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Probabilistic Assessment of Expected Profitability in Housing Development under Land, Regulatory and Spatial Conditions: Evidence from the Greater Valparaíso Conurbation, Chile

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Abstract

This study aims to assess expected profitability in new residential apartment developments by integrating land cost, regulatory conditions, spatial location and probabilistic cost assumptions at the project level. A dataset of 74 new apartment projects in the Greater Valparaíso conurbation, Chile, corresponding to the total supply identified in December 2025, was constructed. Expected margin was estimated through Monte Carlo simulation with 2,000 scenarios per project. An OLS model with HC3 robust standard errors was then estimated to examine associations between expected percentage margin, effective land cost, regulatory parameters and spatial location. The findings show that effective land cost is strongly associated with expected percentage margin: each additional 1 UF/m² is associated with an approximate 0.97 percentage point reduction. Minimum lot size is the only regulatory parameter retained in the parsimonious model. Each additional kilometer from the coastline is associated with an approximate 1 percentage point reduction in expected margin. Land incidence around 20% provides an empirical reference for margin deterioration. Overall, the study provides project level empirical evidence for early stage feasibility assessment in residential development by showing how land incidence, regulatory conditions and locational attributes relate to expected margin deterioration and negative margin risk in the Greater Valparaíso residential development market. This study contributes by integrating land incidence, regulatory conditions, spatial location and probabilistic cost assumptions into a project level profitability framework, extending prior literature mainly focused on housing prices or isolated market attributes.

Keywords

Expected profitability; Housing development; Effective land cost; Monte Carlo simulation

1. Introduction

Real estate development is a complex economic activity that requires large amounts of capital and is exposed to multiple sources of uncertainty. These conditions influence both decision-making and the final performance of projects. The specialized literature agrees that properly identifying and selecting profitability indicators becomes a key element in project evaluation, but in practice their application varies considerably across developers, since it depends on strategic and organizational factors, and on the type of asset being developed (Wyrwoll & Beusker, 2025).

In this context, land use regulation stands out as a first order structural element, given that the evidence shows that higher levels of regulatory restriction are associated with increases in housing prices and with changes in the dynamics of urban expansion (Büchler & v. Ehrlich, 2023). Likewise, when highly productive cities opt for excessive regulation, this not only affects local markets, but also causes an inefficient spatial allocation of labor and a reduction in aggregate output (Parkhomenko, 2023). In this sense, beyond its effects on prices and supply, regulation shapes the institutional framework within which projects are structured. At the individual project level, this may translate into restrictions on land use potential and, therefore, affect the developer's expected profitability.

Economic uncertainty represents another relevant axis. A systematic review of the literature, focused mainly on the housing sector and on developed real estate markets, indicates that when levels of uncertainty increase, investment volumes, returns, and real estate market performance decrease (Ahiadu & Abidoye, 2024). Along these lines, studies that analyze the information flows between economic policy uncertainty and real estate markets show that such transmission is manifested mainly over short term horizons (Bossman et al., 2022),

reinforcing the need to address profitability from a probabilistic perspective, explicitly incorporating cost variability and the risk of negative margins.

Along with regulation and uncertainty, the spatial dimension adds an additional level of complexity to the economic performance of residential projects. Hedonic and spatial models have shown evidence that certain economic activities, port infrastructure, extractive industries, or conservation areas generate differentiated effects on residential prices depending on distance, visibility, and territorial context (Graziano et al., 2025). In a complementary manner, spatial decision support systems have been developed that integrate territorial indicators to construct synthetic real estate risk indices at the submunicipal scale, with the purpose of strengthening ex ante evaluation in urban regeneration processes (Anelli & Tajani, 2023). These approaches show that real estate risk may have a territorial dimension that can be measured and represented cartographically. However, they do not explicitly develop a model that connects this territorial dimension with the financial profitability projected by the developer. In this context, the research problem lies in understanding how the expected profitability of residential apartment projects is configured when regulatory conditions, land related restrictions, and spatial attributes converge.

Taken together, the literature recognizes the relevance of regulation, macroeconomic uncertainty, spatial structure, and information in real estate dynamics (Ahiadu & Abidoye, 2024; Bossman et al., 2022; Büchler & v. Ehrlich, 2023; Chong, 2020; Parkhomenko, 2023; Pollestad & Oust, 2025), however, the literature tends to address these dimensions in a fragmented manner. Studies on regulation focus on its effects on prices and aggregate supply (Büchler & v. Ehrlich, 2023; Parkhomenko, 2023; Zhao & Liu, 2023); analyses of uncertainty examine market performance (Ahiadu & Abidoye, 2024) or information flows (Bossman et

al., 2022); hedonic and spatial models analyze variations in residential values (Graziano et al., 2025; Huang et al., 2024); and research on real estate development discusses value creation at the corporate level (Geltner et al., 2023), while territorial and risk based approaches have been developed in parallel (Anelli & Tajani, 2023). However, it is less common to find studies that explicitly integrate regulatory and territorial variables within a microeconomic modeling of the individual project (Wyrwoll & Beusker, 2025), which reveals a gap in the literature to which this study seeks to contribute.

This gap is especially relevant in the Greater Valparaíso conurbation, one of the main coastal urban systems in Chile. Composed of the municipalities of Valparaíso, Viña del Mar, Concón, Quilpué, and Villa Alemana (Álvarez et al., 2009), it has an approximate population of 970,233 inhabitants, calculated from municipal data from the 2024 Census (Instituto Nacional de Estadísticas, 2024). From an institutional point of view, each municipality operates under its own current territorial planning instrument, establishing specific urban development requirements. From a physical point of view, the territory belongs to a coastal urban system with coastal plains and steep hills, generating structural geographic restrictions associated with its topography. The literature shows that this type of restriction can limit the availability of buildable land and affect its cost (Saiz, 2010). Likewise, proximity to the coastline constitutes a spatial attribute that, according to the international hedonic literature, may affect residential values through amenity effects (Boto-García & Leoni, 2023; Landry et al., 2022). These characteristics make Greater Valparaíso a particularly suitable case for the proposed analysis. In this study, project profitability is operationalized as the expected percentage margin over the unit sale price.

The contribution of this paper is not limited to documenting that land costs or coastal amenities are associated with real estate outcomes. Rather, it operationalizes an ex ante assessment framework that links land incidence adjusted by regulatory development capacity, spatial attributes and probabilistic cost assumptions to expected profitability at the residential project level. This is particularly relevant for early stage feasibility assessment, where detailed project specific cost and financial information is often unavailable to researchers and decision makers. Based on this framework, the study focuses on how regulatory conditions, land cost structure and spatial location are associated with expected profitability at the project level in Greater Valparaíso.

In response to this, the following research questions are posed:

- RQ1: How are regulatory variables associated with the expected percentage margin of residential development projects?
- RQ2: How are land cost and spatial location associated with expected profitability and the probability of negative margin under probabilistic cost assumptions?

The following hypotheses are proposed:

- H1: Regulatory conditions that expand development capacity are positively associated with the expected percentage margin.
- H2: The relative weight of land cost in relation to permitted development capacity and unit sale price differentiates projects with greater exposure to expected margin deterioration and to higher probability of negative margin.

- H3: Unit sale price differentials associated with spatial amenities may partially offset land cost pressures, contributing to higher expected percentage margins under probabilistic cost assumptions.

2. Materials and methods:

The methodology was developed under a quantitative approach, with a non experimental and cross sectional design. Its scope was explanatory in an associational, non causal sense, and it sought to analyze the association between regulatory, land related, and spatial location variables and the expected percentage margin of new residential apartment projects in the Greater Valparaíso conurbation. It was structured in five stages. First, a database of new residential apartment projects offered in the Greater Valparaíso conurbation was constructed and normalized. Second, the regulatory, spatial, and land incidence variables were defined. In a third stage, the relationships between variables and their preliminary econometric compatibility were evaluated. Then, the project margin under uncertainty was estimated through Monte Carlo simulation and, finally, the structural associations between expected percentage margin and land, regulatory and spatial variables were examined through linear regression. Figure 1 graphically summarizes the five stages that structured the methodology of the study.

