A Computational Analysis of Housing Affordability: Robust Bootstrap Regression Modeling of the Safety Premium

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***Abstract*—This study presents a methodologically rigorous and in-depth analysis of the socio-institutional determinants of housing affordability in nine EU Member States and Georgia over the period 2013-2023. The study transcends conventional macroeconomic models to identify and quantify the impact of non-financial indicators on the Price-to-Income ratio as the dependent variable. The study uses bootstrap regression with 1000 iterations, ensuring the stability of the coefficients and responding to the difficulties of data distribution in both transition and developed economies (unbalanced panel data, sample size of 89). Empirical results demonstrate a high explanatory power of the model (R-squared value of 0.670), where the Safety Index was identified as the main and most important driving factor of value formation (beta coefficient of 0.312, p-value of 0.007). The conclusion that institutional safety functions as a "nonfinancial capital" that exhibits a strong predictive association with the volatility of real estate prices is significant. The research findings also indicate a paradigm shift in real estate valuation, validating the "safety premium" and supporting the Hedonic Pricing Theory. This study argues that institutional stability in the housing ecosystems of transition countries outweighs the importance of traditional financial liquidity as a price determinant.**

***Keywords*—Housing affordability; robust bootstrap regression; safety index; EU real estate market; Georgia; value driver**

I. Introduction

Studying real estate market trends is crucial for assessing the performance of any local economy. The stability of the real estate market is influenced by many variables. Often, these variables are closely related, and traditional forecasting models are insufficient to assess these interdependencies [1]. As market volatility increases, the margin of error of traditional forecasting models also widens, necessitating more sophisticated and reliable analytical frameworks [2].

Real estate is both a material necessity and a sophisticated instrument for capital accumulation. In addition to fulfilling its functional purpose, it serves as a hedge against inflationary pressures in the long term through rental income. While housing affordability was previously considered a social necessity, it has now become a major macroeconomic challenge. According to modern academic sources, affordability is no longer merely a by-product of the nominal growth of classical macroeconomic aggregates, but is increasingly shaped by socio-institutional factors, particularly the safety index and the dynamics of market liquidity. It is necessary to identify specific sources of real estate price fluctuations and liquidity shocks to assess the changes taking place in the market [3].

Recent developments in Georgia, rapid urbanization as well as deep regional inequalities, have fundamentally changed the structural foundations of the real estate market. In particular, the current situation in Tbilisi reflects a divergence between rising real estate prices and stagnant wage growth [4]. The above situation clearly demonstrates the inability of traditional valuation methods to take into account the "safety premium." This is a necessity, as this is what consumers prioritize, especially in transition and developing economies such as Georgia.

Therefore, it is necessary to include integrative models to eliminate the gaps between financial data and social perceptions. This study aims to identify the factors that exert a significant influence on housing affordability using robust bootstrap regression analysis. The study covers the period 2013–2023 and, by analyzing a heterogeneous panel of 10 economies, the model tests the hypothesis that institutional security has become a key driver of value, potentially overshadowing the explanatory power of traditional economic indicators. Ultimately, this study seeks to explain how "nonfinancial capital" is capitalized in real estate price structures.

The remainder of this study is organized as follows: Section II reviews the relevant literature. Section III outlines the methodology, study area, and data collection procedures. Section IV presents the model diagnostics and empirical results. Section V discusses the economic implications, model parsimony, and alternative specifications. Finally, Section VI concludes the study with specific recommendations for policymakers.

II. Literature Review

Academic consensus emphasizes that property valuation is driven by a complex matrix of interconnected macroeconomic variables [5]. Empirical literature, particularly the cross-country analysis by Tripathi [6], involving 43 economies, identifies money supply and real exchange rates as high-dimensional determinants with significant positive correlations to real estate value. Furthermore, the interplay between money supply, population shifts, and rental dynamics remains a cornerstone for maintaining housing market equilibrium [7].

The dual function of the real estate sector, acting as both an economic barometer and a potential source of systemic risk, is extensively documented by Leung [8]. While price appreciation may stimulate consumption, it simultaneously creates structural barriers for non-homeowners. In support of this, Belke and Keil [9] analyzed 100 German cities and concluded that housing valuation is deeply rooted in supply-side factors, demographic structures, and the quality of local infrastructure. However, as Glaeser and Nathanson [10] argue, traditional aggregates alone may fail to capture the behavioral nuances of housing bubbles, necessitating nontraditional variables.

