are capitalized in comparable ways into both sale prices and rents. The coastal-context interaction (gdp_balneare) is positive and significant in both equations, but unlike hotels_bnb and commerce, its effect differs significantly across markets according to Table 15, indicating that the "tourism-economy premium" is not transmitted identically into commercial rents and commercial asset prices.

Several determinants remain market-specific. For example, variables such as train_reg, train_regv, and X._centrale enter only the purchase equation, while long_dist_supply, gdp_grandecitta, and park_area enter only the rent equation. Since these regressors are not shared across both equations, they are interpreted within-market only and are excluded from cross-market equality testing.

Table 16: Wald test among mutual variables, Commercial Purchase Price vs Rent.

Variable	F-stat	p-value	Decision
commerce	0.4752	0.4907	Fail to Reject H0 (Equal)
ln_gdp_pc	1000.322	1.83E-173	Reject H0 (Different)
hotels_bnb	1.1925	0.2749	Fail to Reject H0 (Equal)
gdp_balneare	12.425	0.0004347	Reject H0 (Different)
freq	6.5263	0.01071	Reject H0 (Different)
dist_to_centers	0.2646	0.6071	Fail to Reject H0 (Equal)
parking_private	10.879	0.0009923	Reject H0 (Different)
private_parking_Local	0.08707	0.76797	Fail to Reject H0 (Equal)

Table 16 formalizes whether shared determinants have statistically identical effects in commercial purchase and rental markets. The equality hypothesis is rejected for ln_gdp_pc, freq, gdp_balneare, and parking_private, indicating structurally different capitalization into capital values versus annual rents. In contrast, equality is not rejected for commerce, hotels_bnb, dist_to_centers, and private_parking_Local, suggesting broadly comparable effects across tenure markets for these covariates.

Two clarifications strengthen interpretation. First, failure to reject equality does not imply “no effect”, it implies that the effects are statistically indistinguishable across markets, conditional on the model specification. Second, the role of dist_to_centers is weak in this specification: it is statistically insignificant in both equations and shows no evidence of structural difference, suggesting that once station-accessibility and economic controls are included, distance to major centers does not contribute additional explanatory power for commercial valuations.

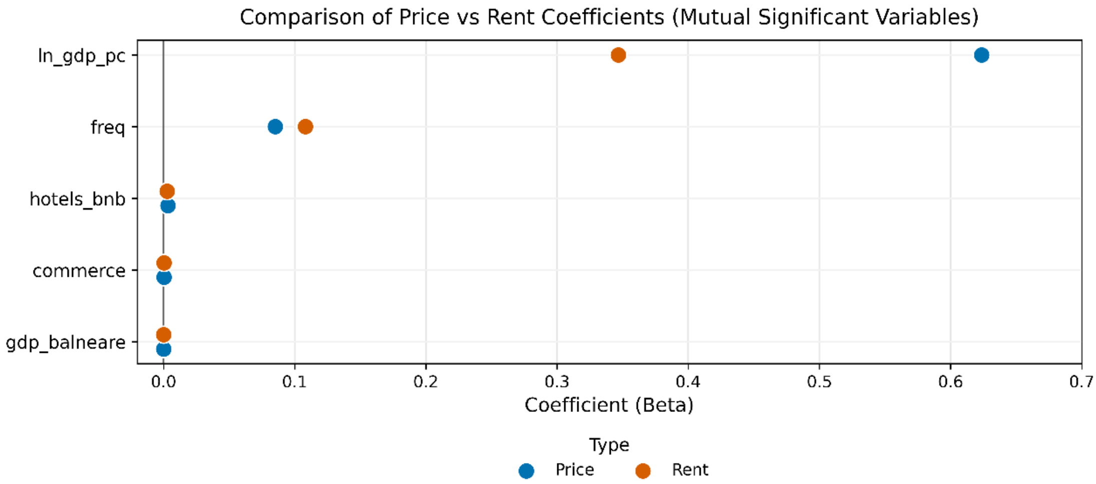

Figure 4: Comparison of Commercial Purchase price vs Rent Coefficients (mutual Significant Variables)

Figure 4 provides a compact visualization of the "mutual significant" set (i.e., the variables that are statistically significant in both commercial purchase and rent equations) and plots their coefficient estimates side by side. Two capitalization regimes emerge.

- Capitalization into asset values (long-horizon channel).

The strong gap between purchase and rent elasticities for ln_gdp_pc indicates that local economic strength is reflected disproportionately in commercial asset values. This is consistent with a forward-looking mechanism: transaction prices embed expectations about demand stability and future cash-flow potential.

- Capitalization into rents (operational channel).