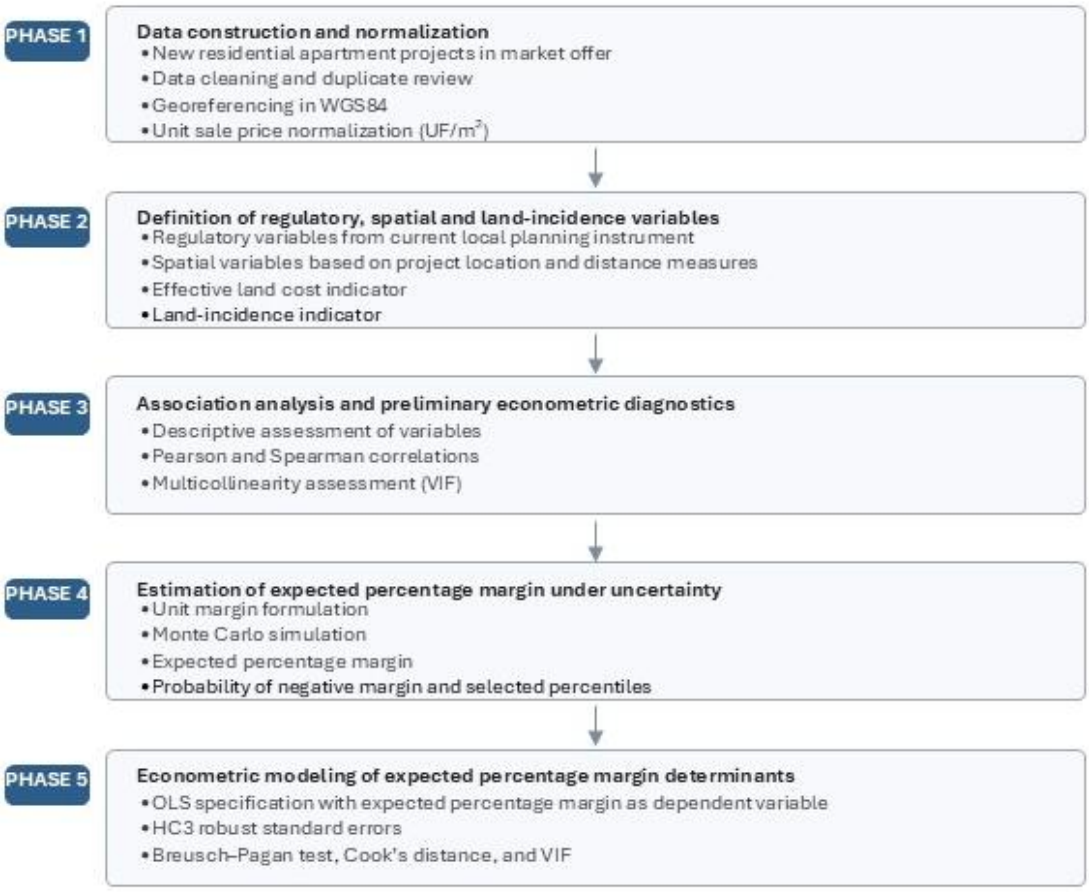


Figure 1. Methodological framework of the study
Source: Authors' own elaboration

2.1 Construction of the dataset and normalization of real estate variables

The study was developed from a survey of 74 new residential apartment real estate projects, corresponding to the total number of projects on offer identified in the Greater Valparaíso conurbation during December 2025. The survey was conducted through a manual search on public access platforms active in the Chilean market, specifically Portalinmobiliario, Toctoc, Yapo, Chilepropiedades, and Goplaceit. Only new projects in the sales stage within the municipalities analyzed were considered, understood as those that had an active listing with a valid commercial offer at the time of the survey. The records were manually reviewed to

eliminate duplicates and confirm their location and active sales status. For data analysis, Python 3.13 (64 Bit) programming language was used. The structuring, cleaning, and transformation of the dataset were developed mainly with pandas and numpy. The specific tools used in the spatial, association, simulation, and econometric estimation analyses are indicated in the corresponding subsections.

Monetary values were expressed in Unidad de Fomento (UF), an inflation indexed instrument widely used in the Chilean real estate sector, which makes it possible to isolate nominal effects and ensure temporal comparability.

In order to standardize the comparison between projects at different levels of development, price normalization by usable area was considered, as it is a methodological practice widely used in the analysis of real estate projects to reduce heterogeneity and allow precise comparisons (Hungria-Gunnelin, 2018; Loberto et al., 2022; Tapia et al., 2025). In this context, each project i was considered an independent unit of analysis. For each project, the total sale price in UF $\left(P_i^{UF}\right)$ and the minimum usable area (A_i) measured in square meters, were collected. From these two variables, the unit sale price was defined according to equation (1):

$$p_i = \frac{P_i^{UF}}{A_i} \tag{1}$$

Where p_i represents the unit sale price of project i, expressed in UF per square meter of usable area (UF/m^2), P_i^{UF} corresponds to the published "starting at" sale price for project i, expressed in UF, while A_i represents the minimum usable area of project i, measured in square meters (m^2). These minimum references were used to construct a homogeneous metric

across projects, avoiding the introduction of non comparable variation across developments due to differences in the internal mix of units (sizes and typologies).

The data obtained from the real estate platforms only contained addresses and approximate locations through pins on base maps, without including explicit geospatial information. Consequently, each project had to be georeferenced by assigning geographic coordinates in the WGS84 reference system.

2.2 Definition of regulatory and spatial variables

The regulatory variables were obtained from the Municipal Regulatory Plans currently in force in the municipalities analyzed, which constitute planning instruments that regulate the physical development of urban areas (Ordenanza General de Urbanismo y Construcciones, 1992). Their selection was based on the nature of those urban planning regulations that make it possible to capture more directly the building development capacity of the land. Accordingly, four regulatory variables were considered: allowed density (D_i), buildable area coefficient (F_i), land occupancy coefficient (O_i) and minimum lot size (S_i).

Based on the georeferenced location of each project, the corresponding urban zone was identified according to the current territorial planning instrument. Then, for each project i, the commercial land value per square meter was imputed, hereinafter referred to as land price (L_i), obtained through the Urban Land Market Observatory of the Chilean Internal Revenue Service (SII). Regarding the variables (F_i) and (D_i), specific cases were identified in which the regulation did not establish an explicit limit (6 cases in total, of which 2 show the simultaneous absence of (F_i) and (D_i)), that is, it did not define a direct quantitative restriction. In such scenarios, development is constrained by the interaction of the other

regulatory variables. Therefore, in order not to introduce an artificial restriction or underestimate the effective building development potential, the maximum observed value for the corresponding variable within the dataset was imputed.

2.2.1 Construction of the land incidence indicator

Considering that the building capacity permitted by regulation is directly related to the development potential of land, an indicator of effective land cost adjusted by the buildable area coefficient (F_i) was constructed, with the purpose of approximating land cost as a function of its building capacity. This indicator does not represent gross land price. Rather, it approximates land cost per unit of permitted development capacity, allowing projects located in zones with different buildable potential to be compared on a more consistent basis. Operationally, the indicator was defined according to equation (2):

$$L_i^{eff} = \frac{L_i}{F_i} \tag{2}$$

Where L_i^{eff} represents the effective land cost of project i per square meter. L_i corresponds to the land price in UF per square meter of project i, and F_i represents the dimensionless buildable area coefficient according to the corresponding urban regulation. Based on this adjustment, and with the purpose of assessing the share of land cost in relation to sales revenue, a land incidence indicator over the unit sale price of the project was constructed, defined according to equation (3):

$$I_i = \frac{L_i^{eff}}{p_i} \qquad I_i^{\%} = 100 \cdot I_i \tag{3}$$

Where I_i corresponds to the proportion of effective land cost relative to the unit sale price of project i, p_i represents the unit sale price of project i in UF/m^2, and $I_i^{\%}$ represents that incidence in percentage terms. Both indicators were constructed for their subsequent use in the descriptive and econometric analysis of the projects.

2.2.2 Operationalization of spatial variables

The selection of spatial variables was aimed at representing differentiated dimensions of urban location commonly considered in the hedonic literature through measures of accessibility to different destinations or amenities, particularly accessibility/centrality, environmental amenities, and urban service amenities (Cellmer et al., 2024; Heyman et al., 2019). Likewise, their selection responded to a criterion of econometric parsimony, consistent with the sample size of the study, prioritizing conceptually differentiated location attributes and avoiding the redundant incorporation of multiple amenities correlated with each other. Based on these criteria, four spatial variables were incorporated: distance to sea ($d_{i,\text{sea}}$), distance to city center ($d_{i,\text{center}}$), distance to gastronomy ($d_{i,gastr}$) and distance to urban green areas ($d_{i,\text{green}}$).