Building upon the baseline empirical frameworks established by Terterashvili and Shaburishvili [11] regarding housing market dynamics, this study introduces a more robust bootstrap regression framework to refine predictive accuracy and capture recent market shifts up to 2023. While the dataset remains an unbalanced panel due to current data availability lags in international databases, the inclusion of the most recent observations is vital for evaluating post-pandemic volatility.

In the academic literature, most scholars identify gross domestic product (GDP) as the main determinant of real estate demand [12]. Empirical studies show that in the long run, economic growth and real estate capitalization are directly related to each other, as GDP growth is usually reflected in an increase in the purchasing power of households [13]. However, it should be noted that this relationship often gives rise to the so-called "paradox of economic development." This means that rising economic prosperity does not necessarily lead to improved housing affordability [14].

In this context, supply elasticity can be identified as a key factor. Tsatsaronis and Zhu [15] argue that the contribution of GDP to price volatility is less important than traditional models suggest. Although economic growth stimulates income levels, supply-side constraints and extensive building regulations often contribute to market shortages, and this shortage increases real estate prices at a rate that significantly exceeds real income growth. Consequently, the price-income ratio increases, effectively reducing housing affordability.

Glaeser and Gyourko [16], further support this argument by showing that under conditions of limited supply, price increases often completely neutralize the positive welfare effects of rising incomes. Consequently, relying solely on macroeconomic aggregates is an incomplete predictive tool for market behavior. Therefore, it is necessary to integrate the socio-institutional determinants that fundamentally change the structure of demand into modern valuation models.

Crucially, recent systematic academic evidence highlights that the integration of emergent technologies is fundamentally reshaping sectoral operations, establishing a pivotal and dynamic field of inquiry that redefines property analysis frameworks [17].

Furthermore, the contemporary digital transformation within real estate ecosystems has catalyzed the integration of advanced data mining techniques and machine learning (ML) into modern property valuation frameworks [1], particularly through automated web scraping technology and algorithmic decision trees used to systematically capture multi-dimensional property attributes [18], integrating digital tools and decision-making systems that are increasingly validated to revolutionize the broader real estate ecosystem [19], as further demonstrated by multi-modal deep learning models that integrate textual description embeddings and geo-spatial neighborhood features to optimize predictive performance [20]. Scholars like Baldominos et al. have demonstrated that computational algorithms can effectively process high-dimensional urban aggregates to predict market trends, aligning with comparative frameworks that evaluate multiple regression analysis against advanced machine learning paradigms like LightGBM and XGBoost to enhance pricing model reliability [21]. However, while predictive ML models often prioritize traditional economic indicators and infrastructure metrics, they frequently exhibit a descriptive limitation by underrepresenting localized socio-institutional regularities, such as the perceived safety domain. This creates a distinct research gap in the current literature: conventional housing affordability models treat macroeconomic aggregates as the sole catalysts for price escalation, failing to capture how intangible "nonfinancial capital" is capitalized into property values within transitional economies.

To address empirical precision under small-sample constraints ($N = 89$), alternative robust computational approaches are required. In this context, Cameron and Miller [22] establish that when dealing with structurally heterogeneous data or small panel dimensions, standard asymptotic assumptions fail, making the implementation of a robust bootstrap resampling framework with cluster-robust error corrections the superior methodological approach to capture stable empirical regularities.

III. Material and Methods

A. Data Collection and Study Area

This study employs a quantitative empirical analysis to evaluate the extent to which institutional safety functions as a fundamental driver of real estate valuation. The empirical framework is constructed using an unbalanced panel dataset covering the period 2013–2023. The sample includes nine EU member states (Austria, Belgium, Bulgaria, Estonia, Germany, Ireland, Latvia, Lithuania, and Poland) and Georgia.

The integration of Georgia into the European panel is a strategic methodological choice. As an EU candidate nation, Georgia serves as an ideal "control case" to test the replicability of European real estate market dynamics within a transitional economy. Following data cleaning and validation of the raw dataset, the final model was estimated using 89 valid observations ($N = 89$). Data were harmonized from global repositories, including Numbeo [23], The World Bank [24], and Eurostat [25].

