Final Report

for the project

Economic Growth and Housing Prices: Insights for India's Housing Market

Submitted to

National Housing Bank

INDIAN INSTITUTE OF TECHNOLOGY KANPUR

Executive Summary

Objective:
The study aims to analyse the determinants of housing price movements in India through an integrated national and regional perspective. At the national level, it seeks to examine how income levels and housing prices have evolved over time and to investigate the influence of key macroeconomic indicators on the Housing Price Index (HPI). At the regional level, the study explores inter-city variations in housing prices across Tier I, II, and III cities by assessing the impact of local factors.

Methodology:
At the national level, the study investigates how broad economic indicators shape housing price movements. Factors considered include population growth, inflation, urbanisation, repo rate, unemployment, GDP growth, exchange rate, housing credit, and GDP per capita. Trends and volatility of these variables were assessed, and highly correlated indicators were identified and filtered to avoid redundancy in the regression model. Finally, an Ordinary Least Squares (OLS) model was applied to identify the statistical relationship between economic indicators and the HPI.
For the Regional-Level Analysis the study focuses on understanding variances in housing prices across different city tiers and regions and explores how local factors such as Livability (Ease of Living), tier classification, infrastructure (such as airport connectivity among others), sustainability rating, government initiatives (such as Smart city mission), and proximity to Tier 1 cities shape housing price trajectories. The study uses the CAGR of HPI as an indicator for growth in housing prices. Data for 50 cities, grouped by tier classification, is used for this analysis.

Outcome:
Key findings from the national analysis:

- Upward long-term trends are observed for HPI, urban population share, housing credit, and the exchange rate, while population growth and unemployment exhibit declining trends.
- HPI exhibits a steep and persistent upward trend across the study period, expanding by a Compounded Annual Growth Rate (CAGR) of 4.75 per cent annually.
- Several variables show strong correlations, notably urbanisation with housing credit ($r = 0.96$) and exchange rate with GDP per capita ($r=0.95$).
- Volatility analysis indicates that GDP growth and housing credit are highly volatile, while inflation, repo, unemployment, exchange rate, and GDP per capita are moderately volatile. Urbanisation is the most stable factor.
- Based on the limited data available for analysis, the OLS results show that the repo rate is inversely related to HPI, whereas GDP per capita is positively related. A unit increase in Repo Rate is found to decrease HPI by 4.08%. However, the large intercept suggests the current set of explanatory economic variables does not fully capture HPI variation, pointing towards additional unobserved drivers. This necessitated the need to conduct regional-level analysis to explore the regional parameters that affect housing prices (in addition to the economic indicators).

Key findings from the regional analysis:

- CAGR of HPI ranges from –0.43% (Delhi) to 8.3% (Hyderabad), with an overall mean of 4.6% and median of 4.7%.

- Tier-wise pattern: Tier I cities (mean: 5.11%), Tier II cities (mean: 4.44%), and Tier III cities (mean: 4.66%). Hyderabad (Tier I) and Gandhinagar (Tier III) show the highest growth in housing prices.
- Correlation between HPI growth and livability indicators is weak (e.g., r for HPI–Ease of Living = 0.10), though scores on Citizen Perception Survey (CPS) show a slightly higher positive correlation (r=0.25).
- Cities designated as Smart Cities under the Smart Cities mission report relatively higher housing price growth (mean: 4.85%) than non-Smart Cities (mean: 4.04%).
- Airport connectivity is associated with stronger growth: cities with international airports record a higher HPI CAGR (4.87%) compared to those with only domestic airports (4.54%), no airports (4.29%), or under-construction airports (4.04%).
- The slow growth of Navi Mumbai (1.71%) despite close proximity to Mumbai probably indicates that infrastructure alone is insufficient to sustain housing demand without robust demand absorption mechanisms, affordability measures, and balanced supply pipelines.
- Hyderabad (CAGR: 8.3%) and Ahmedabad (CAGR: 7.75%) demonstrate the possible catalytic role of infrastructure and emerging job markets in the growth of housing prices.
- Delhi remains the most striking case of stagnation, with an HPI CAGR of –0.4 percent. This is probably due to high entry barriers in the form of affordability ceilings, compounded by severe environmental and infrastructure stresses, including chronic air pollution and increasing congestion, leading to diminished demand within the city's core. Availability of housing in the NCR region could be another reason for stagnation.
- NCR areas like Noida (CAGR: 3.88%), Gurugram (CAGR: 3.71%), and Faridabad (CAGR: 2.18%) have a higher CAGR compared to Delhi (CAGR: -0.43%). New Town Kolkata (CAGR: 6.20%) have higher growth than Kolkata (CAGR: 5.07%).
- Transit-oriented development (TOD) infrastructure also plays an important role in the growth of housing prices. The integration of Meerut (CAGR: 6.4%) into the Namo Bharat RRTS corridor, coupled with major infrastructure linkages such as the Delhi–Meerut Expressway and the Eastern Dedicated Freight Corridor, has generated momentum in real estate development. Similarly, Patna had a CAGR of 7.3 percent, probably driven by transformative infrastructure interventions such as the metro rail Phase I, JP Ganga Path expressway, and new bridges like the Danapur–Bihta and Kacchi Dargah–Bidupur links.

Overall, the findings suggest that while housing prices at the national level are influenced by macroeconomic conditions such as credit expansion, GDP per capita, and monetary policy, regional disparities are more closely tied to structural factors like urbanisation patterns, city tiers, infrastructure status, and governance initiatives (e.g., Smart Cities). The study highlights the need for NHB and policymakers to consider both macroeconomic stabilisation and city-level structural interventions when formulating housing and credit policies.

Specific Recommendation/Action plan for NHB:

- The findings highlight the need for NHB and policymakers to consider both macroeconomic stabilisation and city-level structural interventions when formulating housing and credit policies.

- It emphasises the integration of national and regional insights to guide financial regulation and planning, helping NHB foster a robust, transparent, and inclusive housing market aligned with macroeconomic stability and sustainable urban development.
- The report also notes that monetary policy, particularly the repo rate, acts as an effective dampener of housing prices, suggesting that NHB should monitor these linkages closely when coordinating with the Reserve Bank of India on credit and liquidity policies.
- Typically, it is recommended that efforts be made to align housing finance with planned urban growth projects, such as those under the Smart Cities Mission and other well-connected transport projects, including metros, airports, and expressways. This means supporting housing projects that are part of transit-oriented and balanced development to avoid high inventory overhangs, while also maintaining affordable housing.
- The findings for Delhi and Navi Mumbai revealed that in some cases, infrastructure alone is insufficient to sustain housing demand and prices. There is a need to understand this phenomenon in detail to comprehend how various factors, such as infrastructure availability, employability, demand absorption, affordability measures, and supply pipelines, influence housing prices.
- Accordingly, further research should be conducted to develop more granular models that link livability, infrastructure, and governance to housing price movements at the regional level. The findings emphasise the importance of continuous data integration between NHB's RESIDEX and external datasets (such as the Ease of Living Index, Smart Cities metrics, and infrastructure indices) to support targeted policy and investment decisions.

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Economic Growth and Housing Prices: Insights for India's Housing Market

1. Introduction

Housing markets play a pivotal role in shaping macroeconomic performance, serving simultaneously as indicators of financial stability and as determinants of household welfare. Globally, the cyclical behaviour of housing prices has been closely linked with economic growth, credit availability, and monetary policy, with evidence showing that housing market booms and busts often amplify wider macro-financial vulnerabilities (IMF, 2018). International comparisons of housing affordability further underscore the growing policy challenge of ensuring access to adequate and affordable housing, particularly in developing economies undergoing rapid urban transformation (OECD, 2021; UN-Habitat, 2020).

In India, the housing sector has acquired increasing economic and social significance. It contributes approximately 7.3 per cent to GDP, with projections suggesting this share may rise to 13 per cent by 2025 and remains one of the largest generators of employment with strong multiplier effects across allied industries such as cement and steel (KPMG, 2024). Recognising this, the Government of India has placed housing at the centre of its development agenda through flagship programmes such as the Pradhan Mantri Awas Yojana (PMAY), the Smart Cities Mission, and the Real Estate Regulation Act (RERA), each aimed at expanding access, improving transparency, and enhancing livability in urban centres (MoHUA, 2024). For an institution such as the National Housing Bank (NHB), a nuanced understanding of the drivers of housing price movements is therefore critical for guiding both policy and financial market stability.