Once the spatial variables had been incorporated into the study, it was necessary to measure them through a homogeneous distance metric between each project and the urban or natural reference elements. The geographic coordinates in the WGS84 reference system were transformed into a projected metric system (UTM 19S, EPSG:32719) in order to represent the location of each project i on the Cartesian plane (Jensen et al., 2021; Schirripa Spagnolo et al., 2024) and to enable the direct calculation of distances in meters through Euclidean geometry. It was decided to use Euclidean distance to measure accessibility to urban and

natural amenities, based on what the literature suggests. This makes it possible to reduce potential biases in the cartographic network and to maintain a uniform criterion when measuring proximity (Jensen et al., 2021). Within this framework, the distance between Project i, represented by a point on the Cartesian plane with metric coordinates (x_i, y_i) and a reference urban element j, represented by the point (x_j, y_j), was defined according to equation (4):

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{4}$$

Where $d_{i,j}$ represents the linear distance in meters between project i and urban element j. The spatial processing, including geometry handling and cartographic reprojection, was carried out using geopandas, complemented by contextily for the incorporation of georeferenced basemaps.

Given that the coastline is not a specific point, distance to sea ($d_{i,\text{sea}}$) was calculated as the minimum distance between project i and the coastline, represented as a continuous line on the plane, according to equation (5):

$$d_{i,\text{sea}} = \min\left\{\sqrt{(x_i - x_y)^2 + (y_i - y_y)^2}\right\} \tag{5}$$

Where (x_y, y_y) corresponds to any point belonging to the linear geometry that defines the coastline.

2.3 Association analysis between variables

To evaluate relationships among the real estate variables (regulatory, spatial, and economic), Pearson and Spearman correlation coefficients were calculated in order to assess linear and

monotonic relationships (Benesty et al., 2009; MacFarland & Yates, 2016). Based on these definitions, the Pearson correlation coefficient was expressed according to equation (6):

$$\rho_{XY} = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} \tag{6}$$

Where ρ_{XY} measures the intensity of the linear association between variables (X, Y), $\text{cov}(X, Y)$ represents their covariance, and $\sigma_X \sigma_Y$ the product of their standard deviations.

For its part, the Spearman coefficient, understood as a measure of monotonic association considering the order of the data (ranks) (MacFarland & Yates, 2016) was calculated according to equation (7):

$$\rho_{XY}^{S} = \rho(\text{rank}(X), \text{rank}(Y)) \tag{7}$$

Where ρ_{XY}^{S} captures monotonic relationships between variables based on the ordering of the data. The Pearson and Spearman correlation coefficients were calculated in Python using the pearsonr and spearmanr functions from the scipy.stats module. Likewise, and with the purpose of detecting multicollinearity between variables and retaining only those compatible with stable estimation, the Variance Inflation Factor (VIF) was calculated on the set of variables. This indicator (VIF) measures the increase in the variance of the coefficients due to collinearity among the independent variables (O'Brien, 2007). Following this approach, the VIF for the explanatory variable X_j, was defined according to equation (8):

$$VIF_j = \frac{1}{1 - R_j^2} \tag{8}$$

Where R_j^2 corresponds to the coefficient of determination of the auxiliary regression of variable X_j on the remaining explanatory variables of the model. High values of VIF_j indicate

potential multicollinearity. In the literature, values greater than 10 are considered problematic (O'Brien, 2007; Wang et al., 2024).

2.4 Estimation of project margin under uncertainty through Monte Carlo simulation

This study used Monte Carlo simulation to estimate the unit margin of each project i, this methodology being widely used in quantitative research to estimate numerical quantities through random sampling (Kroese et al., 2014). For each project i and for each simulation s, the unit margin was defined according to equation (9):

$$M_{i,s} = p_i - \left(L_i^{eff} + C_{i,s} + GI_{i,s}\right) \quad (9)$$

Where $M_{i,s}$ represents the unit margin of project i in simulation s, p_i corresponds to the unit sale price of project i, L_i^{eff} to the effective land cost adjusted by building capacity, previously defined as L_i /F_i, $C_{i,s}$ to the simulated construction cost per square meter, and $GI_{i,s}$ to the real estate expense. This formulation makes it possible to move from a deterministic analysis to one that formally incorporates the uncertainty of cost variables (Hoesli et al., 2006).

The costs $C_{i,s}$ and $GI_{i,s}$ were modeled as uniform random variables within intervals defined as operational assumptions of the study, consistent with the Chilean residential context, in the absence of project level cost data. The simulation was therefore used to propagate plausible cost variability across simulated scenarios for the observed projects and to estimate probabilistic feasibility indicators, rather than to assign deterministic project specific costs. In formal terms, both variables were modeled according to equation (10):

$$Ci, s \sim U(13{,}23)\ , \quad GIi, s \sim U(2{,}6) \quad (10)$$

Where $C_{i,s}$ indicates a continuous uniform distribution bounded between 13 UF/m^2 and 23 UF/m^2, and $GI_{i,s}$ indicates a continuous uniform distribution bounded between 2 UF/m^2 and

6 UF/m^2. The choice of continuous uniform distributions responds to the absence of detailed parametric information on the shape of the cost distribution, which makes it possible to represent equiprobable scenarios within the technically possible range (Hoesli et al., 2006). The random generator used was initialized with a fixed seed, guaranteeing computational reproducibility.

Based on the above, for each project i, 2000 random combinations of costs and real estate expenses were defined. Considering the total number of projects analyzed, this procedure made it possible to evaluate 148,000 profit margin scenarios. By virtue of the Law of Large Numbers, the expected margin $\bar{M}_i$, was calculated as the arithmetic mean of the simulations performed according to equation (11) (Kroese et al., 2014):

$$\bar{M}_i = \frac{1}{N}\sum_{s=1}^{N} M_{i,s} \tag{11}$$

Where $\bar{M}_i$ represents the expected margin of project i and N corresponds to the total number of simulations performed. Given the cross sectional nature of the dataset, explicit temporal cash flows are not developed, which would require assumptions about project duration, financing structure, and discount rates. Therefore, profitability is operationalized as the expected percentage margin, rather than net present value or internal rate of return. Then, the empirical probability of a negative simulated margin was estimated according to equation (12):

$$\Pr(M_{i,s} < 0) \approx \frac{1}{N}\sum_{s=1}^{N} \mathbf{1}(M_{i,s} < 0) \tag{12}$$

Where $1(M_{i,s} < 0)$ is an indicator function that takes the value of one when the margin is negative and zero otherwise. This metric is key for uncertainty management, since it makes

it possible to measure the risk that the value of an asset is below a given critical threshold (Hoesli et al., 2006). Finally, the expected percentage margin was normalized with respect to the unit sale price according to equation (13):

$$m_i^{\%} = 100 \cdot \frac{\bar{M}_i}{p_i} \tag{13}$$

Where $m_i^{\%}$ expresses the expected percentage margin of project i as a percentage of the unit sale price.

Likewise, the 5%, 50%, and 95% percentiles of the margin were determined. These metrics make it possible to characterize not only the expected value, but also the risk associated with the distribution, providing a more robust measure of dispersion and tail behavior than traditional point estimates (Hoesli et al., 2006).

2.5 Econometric assessment of structural associations with expected percentage margin

The econometric model was estimated on the complete set of 74 projects. In order to evaluate the association of land, regulatory and spatial variables with the expected percentage margin, an ordinary linear regression model (OLS) was constructed, a fundamental technique for the empirical analysis of land and housing markets (Mackinnon & White, 1985; Morawetz & Klaiber, 2022; Theisen & Emblem, 2021). The dependent variable corresponds to the expected percentage margin derived from the Monte Carlo simulation, according to equation (14):

$$m_i^{\%} = \beta_0 + \beta_1 L_i^{eff} + \beta_2 S_i + \beta_3 D_i + \beta_4 F_i + \beta_5 O_i + \beta_6 d_{i,\text{sea}} + \varepsilon_i \tag{14}$$

Where $m_i^{\%}$ represents the expected percentage margin of project i, L_i^{eff} corresponds to the effective land cost adjusted by building capacity, previously defined as L_i /F_i, S_i represents minimum lot size, D_i corresponds to allowed density, F_i corresponds to the buildable area coefficient, O_i corresponds to the land occupancy coefficient, $d_{i,\text{sea}}$ corresponds to distance to sea, and ε_i corresponds to the error term.

Because effective land cost is also a component of the expected margin formulation, its coefficient is interpreted as a structural sensitivity parameter rather than as an independent causal effect. Its inclusion is justified because land price and regulatory buildable capacity are observable ex ante and constitute central inputs in early stage development feasibility assessment.

The model was estimated using the least squares method, defined in matrix form as indicated in equation (15) (Mackinnon & White, 1985; Morawetz & Klaiber, 2022):

$$\hat{\beta} = (\mathrm{X}'\mathrm{X})^{-1}\mathrm{X}'\mathrm{y} \tag{15}$$

Where X corresponds to the matrix of explanatory variables including the constant term, and y to the vector of the dependent variable.