B. Operationalization of Variables and Model Specification

To determine the relationship between our selected determinants, a multivariate regression model was employed. To test the central hypothesis regarding the "safety premium," the regression equation is specified as follows:

$$y = \beta_0 + \beta_1(x_1) + \beta_2(x_2) + \beta_3(x_3) + \beta_4(x_4) + \beta_5(x_5) + \beta_6(x_6) + \epsilon \quad (1)$$

The study incorporates a set of variables selected for their theoretical relevance and expected impact on the housing market. A detailed description of these variables, including their definitions, operationalization, and expected signs, is presented in Table I.

TABLE I. THE VARIABLES WERE SELECTED BASED ON THEIR THEORETICAL RELEVANCE AND EXPECTED MARKET IMPACT

Variable	Type	Definition and Operationalization	Expected Sign
Price-to-Income Ratio ($\boldsymbol{Y}$)	Dependent	A proxy for housing affordability. An increase signifies a decline in affordability.	N/A
Safety Index ($\boldsymbol{X_1}$)	Independent	Perceived security and safety levels (Numbeo, 2023). The primary value driver.	Positive (+)
Quality of Life Index ($\boldsymbol{X_2}$)	Independent	A composite indicator of urban living standards and infrastructure.	Negative (-)
GDP per capita ($\boldsymbol{X_3}$)	Independent	Real GDP per capita, A traditional measure of economic strength.	Varies
Total Population ($\boldsymbol{X_4}$)	Independent	Total population (in millions), reflecting demographic pressure on the market.	Positive (+)
Inflation (CPI) ($\boldsymbol{X_5}$)	Independent	Consumer Price Index, reflecting changes in purchasing power.	Varies
FDI Net Inflows ($\boldsymbol{X_6}$)	Independent	Net inflows of Foreign Direct Investment.	Positive (+)

[a] Source: Own elaboration based on data integration from [23]-[25].

C. Statistical Procedure: Bootstrap Resampling

To ensure the reliability of the estimates, this study employed the bootstrap regression procedure (1,000 iterations) [26], with calculations performed using IBM SPSS Statistics 29.0. Unlike standard OLS models, which may be sensitive to small sample sizes ($N < 100$), bootstrapping allows for the estimation of empirically stable standard errors and 95% bias-corrected and accelerated (BCa) confidence intervals. This methodology is critical for confirming that the impact of the safety index is a robust empirical regularity and not a statistical artifact or the result of distributional outliers.

While the dataset exhibits a panel structure, this study prioritizes the pooled bootstrap regression approach to maximize the estimator's robustness against non-normality and small-sample bias. By utilizing 1,000 bootstrap iterations, we compensate for the inherent limitations of traditional panel models in transitional contexts, ensuring that the 'safety premium' is captured with higher distributional stability and statistical reliability, as traditional specification tests are structurally constrained by the unbalanced panel dimensions and small-sample limits.

To address the unbalanced structure of the panel data and handle historical data missingness without introducing prediction artifacts, this study utilizes listwise exclusion of missing values, aligning with standard complete-case computational matrix protocols [27]. The estimation framework is restricted strictly to the 89 complete and validated country-year observations. The pooled bootstrap resampling procedure (1,000 iterations) is subsequently executed directly upon this verified complete-case matrix, thereby ensuring that the empirical standard errors and BCa confidence intervals are computed from authentic data points without the need for artificial data imputation.

The selection of 1,000 bootstrap replications is methodologically grounded in the classic econometric framework established by Davidson and MacKinnon (2000) [28] and Efron and Tibshirani (1994) [26]. In robust bootstrap inference, a smaller number of iterations (e.g., $B = 200$) may suffice for stable standard error estimations; however, constructing precise, bias-corrected and accelerated (BCa) confidence intervals and ensuring that the simulated p-values do not suffer from computational random noise requires a significantly higher resampling dimension. Given the structural heterogeneity of combining an emerging transition economy (Georgia) with highly developed EU real estate markets, 1,000 iterations represent an optimal computational threshold that guarantees stable critical values, minimizes the simulation error, and confirms that the statistical significance of the safety premium ($p = 0.007$) is highly robust against non-normal residual distributions.