The complexity of housing markets arises from their dual role as both a consumption good and an investment asset. As a consumption good, housing fulfils the basic human need for shelter, while as an investment asset, it influences wealth accumulation and household spending behaviour. Empirical evidence consistently finds that housing wealth has a stronger and more stable effect on consumption than stock market wealth, underlining the broader implications of housing price movements for macroeconomic stability (Case et al., 2001; Glaeser, 2013). In India, the Housing Price Index (HPI), maintained by the NHB, provides a systematic and comparable measure of price dynamics across time and regions, making it an indispensable tool for understanding affordability and market trends.

While existing literature has examined the macroeconomic determinants of housing prices, such as income, inflation, interest rates and monetary policy (IMF, 2020), and separately analysed regional housing disparities linked to urban growth and infrastructure gaps (World Bank, 2013), there is limited integrated evidence that captures both dimensions together. This study, supported by the NHB, addresses this gap by adopting a two-part framework. Part I (National-Level Analysis) investigates the macroeconomic relationship between housing prices and key variables such as GDP growth, income, inflation, interest rates, and credit

availability. The analysis in Part I uses the HPI data and the economic indicators available at the national level to identify relevant trends. Part II (Regional-Level Analysis) focuses on spatial variances across city tiers and regions, and explores how local factors such as infrastructure, livability, sustainability, government initiatives, and proximity to Tier-1 cities shape housing price trajectories. The analysis in Part II focuses on the HPI data of 50 cities along with unique socio-economic characteristics of different cities and regions to identify spatial trends across cities and regions.

By combining national and regional perspectives, the report provides a comprehensive evidence base to support policy formulation, financial regulation, and planning. The findings are intended to assist the NHB and policymakers in advancing its mandate of fostering a robust, transparent, and inclusive housing market, while aligning India's housing sector with broader objectives of macroeconomic stability and sustainable urban development.

This report is structured in two parts. The first part discusses the national-level analysis (Section 2), and the second part focuses on the regional-level analysis (Section 3). The background context, detailed methodology adopted, corresponding results and insights are presented within each part. Finally, the Conclusion (Section 4) discusses the limitations and future works of this study.

2. Part I- National Level Analysis

The national-level analysis aims to investigate the relationship between housing prices and key macroeconomic fundamentals in India. Housing markets are widely recognised as both indicators of economic health and transmitters of macroeconomic shocks, with previous research highlighting strong linkages between income growth, credit availability, monetary policy, and demographic change and their effects on residential property prices (Case et al., 2005; Égert and Mihaljek, 2007). In the Indian context, studies have shown that housing prices are influenced by macroeconomic drivers such as GDP growth, inflation, and credit expansion (Mahalik and Mallick, 2007), underscoring the importance of a systematic evaluation of these relationships.

The first part of this study examines the macroeconomic relationship between economic growth and housing prices in India. Housing markets are inherently sensitive to changes in the broader economy, and in turn, housing price movements feed back into household welfare, investment behaviour, and financial stability. For a country like India, characterised by rapid urbanisation, evolving income structures, and large-scale policy initiatives, the need to understand these macro linkages is particularly important. To develop insights at the national level, the following objectives were undertaken:

Objective 1.1: To understand how income levels and housing prices have varied over time at the national level.

Objective 1.2: To investigate how key macroeconomic factors, including income levels, GDP growth, inflation, interest rates, and credit availability, influence housing prices.

This focus area allows for a comprehensive evaluation of the national housing market, situating housing price movements within the broader macroeconomic environment, providing insights for policymakers.

2.1 Macroeconomic Determinants of Housing Prices

At the outset, we conducted a brief literature review and examined relevant policy documents to identify and understand the key macroeconomic determinants influencing housing prices. The macroeconomic indicators identified through this preliminary review were subsequently used as key variables in the analysis to examine their impact on housing prices. The findings of the review are summarised below.

The determinants of housing prices have been widely studied in both international and Indian contexts, with income and economic growth consistently identified as fundamental drivers. Cross-country studies of OECD and transition economies emphasise per capita GDP, interest rates, credit, and demographic factors as key influences on housing price movements (Égert & Mihaljek, 2007). Empirical work for India has similarly shown that macroeconomic factors, particularly GDP growth, inflation, and the real effective exchange rate, significantly shape the Housing Price Index (HPI) (RBI, 2023). Some of these indicators are discussed next.

Inflation has a complex impact on housing markets. On one hand, it reduces affordability by raising household expenses and increasing borrowing costs when interest rates rise. On the other hand, housing is often seen as a safe investment that protects wealth against rising prices, which can increase demand during inflationary periods (Égert & Mihaljek, 2007). International evidence from European economies shows that inflation, together with GDP growth and population trends, is a major driver of rising house price indices (Adam & Zhu, 2015). In India, this dual effect is mediated through monetary policy, where the adoption of inflation targeting in 2016 and subsequent adjustments to the repo rate have influenced credit availability and mortgage affordability (RBI, 2018).

Financial conditions and housing credit are equally important. International studies confirm that mortgage credit expansion can stimulate demand but also heighten risks of systemic instability (Goodhart & Hofmann, 2008). Indian evidence, however, is more complex. Mahalik and Mallick (2011) found that real non-food bank credit exerted an adverse long-run effect on housing prices, contrary to theoretical expectations, reflecting institutional and structural constraints. More recent market data illustrate the sector's scale: outstanding housing loans stood at ₹33.53 trillion in Q2 FY25, with middle-income groups accounting for nearly half and weaker segments close to 40% (NHB, 2025). On the supply side, construction cost reports indicate a 39% rise over four years, driven by persistent labour cost inflation despite declining cement prices (Colliers, 2024). These developments demonstrate how financial conditions and rising costs jointly shape affordability and market outcomes in India.

Based on the review, potential economic indicators were identified. Table 1 provides a list of these indicators, their definitions, the rationale for their selection, and the relevant sources from which this data was collected. The indicators identified, combined with the specific research focus and the availability of relevant data, guided the selection of the appropriate methodology for this study, which is discussed in the following section.

2.2 Data and Methodology

The overall methodological flow of the national-level analysis is summarised in Figure 1, which illustrates the sequential process from literature review and variable selection to econometric modelling and insights for decision-making. The methodological approach follows a stepwise process: first, descriptive diagnostics of the selected variables (trend analysis, correlation, and volatility) are conducted to establish preliminary patterns; second, econometric modelling using Ordinary Least Squares (OLS) regression is applied to quantify the relationship between housing prices and macroeconomic indicators. This design ensures a rigorous national baseline against which subsequent regional-level disparities can be assessed.

The analysis covers the period 2013 Q2–2024 Q3, drawing on quarterly data to capture both long-term trends and short-term fluctuations.

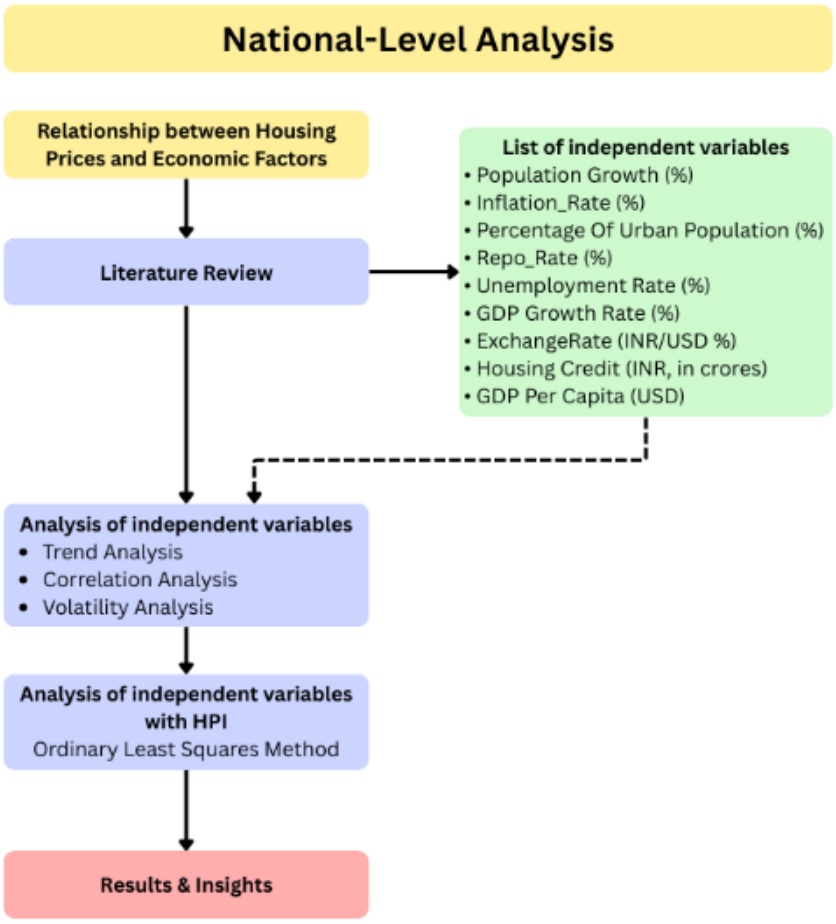

Figure 1 Methodological framework for national-level analysis

2.2.1 Data Sources and Variable Description

The analysis integrates the Housing Price Index (HPI) with a set of macroeconomic and financial indicators compiled from official national and international statistical agencies. The dataset draws on NHB RESIDEX for housing prices, MOSPI and World Bank WDI for GDP-related indicators, RBI sources for inflation, repo rate, housing credit, and exchange rate, and