In order to mitigate possible effects of heteroskedasticity, a frequent situation in hedonic price models and real estate data (Morawetz & Klaiber, 2022; Theisen & Emblem, 2021), the standard errors were estimated using the HC3 heteroskedasticity consistent variance estimator according to equation (16) (Easton, 2012; Mackinnon & White, 1985):

$$\widehat{Var}_{HC3}(\hat{\beta}) = (X'X)^{-1}X'\widehat{\Omega}_{HC3}X(X'X)^{-1} \tag{16}$$

Where $\widehat{\Omega}_{HC3}$ is a diagonal matrix whose elements are defined according to equation (17):

$$\frac{\hat{\varepsilon}_i^2}{(1-h_{ii})^2} \tag{17}$$

And h_{ii} represents the leverage of observation i.

The HC3 estimator was used because of its better performance in small samples compared with other robust estimators, since it reduces the probability of significant inference errors (Mackinnon & White, 1985). Econometric estimations were implemented mainly with statsmodels.api, including OLS models, robust standard errors, and diagnostic tests.

In addition, the Breusch–Pagan test was used to assess the presence of heteroskedasticity (Morawetz & Klaiber, 2022; Theisen & Emblem, 2021), whose null hypothesis establishes constant variance, according to equation (18):

$$H_0: Var(\varepsilon_i) = \sigma^2 \tag{18}$$

The test statistic asymptotically follows a χ^2 distribution.

The influence of individual observations was evaluated through Cook's distance, according to equation (19) (Cook, 1977):

$$D_i = \frac{\hat{\varepsilon}_i^2}{k\hat{\sigma}^2}\frac{h_{ii}}{(1-h_{ii})^2} \tag{19}$$

Finally, VIF was calculated on the regressors of the econometric model $\{L_i^{eff}, S_i, D_i, F_i, O_i, d_{i,\text{sea}}\}$ with the purpose of ruling out multicollinearity that could distort the estimation of the standard errors of the coefficients (Morawetz & Klaiber, 2022; Theisen & Emblem, 2021). Its calculation was carried out using statsmodels.stats.outliers_influence.

3.0 Results

3.1 Descriptive characterization and territorial differentiation

The set of 74 projects analyzed shows marked spatial heterogeneity. In Figure 2, each point represents the location of a residential project, while the intensity of the color indicates its unit sale price (UF/m²), according to the scale shown on the right side; darker tones correspond to higher values and lighter tones to lower values. It is observed that the highest average unit prices are concentrated in the municipalities of Concón (97.7 UF/m²) and Viña del Mar (80.7 UF/m²), while Quilpué (49.9 UF/m²) and Villa Alemana (54.0 UF/m²) make up the lower valuation segment. Valparaíso is located in an intermediate position (64.9 UF/m²), although with greater internal dispersion. A similar situation occurs with gross land value, as shown in Table 1.

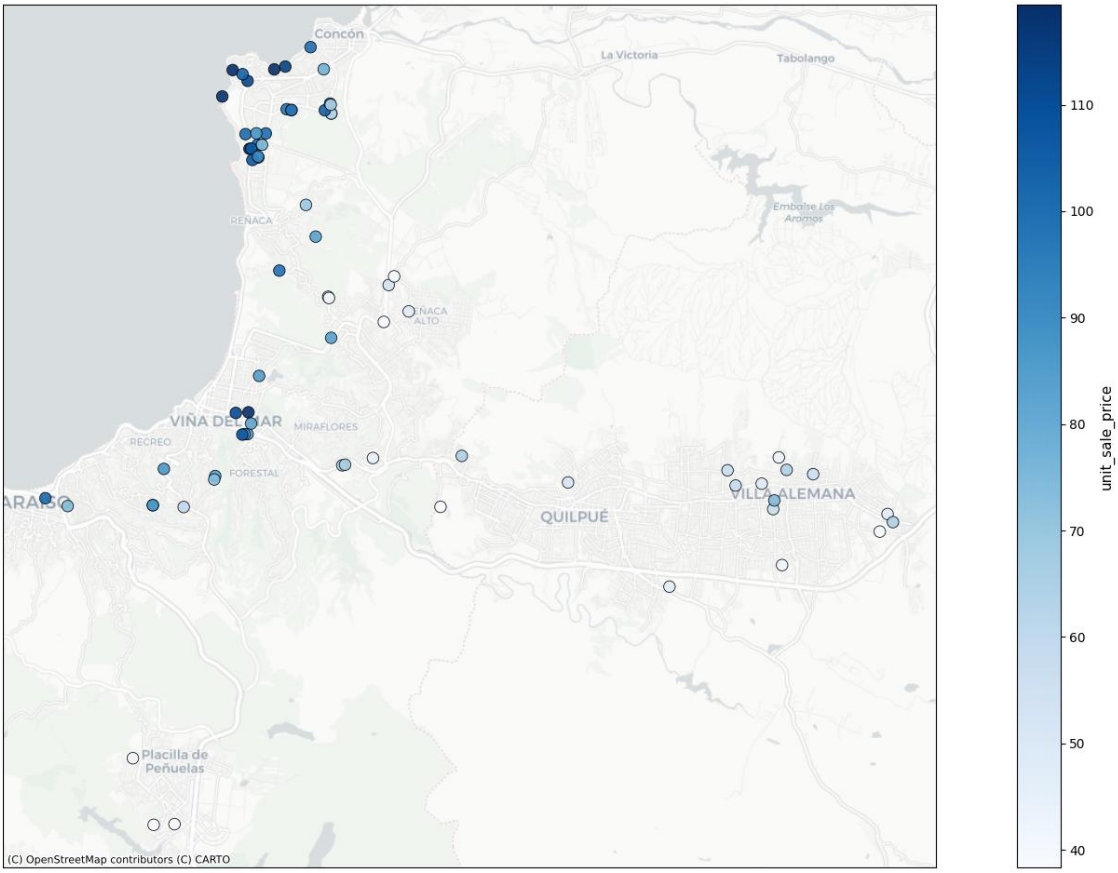


Figure 2. Spatial distribution of unit sale price (UF/m²) across residential development projects in Greater Valparaíso.

Source: Authors' own elaboration based on project-level data. Basemap: OpenStreetMap contributors and CARTO.

By incorporating some regulatory variables, it becomes evident that their structure also varies across municipalities. Valparaíso and Viña del Mar have high average densities, above 1,300 inhabitants/ha, while Quilpué shows a considerably lower mean density (130 inhabitants/ha). In Figure 3, each point represents a project and the intensity of the color indicates the effective land cost adjusted by the buildable area coefficient, so that darker tones correspond to higher values. The spatial distribution shows that the highest values tend to be concentrated in coastal sectors, especially in Concón and in part of Viña del Mar, while in Quilpué and Villa Alemana relatively lower values predominate. Taken together, this evidence shows that both the regulatory variables and the effective land cost present relevant territorial differences across municipalities.