The larger semi-elasticity of freq in the rent equation supports an operational interpretation: service intensity raises the effective market size and footfall of the station area, improving short-run commercial performance and increasing tenants' willingness-to-pay. In contrast, variables such as commerce and hotels_bnb show positive and relatively similar coefficients across the two markets, pointing to activity intensity effects that transmit in a comparable manner to both rents and purchase prices.

Taken together, the commercial SUR results indicate that commercial sale prices and rents are driven by overlapping determinants but exhibit systematically different sensitivities. For station-area stakeholders, this distinction matters because purchase prices represent capital value (a stock), while rents represent cash-flow (a flow). The results suggest that interventions aligned with operational performance and accessibility, particularly service frequency and station functioning, are more directly reflected in rents, whereas broader economic context (proxied by local income) is more strongly capitalized into commercial asset values. Importantly, some high-impact determinants (e.g., frequency) are governance-dependent and may require coordination beyond station-level real-estate actions, reinforcing the value of translating econometric effects into scenario-based decision tables .

Finally, the joint Wald test over the shared regressors (Table 17) strongly rejects coefficient equality ($F = 141.49$, $p < 0.001$), confirming that commercial purchase and rental markets should not be treated as interchangeable outcome measures. The SUR framework therefore provides both a statistically coherent basis for cross-market comparison and a practical bridge from econometric results to policy-relevant scenario evaluation.

Table 17: Wald Test on the Shared Variables Between the Commercial Purchase price and Rent Equations.

Hypothesis	F-stat	df1	df2	p-value	Significance
Overall Test	141.49	8	1721	< 2.2e-16	***

Discussion

To make the results actionable, this chapter reframes the econometric findings into a set of policy-relevant scenarios aligned with the governance reality of station areas. The SUR models quantify how station accessibility, local amenities, and mobility services are capitalized into purchase prices and rents; the scenario tables translate these coefficients into comparable economic metrics and organize them by station archetype. Each lever is chosen to reflect an intervention that is either directly implementable by RFI/Sistemi Urbani (e.g., station-area services, parking and shared mobility agreements, public realm improvements) or feasible through coordination with public administrations and operators (e.g., service frequency).

Building on the SUR estimates, the scenario engine applies standardized changes to selected determinants (“levers”) and generates counterfactual predictions for both purchase price and rent. The outputs are reported in units that correspond to how station-area portfolios are evaluated: baselines in €/sqm and €/sqm/year, scenario deltas in the same units, and impacts scaled to € per 100 m² for easier interpretation at the asset level. In what follows, Table 18 presents an illustrative excerpt for two representative Local archetypes, LOCAL | BALNEARE and LOCAL | NON_TOURISTIC, chosen because Local stations constitute the majority of the sample and because the contrast between a tourism-oriented and a non-touristic context offers an intuitive way to interpret how the same intervention can perform differently across settings.

Table 18: Residential policy scenario excerpt (SUR-based predictions). Baselines are in €/sqm and €/sqm/year; deltas are expressed in €/sqm and €/sqm/year, and scaled to € per 100 m².

Archetype	Lever	Baseline purchase price (€/sqm)	Baseline rent (€/sqm/year)	Δ purchase price (€/sqm)	Δ rent (€/sqm/year)	Δ€ per 100 m² (capital)	Δ€ per 100 m²/year (rent)
LOCAL | BALNEARE	Add car-sharing	1144.0	47.0	40.2	2.24	4022.0	224.0
	+1 km bike lanes	1144.0	47.0	36.7	2.04	3672.0	204.0
	Add bike parking	1144.0	47.0	34.4	1.91	3436.0	191.0

	Add taxi parking	1144.0	47.0	32.8	1.82	3281.0	182.0
	Add bike-sharing	1144.0	47.0	26.9	1.49	2686.0	149.0
	+10 train_reg/day	1144.0	47.0	22.7	0.53	2269.0	52.8
	-10% car catchment	1144.0	47.0	18.7	0.54	1868.0	54.0
	-5 km to education	1144.0	47.0	15.6	0.88	1563.0	88.3
	+IQR hotels/BnB	1144.0	47.0	15.1	0.5	1506.0	49.6
	-5 km to hospital	1144.0	47.0	12.2	0.69	1225.0	69.2
	+10% res intensity	1144.0	47.0	6.16	0.18	616.0	18.0
	+10% commerce intensity	1144.0	47.0	4.84	0.14	484.0	14.1
	+1 ha park area	1144.0	47.0	3.11	0.09	311.0	9.13
	+10% rail catchment	1144.0	47.0	1.33	0.03	133.0	3.1
	Add car-sharing	931.0	39.8	32.7	1.89	3274.0	189.0