PLFS for unemployment, supplemented by World Bank WDI for consistency. Demographic variables such as population growth and urbanisation were obtained from the Census of India and the World Bank WDI. All series were harmonised to quarterly frequency, with level variables (e.g., housing credit) transformed into logarithmic form and rate variables (e.g., GDP growth, inflation) retained as percentages. A full description of the variables, their rationale, and data sources is presented in Table 1.

Table 1 Variables, Definitions, Rationale, and Sources

Name	Details (Definition & Unit)	Rationale	Source	Downloaded/ Accessed on
HPI (Housing Price Index)	Index of residential property prices, base year (2017-18), quarterly	Dependent variable; measures national housing price dynamics	National Housing Bank (NHB) RESIDEX	10-Jun-25
Population Growth	Annualised growth rate of population (%)	Reflects long-term demographic pressure on housing demand	Census of India; World Bank WDI	10-Jun-25
Inflation Rate	Consumer Price Index (CPI) based inflation (%)	Reflects macroeconomic stability, purchasing power, and borrowing costs	RBI Database on Indian Economy; MOSPI	10-Jun-25
Urban Population Share	Share of total population living in urban areas (%)	Proxy for urbanisation and sustained housing demand	Census of India; World Bank WDI	10-Jun-25
Repo Rate	RBI policy repo rate (%)	Indicator of monetary policy stance and cost of credit	Reserve Bank of India (RBI)	10-Jun-25
Unemployment Rate	National unemployment rate (%)	Indicates labour market health and effective demand for housing	Periodic Labour Force Survey (PLFS); World Bank WDI	12-Jun-25

Name	Details (Definition & Unit)	Rationale	Source	Downloaded/ Accessed on
GDP Growth Rate	Real GDP growth rate (%)	Captures macroeconomic activity and demand-side driver of housing	MOSPI National Accounts; RBI	12-Jun-25
Exchange Rate	Average quarterly INR/USD exchange rate	Captures external competitiveness and costs of imported inputs; can affect NRI demand	RBI Handbook of Statistics	12-Jun-25
Housing Credit	Total housing credit outstanding (INR, crores)	Reflects credit availability, leverage, and financing depth in housing market	RBI Handbook of Statistics on Indian Economy	12-Jun-25
GDP per Capita	Real GDP per capita (USD, constant prices)	Measures household prosperity and affordability capacity	World Bank WDI; MOSPI	12-Jun-25

2.2.2 Preliminary Analysis of Independent Variables

Before undertaking econometric modelling, the selected macroeconomic variables were first subjected to descriptive statistical analyses. This step provided an initial understanding of their temporal behaviour, interrelationships, and stability, which is essential for both model specification and interpretation of results (Gujarati & Porter, 2009). Three complementary techniques were applied, which include trend analysis, correlation analysis, and volatility analysis.

2.2.2.1 Trend Analysis

Linear time-series trends were studied for each variable to examine their long-term directional movements. This approach helps identify variables with persistent directional changes, offering insights into structural patterns that may influence housing markets over time (Stock & Watson, 2015).

2.2.2.2 Correlation Analysis

Pairwise correlations were computed between all variables to explore their interrelationships and to detect potential multicollinearity. Pearson correlation coefficients were used, as they provide a simple yet effective measure of linear association. Understanding these associations is critical to ensuring that explanatory variables included in the regression model do not overlap excessively, thereby maintaining the robustness of the estimated coefficients (Wooldridge, 2019).

2.2.2.3 Volatility Analysis

The relative variability of each variable was assessed using the Coefficient of Variation (CV) (see equation below)

$$CV = \frac{Standard\ Deviation}{Mean} x\ 100$$

This technique allows comparability across variables expressed in different units and provides insights into data stability and measurement reliability. Variables exhibiting very high volatility can distort regression outcomes, while stable series contribute to more reliable inference (Enders, 2014).

The outcomes of these three analyses provided the foundation for model specification in the subsequent econometric stage. The detailed results of these steps is available in Section 2.3.

2.2.3 Econometric Analysis of Housing Prices

Following the preliminary diagnostics, the study advanced to econometric modelling of the determinants of housing prices. The analysis employed Ordinary Least Squares (OLS) regression, with the Housing Price Index (HPI) as the dependent variable. To address issues of variance instability and to capture proportional changes more effectively, the natural logarithm of HPI was used in all estimations.

An initial set of nine macroeconomic indicators, which included GDP growth rate, GDP per capita, inflation rate, repo rate, unemployment rate, population growth, urban population share, exchange rate, and housing credit, was considered as a potential explanatory variable. Trend analysis, correlation analysis, and volatility analysis were conducted for these variables. The inferences drawn from these analyses informed the process of dimensionality reduction. Subsequently, the reduced set of variables was employed as independent variables in the OLS regression to mitigate the risk of overfitting.

OLS was chosen as the estimation technique given its interpretability, transparency, and well-established application in housing market research. Under the Gauss–Markov assumptions, OLS estimators provide the best linear unbiased estimators, making the approach suitable for quantifying the linear relationships between housing prices and their macroeconomic determinants. The detailed results are available in Section 2.3.4.

2.3 Results and Discussion

This section presents the findings of the national-level analysis undertaken to evaluate the macroeconomic determinants of housing price movements in India. The objective was to examine how broad economic and demographic variables interact with the Housing Price Index (HPI) over the period 2013 Q2 to 2024 Q3. The analysis proceeds in four stages. First, trends in the HPI and selected explanatory variables are mapped to highlight long-term shifts and cyclical patterns. Second, the correlation structure of variables is assessed to identify interdependencies and redundancies. Third, volatility is examined using the coefficient of variation to capture the relative stability of indicators over time. Finally, an Ordinary Least Squares (OLS) regression model is employed to quantify the relationship between HPI and key macroeconomic drivers. Together, these analyses provide a comprehensive view of the national-level factors shaping housing price dynamics.

The descriptive statistics for variables used in this analysis are presented in Table 2.

Table 2 Descriptive statistics of independent variables

Variable	Mean	Std. Dev.	Min	Max
HPI	106.7	15.3	83.0	138.3
Population_Growth (%)	1.04	0.20	0.68	1.30
Inflation_Rate (%)	6.7	2.2	3.3	11.2
Urban Population (%)	33.7	1.7	31.3	36.4
Repo Rate (%)	6.4	1.4	4.0	8.5
Unemployment Rate (%)	6.9	1.3	4.2	8.2
GDP Growth Rate (%)	5.7	5.3	-23.9	20.1
Exchange Rate (INR/USD)	67.2	11.5	44.7	83.2
Housing Credit (INR cr)	10,82,096	7,01,321	3,49,925	25,61,961
GDP Per Capita (USD)	2,009	387	1,536	2,710

2.3.1 Trends in Housing Prices and Macroeconomic Variables

The Housing Price Index (HPI) exhibits a steep and persistent upward trend across the study period, expanding by CAGR of 4.75 per cent annually. This trajectory, shown in Figure 2, reflects the sustained demand for housing in India's urban centres and underscores the centrality of real estate as both a consumption good and an investment asset.