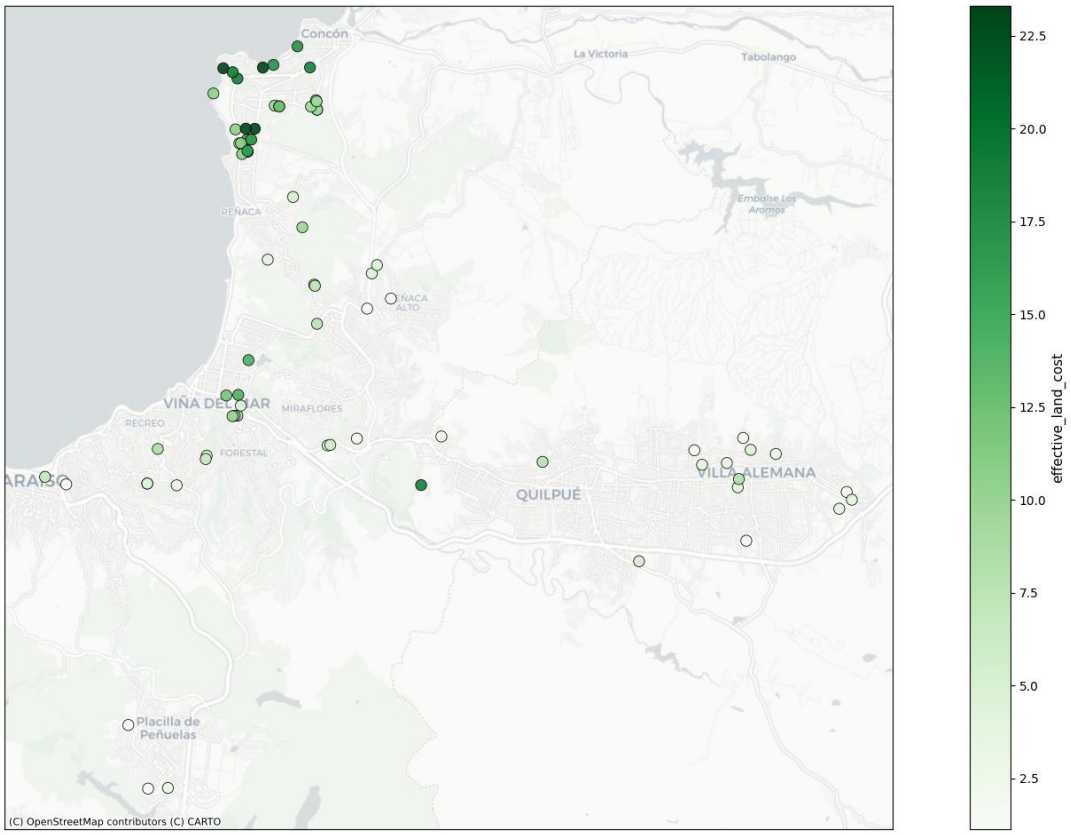


Figure 3. Spatial distribution of effective land cost (UF/m²) across residential development projects in Greater Valparaíso.
Source: Authors' own elaboration based on project-level data. Basemap: OpenStreetMap contributors and CARTO.

3.2 Associations between price, land, and regulatory and spatial variables

Table 1 presents the Pearson and Spearman correlation coefficients among the main economic, regulatory, and spatial variables of the study. From an economic point of view, a positive relationship is observed between land price and the unit sale price of the apartments (0.63 Pearson and 0.75 Spearman). Likewise, a positive relationship is observed between effective land cost and unit sale price (0.32 Pearson and 0.7 Spearman), suggesting a relationship that is more monotonic than linear, even in the presence of extreme values. On the other hand, with respect to regulation, it is possible to observe a positive correlation

between buildable area coefficient and allowed density (0.71 Pearson and 0.74 Spearman), which is expected by regulatory design, that is, more intensive zones usually allow simultaneously greater density and buildability, with the opposite effect occurring in inverse relationships such as land occupancy coefficient and minimum lot size (-0.66 Pearson and -0.80 Spearman), where a greater requirement in minimum lot size is usually accompanied by lower land occupancy.

Table 1. Pearson (upper triangle) and Spearman (lower triangle) correlation coefficients among study variables.

	1	**2**	**3**	**4**	**5**	**6**	**7**
unit sale price	1.000	0.320	0.631	0.000	0.113	-0.164	0.506
effective land cost	0.700	1.000	0.730	-0.306	-0.294	-0.257	0.198
land price	0.749	0.885	1.000	-0.057	0.174	-0.177	0.278
allowed density	-0.049	-0.361	-0.042	1.000	0.711	0.475	-0.279
buildable area coefficient	0.075	-0.167	0.221	0.744	1.000	0.293	-0.028
land occupancy coefficient	-0.194	-0.297	-0.201	0.478	0.196	1.000	-0.661
minimum lot size	0.499	0.476	0.457	-0.406	-0.053	-0.801	1.000

Note: (1) unit sale price; (2) effective land cost; (3) land price; (4) allowed density; (5) buildable area coefficient; (6) land occupancy coefficient; (7) minimum lot size. Upper triangular matrix reports Pearson coefficients; lower triangular matrix reports Spearman coefficients.

To complement the previous analysis, Table 2 presents the variance inflation factors (VIF) of the regulatory variables included in the econometric specification. In all cases, the values remain below 2.5, which rules out severe multicollinearity problems among the regulatory predictors.

Table 2. Variance Inflation Factors (VIF) for normative variables.

Variable	**VIF**
const	32.514
allowed density	2.453
buildable area coefficient	2.190
land occupancy coefficient	2.148

minimum lot size	1.917

Finally, Table 3 presents the correlation between expected margin percentage and unit sale price. The results show a moderate Pearson coefficient (0.353) and a higher Spearman coefficient (0.763), which suggests a more consistent association in monotonic terms than in strictly linear terms.

Table 3. Correlation between expected margin percentage and unit sale price.

Correlation Type	Coefficient
Pearson	0.353
Spearman	0.763

With respect to the sociospatial variables, it can be observed that distance to sea explains 30% of the variability in the unit sale price of apartments, with a relationship of -0.55 Pearson and -0.49 Spearman (see Table 4). The results show that the amenities distance to sea, distance to gastronomy, and distance to urban green areas have a moderate and consistent relationship with unit sale price (see Table 4). However, based on the observed data, it is possible to indicate that the market is not structured primarily around the service poles represented by distance to city center, a variable that presents a weak association with unit sale price (R^2 of 0.020, -0.143 Pearson, and -0.213 Spearman). It is also possible to observe that the amenities are associated with unit sale price, but do not structure effective land cost with the same intensity. When evaluating structural multicollinearity among explanatory variables, high multicollinearity is detected between distance to gastronomy and distance to urban green areas ($r = 0.996$, see Table 5); this is also reflected in the very high VIF values (VIF > 140, see Table 6). Given this level of redundancy, it was decided to retain only the

distance variable with the greatest explanatory capacity with respect to unit sale price and lower collinearity, namely distance to sea.

Table 4. Correlation between spatial variables and economic indicators.

Dependent Variable	Distance	Pearson	Spearman	R^2
unit sale price	distance to sea	-0.553	-0.495	0.305
unit sale price	distance to city center	-0.143	-0.213	0.020
unit sale price	distance to gastronomy	-0.463	-0.386	0.215
unit sale price	distance to urban green areas	-0.474	-0.411	0.224
effective land cost	distance to sea	-0.231	-0.512	0.053
effective land cost	distance to city center	-0.122	-0.165	0.014
effective land cost	distance to gastronomy	-0.151	-0.313	0.022
effective land cost	distance to urban green areas	-0.154	-0.331	0.023

Table 5. Pearson correlation matrix among spatial distance variables.

	1	2	3	4
distance to sea	1.000	-0.12	0.091	0.080
distance to city center	-0.120	1.000	0.739	0.740
distance to gastronomy	0.091	0.739	1.000	0.996
distance to urban green areas	0.080	0.740	0.996	1.000

Note: (1) distance to sea; (2) distance to city center; (3) distance to gastronomy; (4) distance to urban green areas

Table 6. Variance Inflation Factors (VIF) for spatial variables.

Variable	VIF
const	3.752
Distance to sea	1.109
Distance to city center	2.395
Distance to gastronomy	143.373
Distance to urban green areas	142.469

3.3 Monte Carlo simulation and risk structure

The Monte Carlo simulation considered 2,000 simulations per project, which made it possible to estimate the unit margin under varying construction cost and real estate expense scenarios.

The average expected margin reached 43.07 UF/m², with a median of 43.14 UF/m², which shows a limited difference between both measures. However, the standard deviation is high (27.80 UF/m²), yielding a coefficient of variation of 0.646, which evidences considerable dispersion in the expected margin (see Table 7).

In percentage terms, the average expected percentage margin is 53%, with minimum values of -69% and maximum values close to 75%; this range reveals the coexistence of profitable projects with others that are not. The average probability of a negative margin is 4%, although there are specific cases where this probability reaches 100%, which indicates that most scenarios are concentrated in positive results, with 75% of the projects showing a probability of negative margin equal to 0. This shows that risk is not distributed homogeneously, but rather is concentrated in certain developments with adverse combinations of land cost and location. Figure 4 shows the spatial distribution of expected percentage margin, revealing a differentiated pattern with respect to unit sale price, that is, areas with high unit sale price do not necessarily coincide with higher expected percentage margins. Although effective land cost is visibly higher in Concón and lower in Villa Alemana and Quilpué, the expected percentage margin does not show a proportional reduction in Concón relative to the municipalities with cheaper land, which suggests that the higher sale price in areas close to the sea offsets the higher land cost.

Table 7. Summary statistics of Monte Carlo simulation results.

Metric	Value
Mean unit margin (UF/m²)	43.074
Std. unit margin (UF/m²)	27.816
P5 unit margin (UF/m²)	8.239
Median unit margin (UF/m²)	43.144
P95 unit margin (UF/m²)	80.007
Mean expected percentage margin (%)	53.039
Mean probability of negative margin	0.040

Note: Results based on project-level Monte Carlo simulations.