LOCAL | NON_TOURISTIC	+1 km bike lanes	931.0	39.8	29.9	1.73	2989.0	173.0
	Add bike parking	931.0	39.8	28.0	1.62	2797.0	162.0
	Add taxi parking	931.0	39.8	26.7	1.54	2670.0	154.0
	Add bike-sharing	931.0	39.8	21.9	1.26	2186.0	126.0
	+10 train_reg/day	931.0	39.8	18.5	0.45	1847.0	44.7
	-5 km to education	931.0	39.8	17.2	1.01	1716.0	101.0
	-10% car catchment	931.0	39.8	15.2	0.46	1521.0	45.7
	-5 km to hospital	931.0	39.8	13.4	0.79	1336.0	78.6
	+IQR hotels/BnB	931.0	39.8	12.3	0.42	1226.0	42.0
	+10% res intensity	931.0	39.8	5.37	0.16	537.0	16.3
	+10% commerce intensity	931.0	39.8	3.54	0.11	354.0	10.7
	+1 ha park area	931.0	39.8	2.53	0.08	253.0	7.73

	+10% rail catchment	931.0	39.8	1.49	0.04	149.0	3.62

Note: The "Regionale trains/day" lever represents an interquartile-range (IQR) increase in daily Regionale services (distribution-based increment), rather than a one-train change.

Table 18 should be read as a ranking tool rather than a single-point forecast. Each row describes the predicted change associated with one lever, holding the remaining archetype characteristics constant. The purpose is therefore comparative: to identify which interventions are expected to generate the largest uplift in capital values, in rents, or in both, within a given station context.

Across the two displayed archetypes, a consistent pattern emerges: interventions that improve last-mile usability, such as adding car-sharing, bike lanes, bike parking, bike-sharing, and taxi facilities, produce the largest combined uplifts in both residential purchase values and rents. In the LOCAL | BALNEARE archetype, for example, "Add car-sharing" is associated with an increase of roughly €4,022 per 100 m² in capital value and €224 per 100 m²/year in rents, with similarly large uplifts in the LOCAL | NON_TOURISTIC archetype. This aligns with the econometric results: variables capturing station-area usability and shared mobility tend to transmit strongly into rental willingness-to-pay and also capitalize into sale prices, especially in Local contexts where baseline frictions in access and first/last-mile connectivity are more binding.

A second group of levers, those that reduce effective access costs to essential poles (e.g., "−5 km to hospital/education," implemented via the distance composite), also shows consistent positive effects. These should not be interpreted as literal spatial relocation of hospitals or schools; rather, they represent interventions that reduce generalized access impedance, such as safer pedestrian connections, improved feeder services, continuous cycling links, or integrated local mobility services that shorten effective travel time and cost. Presenting these effects in €/sqm and €/sqm/year makes the accessibility channel visible in the same units used in real-estate appraisal and planning evaluation.

Levers related to broader station connectivity and service supply (e.g., "+10 train_reg/day" and "+10% rail catchment") remain positive but typically generate smaller marginal deltas than last-mile packages in this excerpt. This should not be read as a claim that rail service is unimportant; rather, it reflects that (i) service changes often require coordination and have higher governance complexity, and (ii) marginal effects may be smaller where baseline service is already present. Where service changes are expressed as interquartile-range increments, the lever is explicitly distribution-based, reflecting realistic shifts observed in the data rather than arbitrary unit increases.

From an RFI perspective, particularly for Sistemi Urbani, which manages and valorizes station areas, the scenario tables provide a decision-support layer between econometric evidence and investment planning. They enable stakeholders to rank interventions by archetype depending on whether the objective is to increase capital value, rental income, or both; to translate effects into portfolio-relevant scales (e.g., € per 100 m^2); and to compare interventions that fall under different governance domains, from place-based upgrades (shared mobility, cycling facilities, public realm) to measures that require coordination with operators and public administrations (service intensity and frequency).

Importantly, reporting purchase price and rent deltas side-by-side also supports more responsible station-area planning. Interventions that disproportionately increase rents may enhance revenue potential but can also intensify affordability pressures if implemented without complementary safeguards. The contribution of the framework is not to prescribe policy, but to enable decision-makers to identify ex ante whether an intervention's benefits concentrate on the rental channel versus the capital channel, and to design balanced packages accordingly. In contexts where displacement risk is salient, public administrations can couple accessibility improvements with affordability mechanisms (e.g., inclusionary housing targets, allocation of social housing near transit, or phased development), while RFI/Sistemi Urbani can pursue station-area improvements that raise functionality and quality without unintentionally accelerating rent escalation.

Overall, the scenario tables operationalize the SUR results into a format that is immediately interpretable for both investment and planning. They preserve the central econometric insight, purchase and rental markets respond differently to the same determinants, while translating those differences into € impacts by archetype and lever. This provides a practical bridge from statistical estimation to station-area governance, supporting more targeted investments and more transparent evaluation of potential economic and distributional implications.