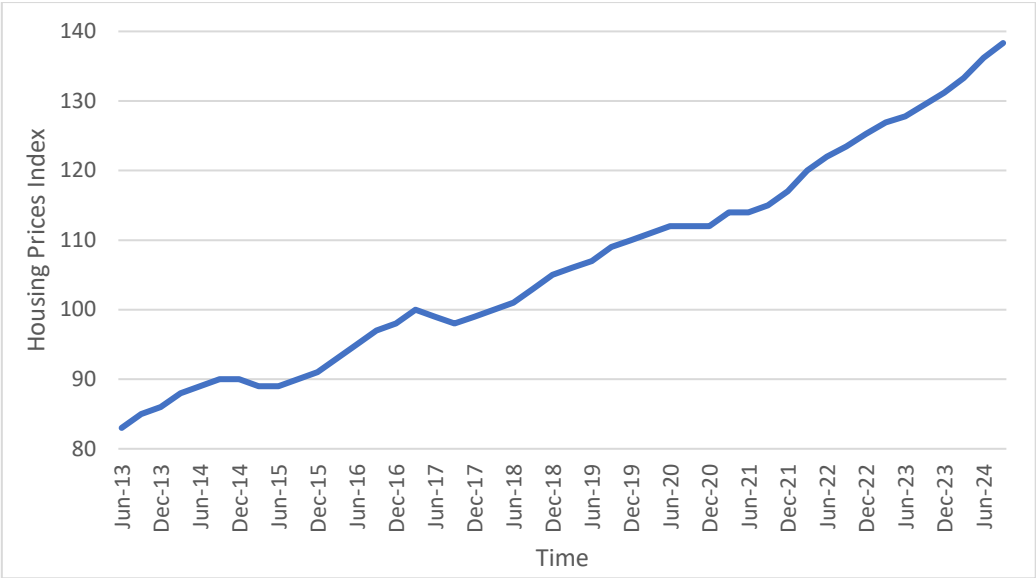

Figure 2 Trend of the Housing Price Index (HPI) in India, 2013Q2–2024Q3

Supporting indicators display similar upward dynamics. As illustrated in Figure 3, the proportion of the urban population increased steadily at an average rate of 1.37 per cent per year, consistent with the continuing pace of rural–urban migration and metropolitan expansion. Housing credit grew even more dramatically, at nearly 50 per cent annually, with outstanding credit expanding more than six-fold during the period, evidence of the financial sector's critical role in sustaining demand. The exchange rate also depreciated consistently, weakening by about 6.8 per cent annually. This depreciation raised input costs for construction materials and, at the same time, reinforced the perception of housing as a hedge against currency weakness.

In contrast, other macroeconomic indicators moved in the opposite direction or showed instability. Population growth declined by 3.2 per cent annually, reflecting demographic transition, while unemployment rates fell by about 3.8 per cent annually as urban labour markets absorbed more workers. Inflation trended moderately downward but remained volatile, while GDP growth displayed no stable pattern, punctuated by sharp contractions such as the 23.9 per cent decline during the COVID-19 pandemic. Monetary policy mirrored these cycles: repo rates peaked during high-inflation episodes (2012–13) but were reduced sharply during downturns, most notably in 2020–21 when a nearly 30 per cent cut supported countercyclical policy. Notably, despite these stresses, housing credit continued to expand, highlighting the resilience of credit flows into the sector.

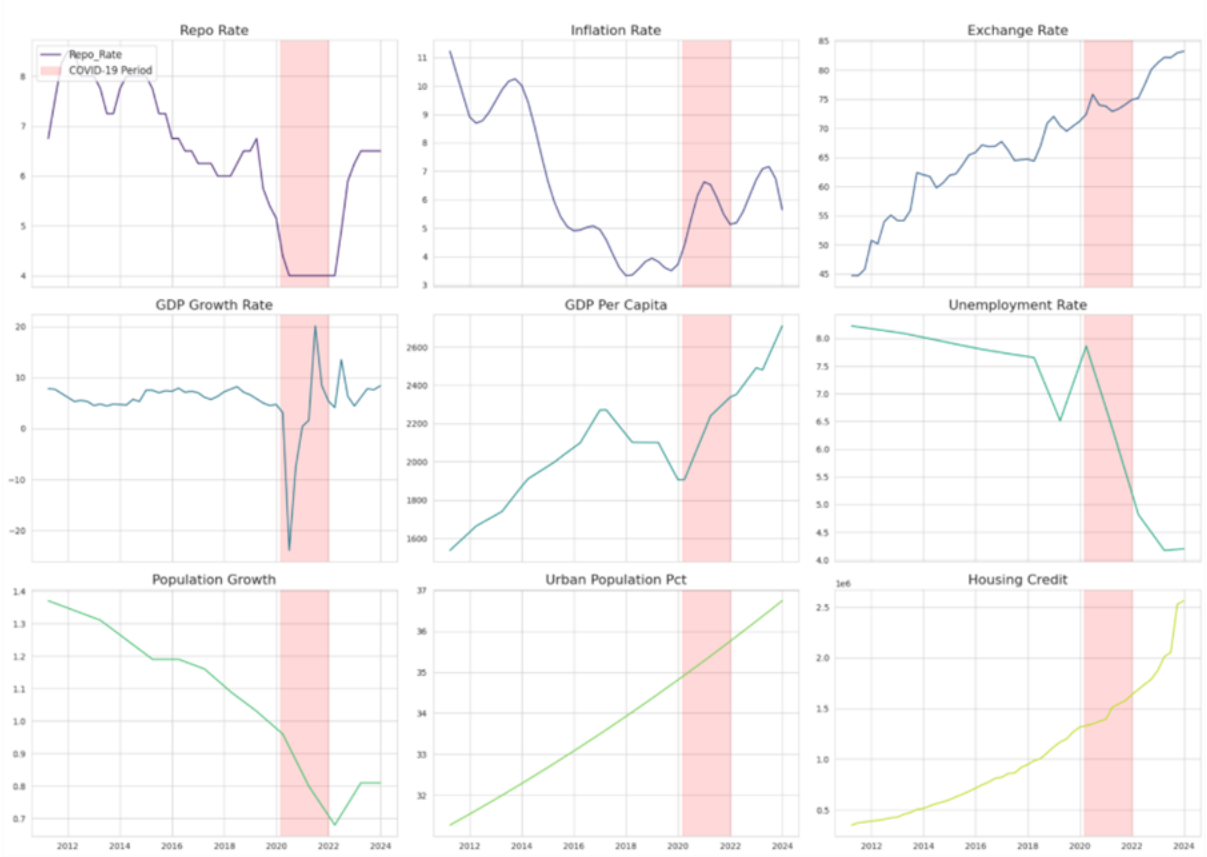

Figure 3 Trends in Macroeconomic Variables, 2013Q2–2024Q3

Taken together, the trends suggest a dual narrative. Long-run structural drivers, urbanisation, credit deepening, and currency depreciation have persistently reinforced housing demand and price growth, while cyclical factors such as inflation, GDP growth shocks, and monetary policy adjustments have acted as short-term disruptors.

2.3.2 Correlation analysis

The correlation analysis reveals strong patterns of association between the key macroeconomic variables (Figure 4). The urban population and housing credit are strongly correlated ($r = 0.96$), while exchange rate displays very high associations with both housing credit ($r = 0.97$) and GDP per capita ($r = 0.95$). Together, these indicators form a "development cluster," highlighting the reinforcing role of urbanisation, financial deepening, currency depreciation, and income growth in driving housing prices.

In contrast, population growth is negatively correlated with most development indicators, including urban population ($r = –0.97$), housing credit ($r = –0.90$), exchange rate ($r = –0.92$), and GDP per capita ($r = –0.88$). Unemployment also shows significant negative correlations with housing credit ($r = –0.87$). These patterns form a "stress cluster," where declining population growth rates and unemployment appear inversely related to urban development dynamics.