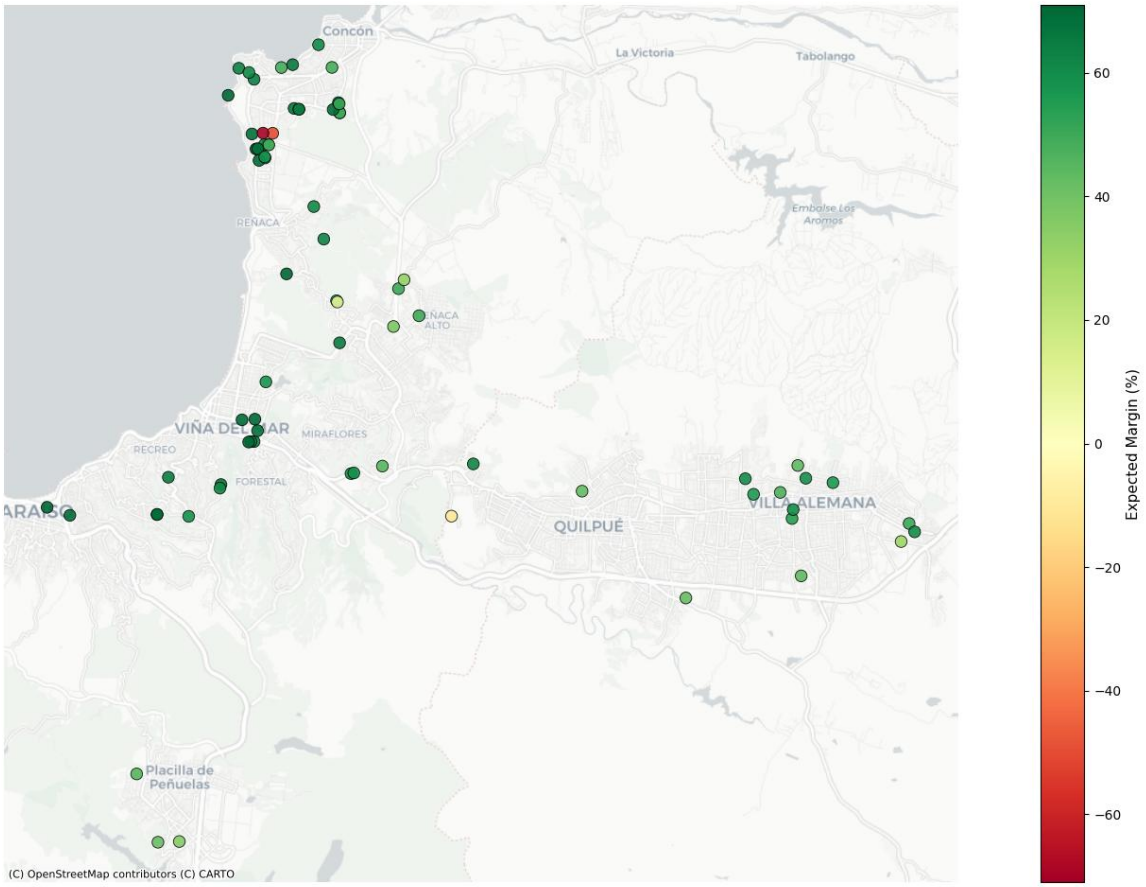


Figure 4. Spatial distribution of expected percentage margin (%) across residential development projects in Greater Valparaíso.
Source: Authors' own elaboration based on project-level data. Basemap: OpenStreetMap contributors, CARTO.

The distribution of unit margin shows positive skewness and slight multimodality, departing from a normal shape (see Figure 5). The cumulative distribution function confirms that the probability of a negative margin is low but not nonexistent, configuring a market with a positive bias but exposed to localized extreme events (see Figure 6).

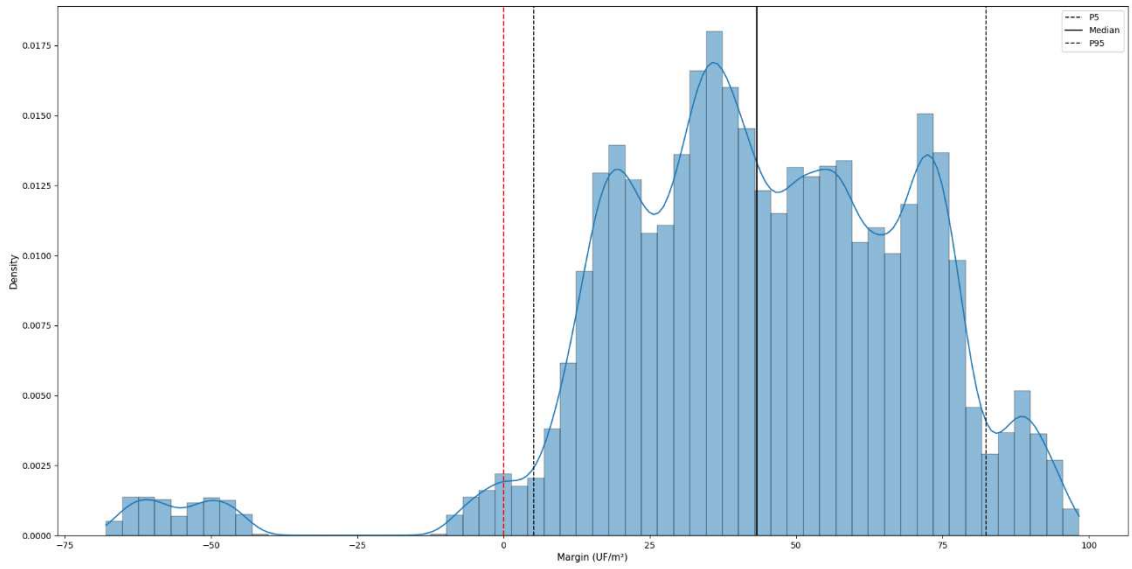


Figure 5. Monte Carlo distribution of unit margin (UF/m²).
Source: Authors' own elaboration.

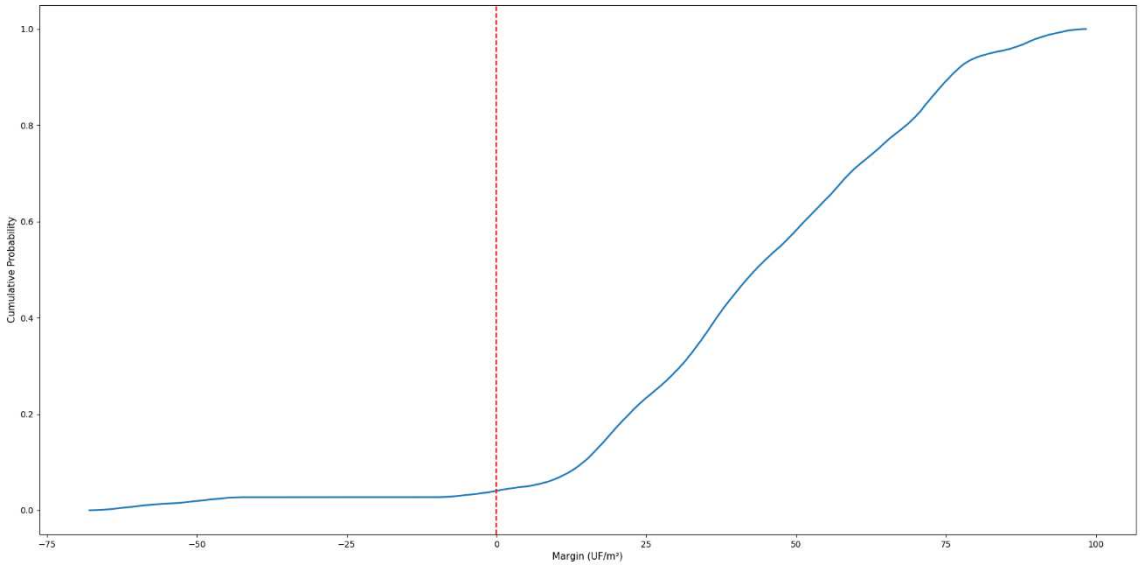


Figure 6. Cumulative distribution function of simulated unit margin (Monte Carlo).
Source: Authors' own elaboration.

A relevant empirical pattern emerges when land incidence is examined together with expected percentage margin (see Figure 7). Up to approximately 20% land incidence, most projects maintain expected percentage margins within a relatively high range, approximately

between 40% and 75%. However, above this level, expected margins decline sharply in several cases and may become negative. This result suggests that land incidence operates as a practical feasibility threshold rather than as a merely descriptive ratio.