IV. RESULTS

A. Model Diagnostics and Goodness-of-Fit

The empirical analysis of the explanatory factors affecting housing affordability as a dependent variable was conducted using a multiple regression model. Diagnostic tests, under the conditions of our model, indicated robust explanatory power. The coefficient of determination $R^2 = 0.670$ (see Table II), indicates that the variables included in our model account for 67% of the variance in the price-income ratio. In addition, the results of the analysis of variance (ANOVA) ($F = 27.691$, $p < 0.001$) confirm that this model is statistically significant (see Table III) and that the observed data patterns are not the result of chance.

It is critical to emphasize that the statistical non-significance ($p > 0.05$) of certain macroeconomic aggregates does not warrant their exclusion from the structural equation. Methodologically, as underscored by Wooldridge (2015) [29], retaining theoretically grounded control variables is imperative to mitigate omitted variable bias and ensure the internal validity of the regression parameters. In transitional housing markets like Georgia, conventional macroeconomic indicators often exhibit delayed transmission channels due to institutional friction. Therefore, the lack of statistical significance for these baseline aggregates does not diminish the model's explanatory power; rather, it provides empirical evidence that localized, socio-institutional regularities, specifically the safety premium, exert a more immediate and capitalized impact on property valuation dynamics than broad macroeconomic shifts.

TABLE II. MODEL SUMMARY

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.818	0.670	0.645	2.854
Note: Predictors: (Constant), Safety Index, Quality of Life Index, GDP per capita, Population, Inflation, FDI Net Inflows. Dependent Variable: Price-to-Income Ratio.				

b. Source: Own elaboration based on data integration from [23]-[25].

TABLE III. ANALYSIS OF VARIANCE (ANOVA)

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	1,353.540	6	225.590	27.691	0.000
Residual	668.040	82	8.147		
Total	2,021.580	88			
Note: Dependent Variable: Price-to-Income Ratio.					

c. Source: Own elaboration based on data integration from [23]-[25].

Additionally, to evaluate potential multicollinearity among the explanatory variables, Variance Inflation Factors (VIF) were calculated. Methodologically, as established by Gujarati (2012) [30], a VIF threshold below 5.0 indicates the absence of severe multicollinearity, ensuring that the variance of the regression coefficients is not artificially inflated. All selected determinants in our model exhibited VIF values well within the acceptable econometric range (ranging between 1.15 and 2.40), thereby confirming the structural stability of the estimated equations and verifying that the empirical parameters of the safety premium remain stable and unbiased by collinear relationships.

V. DISCUSSION

A. The Safety Index as a Dominant Value Driver (= 0.312)B

The data obtained using the bootstrap regression method (see Table IV) confirm the central hypothesis of the study, validating the existence of a "safety premium." In our case, the Safety index X_1 emerged as the most statistically significant determinant of the dependent variable (B = 0.312, p = 0.007).

It is important to note that this conclusion closely coincides with the hedonic pricing theory [31], which claims that the value of real estate is a combination of various key attributes. These results once again support the opinion of scholars who claim that intangible assets, in particular institutional safety, often function as stronger price determinants than the physical characteristics of the property. The regression results (see Table IV) demonstrate that safety is the most important structural driver of the market; hence, we can conclude that the perception of safety is considered by consumers as a "scarce commodity" in the housing ecosystem.

B. The "Silence" of Macroeconomic Variables and Market Paradoxes

The model and the analysis of the resulting indicators revealed a sharp deviation from classical economic models: key macroeconomic variables, including GDP per capita (p = 0.189) and foreign direct investment (p = 0.843), were found to be statistically inert (see Table IV).

This result is consistent with the discourse of modern urban economics [14], which involves explaining the dynamics of access to transitional markets in relation to the limitations of traditional macroeconomic indicators. In contrast to other studies that consider financial liquidity as the sole catalyst for price escalation, this model shows that market conditions respond more clearly to socio-institutional stability. This "economic silence" shows us that housing policy should be aimed primarily at improving the safety environment, and not solely relying on monetary incentives.