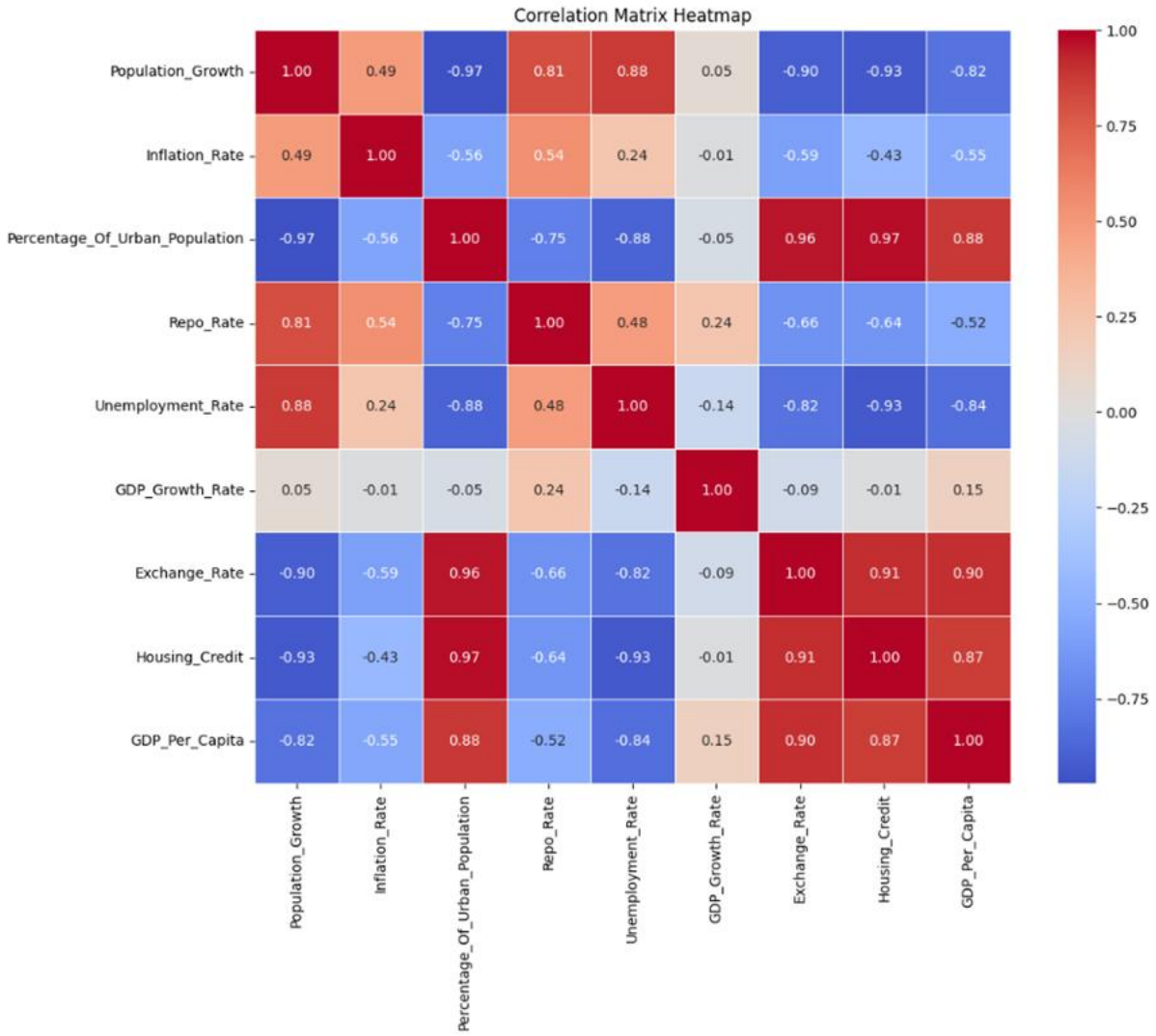

Figure 4 Correlation matrix between selected macroeconomic variables (2013Q2–2024Q3)

Overall, the correlation matrix highlights substantial redundancy, as many variables move together and essentially convey the same inference. This creates a risk of multicollinearity if all are included in the regression analysis. To address this, only a subset of explanatory variables was retained in the OLS model, focusing on those that capture distinct and policy-relevant drivers of housing price movements.

2.3.3 Volatility Analysis

The coefficient of variation (CV) was used to assess the relative volatility of macroeconomic indicators over the study period (2013Q2–2024Q3), and is presented in Figure 5. The results highlight significant heterogeneity across variables. GDP growth rate emerges as the most volatile indicator, with a CV of 96 per cent, reflecting sharp fluctuations including the contraction of –23.9 per cent during the COVID-19 pandemic and subsequent rebounds. Housing credit also demonstrates high volatility (CV ≈ 55 per cent), owing to the rapid pace of credit expansion and sensitivity to financial cycles.

In contrast, inflation, repo rate, unemployment, exchange rate, and GDP per capita show moderate volatility, consistent with their cyclical yet more contained behaviour. The percentage of urban population is the least volatile variable (CV ≈ 4.8 per cent), reflecting its slow-moving, structural nature. These differences underscore the dual character of the drivers of housing prices: while structural forces such as urbanisation remain steady, cyclical factors such as GDP growth and credit expansion introduce instability into housing markets.

Notably, two special episodes reinforce these findings. The period of economic stress in 2012–13 was marked by high inflation and elevated repo rates, amplifying volatility in macroeconomic conditions. Similarly, the COVID-19 shock in 2020–21 generated unprecedented GDP contraction, a nearly 30 per cent cut in repo rates, and continued credit expansion despite the downturn. These episodes illustrate how volatility in macroeconomic fundamentals interacts with housing price dynamics in both crisis and recovery phases.

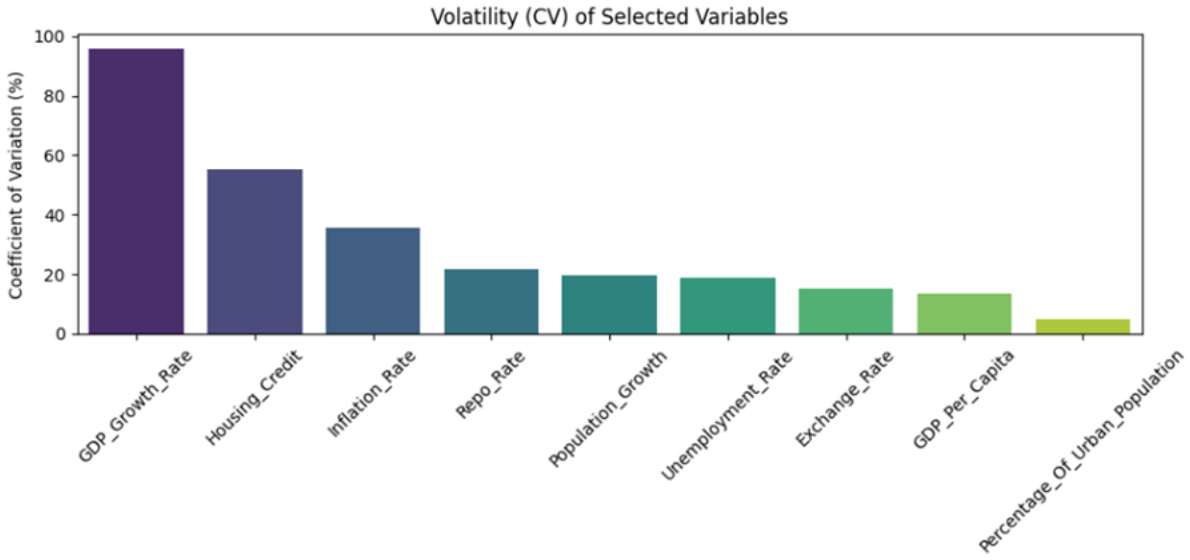

Figure 5 Coefficient of Variation of macroeconomic variables(2013Q2–2024Q3)

2.3.4 Regression Analysis (OLS)

Following the trend, correlation, and volatility analysis, an Ordinary Least Squares (OLS) regression was estimated to examine the impact of macroeconomic indicators on housing prices. The dependent variable was the natural logarithm of the Housing Price Index (ln HPI), while the explanatory variables retained after variable reduction were inflation rate, repo rate, GDP growth rate, and GDP per capita. The model (equation 2) was estimated using 46 quarterly observations covering 2013 Q2–2024 Q3.

$$\ln(HPI\_t) = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \ldots + \beta_k X_{kt} + \varepsilon_t \quad (2)$$

A logarithmic transformation was applied to address issues of variance instability and distributional skewness. In levels, HPI exhibits a mean of 104.72 with a standard deviation of 13.72 (variance 188.23) and a coefficient of variation (CV) of 0.1310, reflecting sizable scale-dependent spread as the index rises over time. After a natural-log transformation, the mean of ln (HPI) is 4.6430 with a standard deviation of 0.1303 (variance 0.0170) and CV of 0.0281

(absolute value), implying substantially more uniform variability on a relative basis across the sample.

The regression results demonstrate strong model performance. The adjusted R^2 of 0.810 indicates that the four macroeconomic variables together explain about 81 percent of the variation in ln HPI. The fit of the model is further illustrated in Figure 6, which plots the actual versus fitted values of ln HPI.