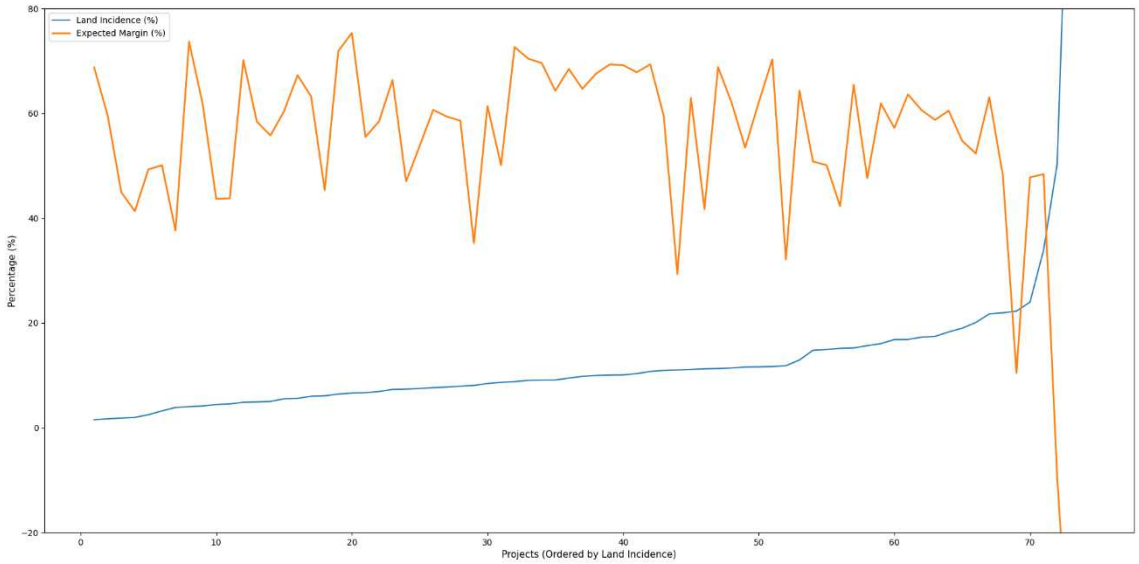


Figure 7. Land incidence vs. expected margin (%) (projects ordered by incidence)
Source: Authors' own elaboration

3.4 Econometric model

For the dependent variable expected percentage margin, obtained through Monte Carlo, an OLS model with HC3 robust standard errors was estimated, which considered effective land cost, the four regulatory parameters, and distance to sea. The results of the full specification (see Table 8) show that only minimum lot size presents statistical significance among the regulatory parameters, while allowed density, buildable area coefficient, and land occupancy coefficient are not significant. Given the lack of statistical significance of these three parameters, and in order to avoid overparameterization in a reduced set of observations, a parsimonious specification was estimated, retaining only the significant regulatory variable (minimum lot size), resulting in a reduced model with 3 variables. This result is relevant

because the most visible development capacity indicators, such as density and buildable area coefficient, do not remain statistically significant in the multivariate specification, whereas minimum lot size appears as the regulatory parameter most consistently associated with expected profitability in this sample.

Table 8. OLS regression results: full regulatory specification (HC3 robust standard errors)

Variable	Coefficient	Robust Std Error HC3	t-value	p-value	Lower 95	Upper 95
Constant	45.762	12.325	3.713	<0.001	21.606	69.918
Effective land cost	-0.911	0.143	-6.353	<0.001	-1.193	-0.630
Minimum lot size	0.013	0.004	3.417	0.001	0.006	0.021
Allowed density	0.000	0.002	0.053	0.958	-0.004	0.004
Buildable area coefficient	2.631	2.191	1.201	0.230	-1.663	6.924
Land occupancy coefficient	20.480	15.222	1.345	0.178	-9.354	50.314
Distance to sea	-0.001	0.000	-2.874	0.004	-0.001	-0.000

The reduced model reached an R^2 of 0.678 (adjusted R^2 = 0.664, see Table 12), which indicates substantial explanatory power given the cross sectional nature of the dataset. The results show that effective land cost presents a highly significant negative coefficient (β = -0.971; $p < 0.001$). As noted in the methodological section, this coefficient is interpreted as the structural sensitivity of expected margin to land cost adjusted by buildable capacity, rather than as an independent causal estimate. In practical terms, each increase of 1 UF/m² in effective land cost is associated with a reduction of 0.97 percentage points in expected percentage margin.

Minimum lot size exhibits a significant positive effect ($\beta = 0.009$; $p < 0.001$). Although the coefficient may appear low, it is necessary to consider the scale of the unit of measurement. In other words, for every 100 m^2 increase in lot size requirement, the margin would increase by approximately 1 percentage point, suggesting that projects in areas with greater minimum lot size requirements tend to operate with higher margins.

Distance to sea presents a significant negative coefficient ($\beta = -0.001$; $p < 0.001$), indicating that greater proximity to the coastline is associated with higher expected percentage margin. As in the previous case, it is necessary to consider the scale of the unit because, although the coefficient appears numerically small due to measurement in meters, under realistic spatial variations it would imply economically significant changes in expected margin. In the case of Greater Valparaíso, there are distances on the order of kilometers to the coastline, implying economically significant changes in expected margins.

The Breusch–Pagan test (see Table 9) did not detect heteroskedasticity ($p \approx 0.71$) and the VIF values of the model remain close to 1, ruling out problematic collinearity among explanatory variables (see Table 10). Although Cook's statistic identifies influential observations that exceed the threshold of $4/n$, these were retained in order to preserve sample integrity, and the diagnostic is reported (see Table 11).

Table 9: Breusch–Pagan test

Metric	Value
LM Statistic	1.417
LM p-value	0.701
F Statistic	0.456
F p-value	0.714

Note: The null hypothesis of homoskedasticity cannot be rejected.

Table 10. Variance Inflation Factors (VIF) for the profitability model

Variable	VIF
effective land cost	1.081
minimum lot size	1.087
distance to sea	1.103

Table 11. Influence diagnostics for the profitability model

Metric	Value
Max Cook's Distance	0.633
Cook's threshold (4/n)	0.054
Max Leverage	0.452

Table 12. OLS regression results Parsimonious profitability model (HC3 robust standard errors)

Variable	Coefficient	Robust Std Error HC3	t-value	p-value	Lower 95	Upper 95
Constant	64.656	3.730	17.336	< 0.001	57.346	71.966
effective land cost	-0.971	0.131	-7.368	< 0.001	-1.230	-0.713
minimum lot size	0.009	0.00234	3.894	< 0.001	0.005	0.014
distance to sea	-0.001	0.00028	-3.905	< 0.001	-0.002	-0.001
-	-	-	-	-	-	-
Metric	Value					
R squared	0.678					
Adj R squared	0.664					
F statistic	27.848					
Prob F	<0.001					
AIC	601.110					
BIC	610.326					
N observations	74					

3.5 Synthesis of findings

The results show that expected percentage margin is shaped by the combined role of effective land cost, spatial location and a more limited regulatory incidence represented by minimum lot size. Effective land cost constitutes the main structural component negatively associated with expected percentage margin, while distance to sea remains statistically significant, suggesting that coastal location may partially offset higher effective land costs through higher unit sale prices. Although the average expected percentage margin is 53%, there is substantial dispersion across projects, indicating that performance varies according to specific combinations of land cost, permitted development capacity, unit sale price and location. In this context, risk is concentrated in specific projects rather than distributed uniformly across the market. The evidence also shows that minimum lot size is the only regulatory parameter that remains statistically significant in the parsimonious specification, suggesting that regulatory effects do not operate uniformly across the urban planning variables considered in the study.

4.0 Discussion and conclusions

The first research question examined how regulatory variables are associated with expected percentage margin. The results show that this incidence is not homogeneous across the parameters considered. In particular, minimum lot size was the only regulatory parameter that maintained a statistically significant association in the multivariate specification. This is a relevant finding because density and buildable area coefficient, which are usually interpreted as direct indicators of development capacity, did not remain statistically significant in the model. This result is consistent with the literature that incorporates minimum lot size as one of the requirements used to characterize density restrictions in

residential development (Büchler & v. Ehrlich, 2023). In this sense, the results provide partial support for H1, since regulatory incidence did not manifest itself uniformly across the parameters considered.