Conclusion

This thesis develops a quantitative, station-level decision-support framework to understand how railway accessibility, urban structure, and local context are capitalized into real-estate outcomes in Italy. Using a dataset of approximately 985 stations, the analysis first estimates separate hedonic models for four market segments, residential purchase, residential rent, commercial purchase, and commercial rent, and then adopts hybrid log–level Seemingly Unrelated Regressions (SUR) to compare how shared determinants transmit into purchase prices and rents within each market. This two-stage design bridges interpretability and comparability: the hedonic specifications identify salient drivers, while the SUR systems enable cross-equation comparisons and formal equality tests, highlighting where purchase and rental markets respond differently to the same station-area attributes.

Across the four market segments, three substantive messages emerge:

First, local demand fundamentals dominate and consistently raise both purchase prices and rents. Higher GDP per capita and tourism-related intensity are strongly associated with higher residential and commercial values. These variables capture broader demand conditions rather than station-level policy levers, but they provide a crucial baseline for realistic expectations: identical interventions implemented in different contexts will not yield the same returns because underlying demand conditions differ substantially across places.

Second, accessibility matters through distinct capitalization channels for purchase prices versus rents. The evidence supports a dual horizon of returns. Purchase prices respond more strongly to structural, longer-horizon components of accessibility and urban structure, such as centrality and connectivity, consistent with asset markets capitalizing expected future benefits and long-run neighbourhood trajectories. Rents, by contrast, display stronger sensitivity to day-to-day usability and operational accessibility, especially service intensity and everyday multimodal convenience, consistent with the shorter decision horizon of tenants and the direct role of travel time, reliability, and last-mile friction in monthly or annual willingness-to-pay.

Third, car dependence is penalized while multimodal and last-mile solutions generate measurable uplifts, especially for lower-tier stations. Indicators associated with car-oriented catchments are negatively related to residential values, suggesting that car dependence may proxy congestion externalities, lower walkability, and weaker station-oriented urbanity. Conversely, shared mobility provision and active-access improvements (bike lanes, bike parking, bike-sharing, car-sharing, taxi facilities) are positively capitalized, often with particularly strong impacts around Local and Local Plus stations, where baseline multimodal options are more constrained and marginal improvements are more valuable.

A central practical contribution of the thesis is the translation of model estimates into scenario-based policy tables. Rather than leaving results at the level of coefficients, the scenario engine applies standardized levers to archetype-specific profiles and reports impacts in units that match station-area governance and portfolio management: €/sqm (capital values), €/sqm/year (rental flows), and € per 100 m^2 (asset-scale interpretation). This makes the framework directly usable for RFI and, in particular, Sistemi Urbani, which manages and valorizes assets around stations. A simple workflow follows naturally: classify a station into its archetype, read baseline levels, test candidate interventions, scale impacts by the floorspace under management, and prioritize options by uplift relative to expected capex/opex and feasibility constraints.

From a governance perspective, the findings also suggest a clear distinction between place-based and coordination-dependent strategies. Place-based upgrades, such as last-mile packages and public-realm improvements, are often directly implementable within station-area management and can generate meaningful uplifts in both rents and purchase prices. In contrast, levers related to service supply and frequency may generate large benefits but typically require coordination with operators and public authorities. The scenario tables help clarify these trade-offs by placing all levers on a comparable economic scale, allowing stakeholders to evaluate not only magnitude but also implementability.

For public administrations, the quantified uplifts strengthen the economic case for transit-oriented development and provide a transparent basis for value-capture and accountability. At the same time, the thesis treats distributional outcomes as a serious implementation constraint. When interventions disproportionately raise rents, especially in tourism-oriented or high-demand contexts, affordability pressures can intensify. The policy implication is therefore not "avoid investment," but "design investment packages responsibly": capture part of the uplift to fund infrastructure and public space, and reinvest a share into inclusion measures such as affordable housing requirements, social rent quotas, phased redevelopment, or systematic monitoring of rent burdens near stations. The value of the framework is that it helps decision-makers anticipate where benefits concentrate in the rental channel versus the capital channel, enabling more balanced strategies.

Finally, the thesis has limitations that also define a clear agenda for future work. The analysis is cross-sectional and therefore identifies capitalization patterns rather than causal treatment effects. Future research should integrate panel designs around timetable changes and station upgrades, explicitly model spatial dependence, and incorporate distributional indicators such as affordability and displacement risk. Extending the framework with additional real-estate categories and repeated observations over time would also enable backcasting validation and stronger causal interpretation. Despite these limits, the thesis provides a coherent and scalable bridge between econometric evidence and station-area decision making, supporting both efficiency-oriented investment prioritization and more transparent consideration of distributional impacts.

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