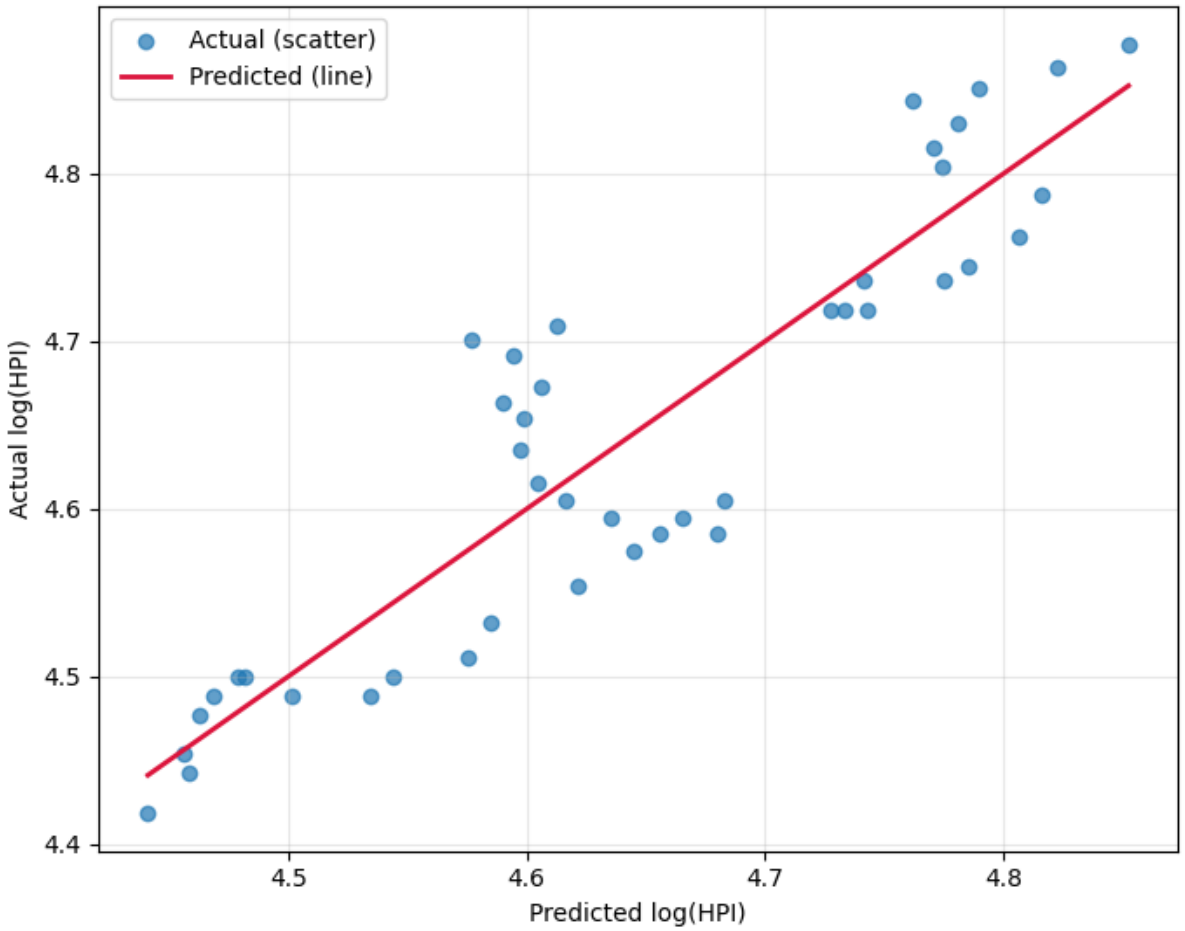

Figure 6 Fitted versus actual values of lnHPI

A closer inspection of the developed model reveals that Repo Rate (-0.0416, p<0.001) is the only statistically significant indicator that has a negative effect, meaning a higher repo rate significantly lowers housing prices. This is consistent with the theory that increased loan costs dampen demand. Moreover, GDP Per Capita (0.0004, p<0.001) is found to be significant and positive, indicating regions or years with higher per-capita income see higher housing prices. On the other hand, Inflation_Rate (0.0003, p = 0.938) and GDP_Growth_Rate (-0.0025, p = 0.020) are found to be relatively insignificant indicators.

The intercept (3.995, p < 0.001) is large, suggesting that structural and policy-related variables not captured in the model, such as construction costs and regulatory factors, also influence price movements. The higher intercept suggests that beyond the identified macroeconomic determinants, other factors might play an important role in influencing housing prices. These localised factors often create heterogeneity that cannot be fully captured by aggregate national

indicators alone. Therefore, a deeper regional analysis is required to examine spatial variations and identify location-specific drivers of housing prices. This will enable a more comprehensive understanding of price movements.

These coefficient estimates with their 95 per cent confidence intervals are presented in Table 3.

Table 3 Coefficient estimates with 95% confidence intervals for the OLS regression model

Variable	**Coefficient**	**Std. Error**	**z-value**	**P-value**	**95% Confidence Interval (Lower)**	**95% Confidence Interval (Upper)**
Intercept	3.9951	0.157	25.479	0.000	3.688	4.302
Inflation Rate	0.0003	0.004	0.078	0.938	-0.008	0.009
Repo Rate	-0.0416	0.007	-5.798	0.000	-0.056	-0.028
GDP Growth Rate	-0.0025	0.001	-2.334	0.020	-0.005	-0.000
GDP Per Capita	0.0004	0.000053	7.937	0.000	0.000	0.001

For better understanding, the derived relationship between lnHPI and the economic variables was converted to HPI terms in Table 4. Each ln_HPI regression coefficient was converted to an HPI multiplicative effect by taking its exponential ($e^{coefficient}$). This is because the log-linear model describes proportional changes, so exponentiating the coefficient gives the actual factor by which HPI multiplies for a one-unit change in the variable. For example, a ln_HPI coefficient of -0.0416 becomes $e^{-0.0416} = 0.9592$. Meaning HPI decreases by about 4.08% for each unit increase in the repo rate.

Table 4 Conversion of independent variables

Factor	ln_HPI Coefficient	HPI Multiplicative Effect	Inference
Intercept	3.9951	54.41	The constant (intercept) reflects the baseline HPI value when all other variables are zero.
Inflation Rate	0.0003	1.0003	A unit increase in the Inflation Rate multiplies HPI by 1.0003 (a 0.03% increase)
Repo Rate	-0.0416	0.9592	A unit increase in Repo Rate multiplies HPI by 0.9592 (a 4.08% decrease).
GDP Growth Rate	-0.0025	0.9975	A unit increase in GDP Growth Rate multiplies HPI by 0.9975 (a 0.25% decrease).
GDP Per Capita	0.0004	1.0004	A unit increase in GDP Per Capita multiplies HPI by 1.0004 (a 0.04% increase)

Overall, the regression analysis indicates that the monetary policy instrument (repo rate) operates as an effective dampener of housing prices, while income growth remains the primary long-term driver.

2.4 Summary of National Level Analysis

The national-level analysis reveals that housing price movements in India are shaped by a combination of long-run structural drivers and short-run cyclical influences. The trend analysis highlighted persistent upward momentum in HPI, urbanisation, housing credit, and exchange rate depreciation, all of which reinforce demand for housing. At the same time, population growth and unemployment have steadily declined, reflecting India's demographic transition and shifting labour markets, while cyclical factors such as inflation, GDP growth, and repo rates introduced volatility into the system.

The correlation structure underscored the existence of two clusters of indicators. The "development cluster," comprising urbanisation, housing credit, exchange rate, and GDP per capita, exhibited very high positive correlations, reflecting their mutually reinforcing effects on housing demand. Conversely, the "stress cluster," formed by population growth and

unemployment, showed strong negative correlations with related development indicators. The high correlation between variables suggested the need for dimensionality reduction before regression modelling.

Finally, the OLS regression showed that the repo rate exhibits a significant negative impact on housing prices, where each unit increase reduces HPI by approximately 4.08%. Additionally, GDP per capita has a strong positive effect, while GDP growth rate also shows a small but significant negative influence; inflation rate does not significantly affect housing prices in this model. The large intercept in the regression model (3.995, $p < 0.001$) indicates that factors beyond the modeled macroeconomic variables affect housing prices. This suggests that potentially regional and localised factors could create variations that are not captured by national-level indicators, highlighting the need for more detailed regional analysis (incorporating region specific information) to better understand the drivers of housing price movements.