In relation to land, the results are consistent with H2, as they show that the relative weight of land cost, when considered together with permitted development capacity and unit sale price, differentiates projects with greater exposure to expected margin deterioration and negative margin scenarios. More than the gross land price, the central factor is its value adjusted by building capacity, which suggests that the pressure of land on the expected performance of the project depends on its effective cost as a function of the permitted development potential. It is important to note that effective land cost is used both in the margin formulation and in the regression model. This double role is intentional, because the objective is not to isolate an external causal effect of land cost, but to assess how project feasibility responds to an ex ante observable cost component that is structurally embedded in the development margin. In this sense, the coefficient should be interpreted as a sensitivity measure within the profitability framework, rather than as evidence of an independent causal mechanism. While the negative direction of the relationship between effective land cost and expected margin could be anticipated from the profitability formulation, the econometric model made it possible to quantify its empirical magnitude in the Greater Valparaíso context. The results show that each additional 1 UF/m² of effective land cost is associated with an approximate 0.97 percentage point reduction in expected percentage margin. This interpretation is consistent with the literature that links land value to its development potential and shows that more restrictive regulations may reduce its value by limiting such potential (Moon, 2019; Moon & Ahn, 2022). Along the same lines, the literature identifies land cost as one of the

main sources of risk in real estate development and argues that its proper evaluation requires considering in advance site constraints, construction costs, and projected revenues (Loizou & French, 2012). Taken together, there is consistency with the idea that the effect of land on expected margin does not depend solely on its gross price, but also on its relationship with the effective development capacity of the site.

Regarding spatial location, the results show that at least one spatial attribute is significantly associated with the expected percentage margin obtained through probabilistic simulation. In particular, a shorter distance to sea is associated with higher expected margins, which suggests that certain location advantages may compensate, at least partially, for higher land costs. This is consistent with the hedonic literature on coastal amenities, which recognizes a differential housing valuation associated with coastal proximity, although this relationship has been modeled in a nonlinear way in hedonic housing price studies (Conroy & Milosch, 2011). In a complementary way, the literature has also pointed out that proximity to the coast may exert an attractive force that can offset the expected costs associated with risk, and influence development and land and housing values in coastal areas (Walls et al., 2018). This helps explain why municipalities with higher land values do not necessarily show lower expected margins. In this sense, the results provide partial support for H3, since only distance to sea remained statistically associated with expected percentage margin. While prior hedonic literature mainly relates coastal proximity to housing prices, this study extends that discussion to expected profitability at the project level.

The empirical contribution of this result lies in showing that the relationship between land, location and profitability is not mechanical in a simple sense. Projects located in high value coastal areas may face higher effective land costs, but higher unit sale prices can partially

offset these costs. Conversely, projects with lower land prices do not necessarily achieve higher expected margins if their market price structure is weaker. This interaction helps explain why land incidence, rather than gross land price alone, is a more informative indicator for early stage feasibility assessment.

Likewise, the results show that, although the average expected percentage margin is positive, risk is not distributed homogeneously across projects. While an important part of the market operates with favorable expected margins, there is a reduced subset in which the probability of loss increases considerably. In this sense, the average value conceals relevant heterogeneity and suggests that risk is not distributed uniformly across projects, which is consistent with recent evidence showing that uncertainty does not affect real estate assets uniformly and that its proper identification makes it possible to distinguish cases with greater exposure to adverse outcomes (Pollestad & Oust, 2025). In practical terms, this reinforces the analytical usefulness of jointly observing expected margin, land incidence, and the probability of unfavorable scenarios.

4.1 Theoretical implications

In general terms, the literature has shown that urban development and the response of housing supply depend simultaneously on regulatory and physical constraints, and that geography may have both a direct and an indirect effect through its impact on land value and regulatory incentives (Saiz, 2010). In addition, it has been argued that land use regulation forms part of a spatial equilibrium in which productivity, amenities, and urban rents interact, generating effects that cannot be understood on the basis of a single isolated parameter (Parkhomenko, 2023). In this sense, this study contributes empirical evidence to the literature by moving from broader relationships among regulation, land value and housing prices toward a project

level assessment of expected profitability, where effective land cost, regulatory conditions and spatial location are jointly evaluated within a probabilistic framework. Table 13 summarizes how the main empirical findings of this study are positioned relative to prior literature and clarifies the specific contribution of each result.

Table 13. Empirical contribution of the study relative to prior literature

Dimension	Prior literature	Empirical finding in this study	Empirical contribution
Land cost and development capacity	Land value has been linked to development potential and regulatory constraints (Moon, 2019; Moon & Ahn, 2022). In real estate development, land cost, site constraints, construction costs and projected revenues are also recognized as relevant components of risk assessment (Loizou & French, 2012).	Effective land cost is negatively associated with expected percentage margin: $\beta = -0.971$; $p < 0.001$. This means that each additional 1 UF/m² adjusted by buildable capacity is associated with an approximate 0.97 percentage point decrease in expected margin.	The study provides a project level and territorially specific quantification of the relationship between land cost and expected profitability in Greater Valparaíso, using an indicator that incorporates permitted buildable capacity rather than gross land price alone.
Urban regulation	Land use regulation has been associated with higher housing prices and changes in urban expansion patterns (Büchler & v. Ehrlich, 2023). It has also been modeled as part of a spatial equilibrium that links regulation with land rents, housing supply and urban productivity (Parkhomenko, 2023).	Among the regulatory variables analyzed, minimum lot size is the only one retained with statistical significance in the parsimonious model: $\beta = 0.009$; $p < 0.001$. A 100 m² increase is associated with approximately +0.9 percentage points in expected margin.	The study shows that the regulatory association with profitability is not distributed evenly across planning parameters. In this sample, minimum lot size captures a more relevant association with expected margin than allowed density, buildable area coefficient or land occupancy coefficient.

Coastal location and spatial amenities	Coastal proximity has been associated with residential price premiums in hedonic housing studies (Conroy & Milosch, 2011). Related evidence also shows that coastal amenities, beach characteristics and coastal risk conditions can influence residential values and development patterns (Boto-García & Leoni, 2023; Landry et al., 2022; Walls et al., 2018).	Distance to sea is statistically significant: $\beta = -0.001$; $p < 0.001$. Since it is measured in meters, one additional kilometer from the coastline is associated with an approximate 1 percentage point decrease in expected margin.	The study moves the coastal premium discussion from residential prices toward project level expected profitability, showing that spatial location is also relevant when margins, land cost and development feasibility are jointly assessed.
Land incidence and feasibility	Real estate development risk assessment requires considering land cost, site constraints, construction costs and projected revenues (Loizou & French, 2012). In parallel, land value has been linked to development potential and regulatory constraints (Moon, 2019; Moon & Ahn, 2022).	Around 20% land incidence, the observed pattern changes: below this level, most projects maintain high expected margins; above it, several cases show marked margin deterioration or negative values.	The study contributes by operationalizing land incidence as a project level feasibility indicator. In the Greater Valparaíso context, the observed 20% level provides an empirical reference for identifying projects more exposed to margin deterioration, without treating it as a universal threshold.
Uncertainty and downside risk	Economic uncertainty has been shown to affect real estate performance (Ahiadu & Abidoye, 2024). More recent decision support approaches also emphasize the relevance of measuring uncertainty at the asset level for real estate investment	The Monte Carlo simulation reports an average expected margin of 53%. In most projects, downside risk remains low, with 75% of projects showing a zero probability of negative margin; however, a small	The study provides empirical evidence that, in Greater Valparaíso, downside risk is not evenly distributed across residential developments, but concentrated in specific projects. This offers a local benchmark for early

	decisions (Pollestad & Oust, 2025).	subset reaches a 100% probability of negative margin.	stage feasibility assessment and may inform studies in similar coastal urban markets.

Overall, these findings show that the study contributes not by restating general relationships already recognized in the literature, but by quantifying their project level expression in the Greater Valparaíso residential development market.

4.2 Practical implications

From a practical perspective, the results may be useful for developers, investors, and evaluators of residential projects, by showing that the expected profitability of the project, operationalized here through the expected percentage margin, would not be explained solely by the sale price or gross land cost. Therefore, early stage feasibility assessment should also consider the way in which regulatory conditions, land cost adjusted by development capacity, and project location are combined. In particular, the results on land incidence relative to expected margin and the probability of negative margin may provide additional criteria for the early evaluation of residential apartment projects in similar urban contexts.

4.3 Limitations and future research

The existence of endogenous relationships among land value, regulation, amenities, and expected percentage margin cannot be completely ruled out. This limitation is consistent with the literature, which has warned that, in coastal markets, the lack of treatment of endogeneity may bias the estimates obtained through standard OLS models (Landry et al., 2022). In addition, effective land cost is included both in the expected margin formulation and in the regression model; therefore, its coefficient should be understood as a structural sensitivity

measure within the proposed profitability framework, rather than as a causal estimate. The modeling of costs through uniform distributions also constitutes an operational simplification derived from the absence of project level cost microdata. Finally, the cross sectional nature of the analysis prevents the incorporation of an explicit temporal dimension and, therefore, the estimation of dynamic profitability indicators such as internal rate of return, net present value or payback period. Future research could extend this framework by incorporating project level cost data and longitudinal information, allowing the analysis of dynamic profitability measures while preserving the ex ante assessment logic developed in this study.

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