C. The Predictive Analysis and Scientific Significance

The model analysis adopted in the study has significant predictive power. In particular, each marginal increase in the Safety index (1 unit) corresponds to an increase in the price-to-income ratio by 0.312 units (see Table IV).

TABLE IV. BOOTSTRAP FOR REGRESSION COEFFICIENTS

Variable	B	Bias	Std. Error	Sig. (2-tailed)	95% BCa Confidence Interval
					Lower — Upper
(Constant)	2.991	0.030	1.924	0.146	[-1.600, 6.863]
GDP per capita (USD)	0.000	0.000	0.000	0.189	[-0.000, 0.000]
Total Population	0.000	0.000	0.000	0.368	[-0.000, 0.000]
Inflation Rate (%)	-0.238	0.041	0.189	0.298	[-0.686, 0.184]
Quality of Life Index	-0.099	0.006	0.031	0.066	[-0.152, -0.032]
Safety Index	0.312	0.013	0.073	0.007*	[0.171, 0.415]
FDI Inflows (USD)	0.000	0.000	0.000	0.843	[-0.000, 0.000]
Note: Bootstrap results are based on 1,000 bootstrap samples. Significant at p < 0.01. Dependent Variable: Price-to-Income Ratio.					

d. Source: Own elaboration based on data integration from [23]-[25]

The above analysis provides a solid basis for the following conclusion: safety acts as a "nonfinancial capital" that is strongly associated with real estate value. From a scientific point of view, this means that the study offers new empirical evidence in the field of security for countries on the path of European integration, where institutional reforms directly affect the competitiveness and price structure of the national real estate market.

VI. Conclusion

The results obtained within the framework of the study confirm that the dynamics of housing affordability in the EU Member States and Georgia are a multifaceted process, where socio-institutional stability plays a crucial role. Based on the empirical results obtained from the model, we can confidently formulate the following fundamental conclusions:

1) Validation of the "safety premium": The study showed that the Safety index (X_1) is the most important structural driving factor affecting price formation ($B = 0.312$, $p = 0.007$). The results obtained confirm the theory that the real estate market considers institutional security to be the most important asset. This "Safety premium" is directly reflected in price growth, and this often exceeds the growth rate of household incomes and creates a barrier to housing affordability.

2) Macroeconomic paradigm shift: The statistical inertia of traditional economic variables such as GDP and foreign direct investment (FDI) suggests that the affordability crisis in modern transition markets is increasingly determined by institutional and social factors rather than purely monetary aggregates.

A. Recommendations for Policy Makers

Based on empirical evidence, we can formulate the following strategic recommendations for stabilizing the housing market:

1) Integrating institutional factors into urban planning: Urban development strategies should consider "Safety environment" as a nonfinancial instrument for market stabilization. It is necessary to strengthen public safety and increase institutional transparency in order to reduce the "artificial inflation" of real estate prices caused by local "safety premiums." If safety standards are uniform throughout the city, this will eliminate sharp price jumps in the so-called "safe zones."

2) Targeted housing strategies for transition economies: For countries like Georgia, which are embarking on the path of European integration, a balanced housing policy is vital. As institutional reforms improve safety ratings and, accordingly, increase property values, the state should implement social housing programs or rent control mechanisms. This avoids the forced displacement of low-income populations from "unsafe and expensive" urban centers.

3) Diversify affordability indicators: Regulators should move beyond traditional economic indicators and use socio-institutional indices (such as Safety Index and Quality of Life) when monitoring the housing market.

In summary, the scientific value of this study lies in the empirical confirmation of safety as an endogenous factor in price formation. By showing that institutional stability is a key driver of housing affordability, this study paves the way for future research to explore in more depth the impact of various institutional risks on the long-term sustainability of real estate markets.

B. Research Limitations and Future Directions

The primary limitation of this study arises from the unbalanced structure of the panel data and the reliance on subjective composite indicators, such as the Numbeo Safety Index, which reflect public perception rather than official institutional crime statistics. Additionally, due to the complete-case protocol constraints, the sample size is limited to 89 country-year observations. Future research should leverage high-frequency geospatial property listings and structural equation modeling (SEM) to unpack the underlying transmission mechanisms between institutional stability and localized housing markets.

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