3. Part II- Regional Level Analysis

3.1 Focus area of regional level analysis

The regional-level analysis in this study aims to uncover the variations in housing prices across different city tiers. It investigates how localised factors such as livability (measured through Ease of Living indices) and critical infrastructure elements like airport connectivity influence housing price dynamics. Additionally, government-led initiatives such as the Smart Cities Mission and proximity to Tier I cities are considered to assess their combined impact on housing markets.

To measure price growth, the analysis employs the Compounded Annual Growth Rate (CAGR) of the Housing Price Index (HPI) as a key indicator. The study utilises data from 50 cities to capture infrastructural and regional differences in housing price behavior.

3.2 Methodology

Figure 7 shows the methodology adopted for the regional-level analysis of Housing Price Index (HPI) data. The process began with collecting relevant HPI data for different cities. The HPI data compiled by the National Housing Bank provides quarterly data for 50 Indian cities over an eleven-year period from 2013 to 2024, with 2017–18 as the base year. For this analysis, quarterly values have been consolidated into annual averages, and long-term growth has been assessed using the compound annual growth rate (CAGR). It is important to note that the study examines how the housing prices index has compounded over time. Since there was a base-year adjustment in HPI in 2017-18, this might not exactly reflect the actual increase in housing prices. Nevertheless, HPI can be used as an indicator to understand variations in housing prices in different cities.

In addition to the HPI data, information about various regional factors affecting housing prices was collected. The key regional factors studied in this study include (a) Ease of Living Index,

(b) Quality of Life, (c) Economic Ability, (d) Sustainability, (e) Citizen Perception Survey results, (f) Smart Cities initiatives, (g) Presence of Airports, and (i) Distance from Tier I cities. The housing price of cities was studied with factors to understand region-specific patterns and their influences on housing prices. The process culminates in generating actionable insights about regional housing markets, supporting more targeted policy or investment decisions. Table 5 provides details about the relevant data sources, their rationale, and the date on which this data was assessed.

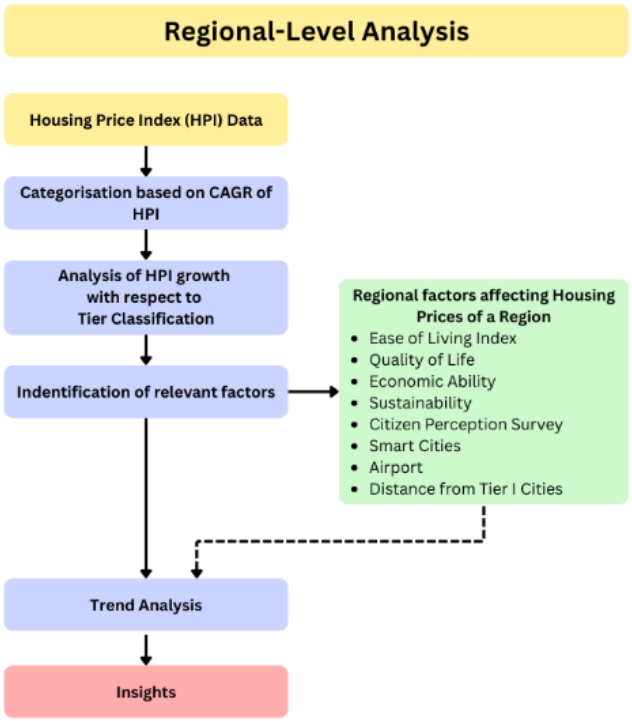

Figure 7 Methodological framework for Regional level analysis

3.3 Data sources

The relevant indicators used in the regional analysis are provided in Table 5.

Table 5 Data Sources of regional analysis indicators

Variable Name	Description	Rationale	Source Name	Download Date
HPI (Housing Price Index)	Index of residential property prices, base year (2017-18=100), quarterly	Dependent variable; measures national housing price dynamics	National Housing Bank (NHB) RESIDEX	13-Jul-25
Airport	Type of Airport in a city (International/Domestic/Airport Under Construction/None)	The presence of an airport may increase the housing prices	Wikipedia	14-Jul-25
Ease of Living Index	The aggregate score of the 'Ease of Living Index' and scores of its individual pillars	People would prefer cities where the Ease of Living Index is high, pushing the housing prices upwards.	Ministry of Housing and Urban Affairs	14-Jul-25
Smart City	Smart City status of a city (Yes/No)	The smart cities might have higher development, which, in turn, might translate into higher housing prices.	Atal Innovation Mission	13-Jul-25
Distance from nearest Tier I City	Distance from nearest Tier I City for Tier II & III Cities (in km)	The cities closer to Tier I cities have an ease of development advantage, potentially the housing prices	Google Maps	02-Aug-25
Population	Population of a city	The higher population indicates higher demand, thereby maybe increasing the housing prices.	Census 2011	13-Jul-25

3.4 Results

This section provides a summary of the findings from the regional level analysis. It begins with a general overview of housing price trends, followed by an analysis of tier classifications and HPI growth patterns. The discussion then explores how liveability (including factors such as Citizen Perception Survey, Sustainability, Economic Ability, and Quality of Life), government initiatives (such as Smart Cities mission), and airport connectivity influence price movements. Finally, it explores the spillover effect from Tier I cities on surrounding regions.

The regional analysis is based on actual data; however, the underlying reasons mentioned are derived from the author's hypotheses and informed conjecture. Further research and empirical data are required to validate and deepen this understanding.

3.4.1. General Overview

The Housing Price Index (HPI) compiled by the National Housing Bank provides quarterly data for 50 Indian cities over an eleven-year period from 2013 to 2024, with 2017–18 as the base year. For this analysis, quarterly values have been consolidated into annual averages, and long-term growth has been assessed using the compound annual growth rate (CAGR). It is important to note that the study examines how the housing prices index has compounded over time. Since there was a base-year adjustment in HPI in 2017-18, this might not exactly reflect the actual increase in housing prices. Nevertheless, HPI can be used as an indicator to understand variations in housing prices in different cities.

At the national scale, the housing market has exhibited moderate but uneven growth. Across the 50 cities, the mean CAGR of HPI is 4.6 percent, while the median is close to 4.7 percent. Figure 8 suggests a broadly stable appreciation in housing values over the past decade. However, the variation across individual markets is significant: Hyderabad recorded the highest growth at 8.3 percent, supported by IT-sector expansion and large-scale infrastructure projects, whereas Delhi experienced a marginal decline of –0.4 percent, reflecting structural stagnation in its core market. The distribution of cities across different CAGR bands is presented in Table 6.

The table indicates that a majority of cities fall within the 2–6 percent growth range, underscoring steady but moderate appreciation across much of the urban system. Only a few cities show either contraction or very rapid growth, highlighting the divergence in housing demand and market dynamics.

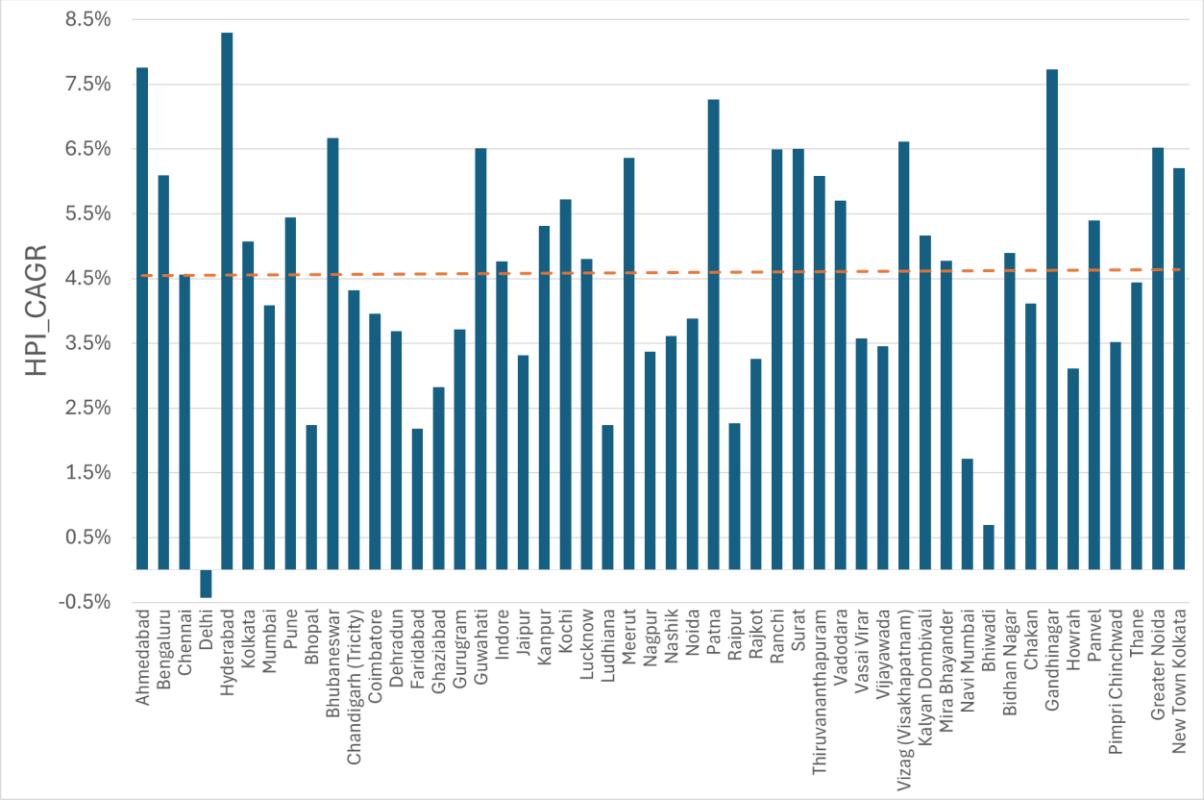

Figure 8 CAGR of Housing Price Index (HPI) across 50 Indian cities (2013–2024)

Table 6 Distribution of cities by HPI growth rate, 2013–2024

CAGR of HPI Range	Count of Cities	Name of the Cities
< 0%	1	Delhi
0–2%	2	Bhiwadi, Navi Mumbai
2–4%	17	Faridabad, Ludhiana, Bhopal, Raipur, Ghaziabad, Howrah, Rajkot, Jaipur, Nagpur, Vijayawada, Pimpri Chinchwad, Vasai Virar, Nashik, Dehradun, Gurugram, Noida, Coimbatore
4–6%	16	Mumbai, Chakan, Chandigarh, Thane, Chennai, Indore, Mira Bhayander, Lucknow, Bidhan Nagar, Kolkata, Kalyan Dombivali, Kanpur, Panvel, Pune, Vadodara, Kochi
6–8%	13	Thiruvananthapuram, Bengaluru, New Town Kolkata, Meerut, Ranchi, Surat, Guwahati, Greater Noida, Visakhapatnam, Bhubaneswar, Patna, Gandhinagar, Ahmedabad
> 8%	1	Hyderabad

To further examine these differences, cities have been grouped into Tier I, Tier II, and Tier III categories. The final classification is based on a review of multiple sources, including the

Government of India's HRA classification under the Central Pay Commission (which uses Census-based population thresholds) [Department of Expenditure, Ministry of Finance, 2017], and ICAI Classification of Cities. The consolidated tier structure is presented in Table 7 below.

Table 7 Tier Classification of cities

Tier	Names of Cities
Tier – 1	Ahmedabad, Bengaluru, Chennai, Delhi, Hyderabad, Kolkata, Mumbai, Pune,
Tier – 2	Bhopal, Bhubaneswar, Chandigarh, Coimbatore, Dehradun, Faridabad, Ghaziabad, Gurugram, Guwahati, Indore, Jaipur, Kanpur, Kochi, Lucknow, Ludhiana, Meerut, Nagpur, Nashik, Noida, Patna, Raipur, Rajkot, Ranchi, Surat, Thiruvananthapuram, Vadodara, Vasai Virar, Vijayawada, Visakhapatnam, Kalyan Dombivali, Mira Bhayander, Navi Mumbai
Tier - 3	Bhiwadi, Bidhan Nagar, Chakan, Gandhinagar, Howrah, Panvel, Pimpri Chinchwad, Thane, Greater Noida, New Town Kolkata

Figure 9 illustrates the dispersion of HPI growth rates across these tiers. Tier I cities show the widest variance, including both the strongest (Hyderabad, Ahmedabad) and weakest (Delhi) markets. Tier II and Tier III cities, while more clustered, also reveal distinct sub-patterns that merit closer analysis.

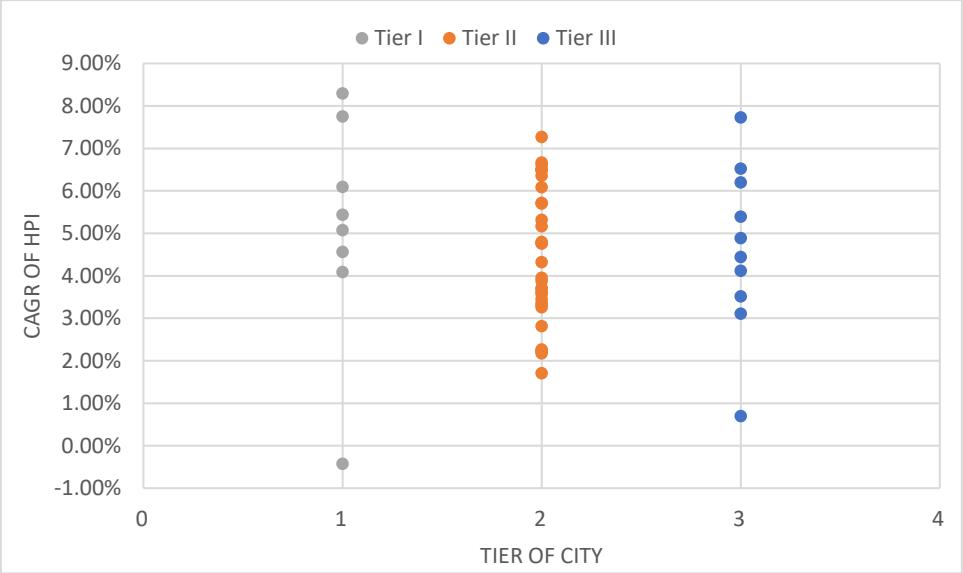

Figure 9 Dispersion of HPI growth rates (CAGR, 2013–2024) across Tier I, Tier II, and Tier III cities

The following sections provide a tier-wise assessment, focusing on growth drivers, constraints, and policy implications emerging from these differentiated trajectories.

3.4.2. Tier Classification and HPI Growth

This section explores the relationship between tier classification and HPI growth across three city categories: Tier I cities as mature metros with divergent trajectories, Tier II cities as regional hubs with uneven momentum, and Tier III cities as emerging growth poles.

3.4.2.1 Tier I Cities: Mature Metros with Divergent Trajectories

Between 2013 and 2024, Tier I cities recorded housing price growth predominantly in the 4–6 percent CAGR band, consistent with the maturity and partial saturation of these urban markets. Yet this category also displays the widest divergence nationally, with Delhi at one extreme registering outright contraction, while Hyderabad and Ahmedabad posted some of the strongest growth rates across the country. These contrasting outcomes underscore how affordability constraints, infrastructure investments, sectoral anchors, and liveability conditions shape urban housing trajectories in distinctive ways.

Delhi remains the most striking case of stagnation, with an HPI CAGR of –0.4 percent. This is probably due to high entry barriers in the form of affordability ceilings, compounded by severe environmental and infrastructure stresses, including chronic air pollution and increasing congestion, leading to diminished demand within the city's core. It is likely that home demand has shifted to nearby NCR areas like Noida (CAGR: 3.88%), Gurugram (CAGR: 3.71%), and Faridabad (CAGR: 2.18%), where newer stock, relatively lower price points, and improved connectivity probably created more attractive options. These cities have a higher CAGR than Delhi. Overall, this is an interesting and somewhat surprising finding that Delhi's HPI has not shown any considerable increase over the years, requiring further research regarding this.

At the other end of the spectrum, Hyderabad recorded the fastest national growth with an HPI CAGR of 8.3 percent. This expansion is probably driven by sustained IT-sector growth, substantial in-migration of professionals, proactive state-level policies and large-scale infrastructure investments, including the Metro Rail and Outer Ring Road. Ahmedabad follows a similar pattern, with a CAGR of 7.8 percent. This could be due to industrial diversification, proximity to Gujarat International Finance Tec (GIFT) City, and infrastructure commitments associated with India's bid to host the 2036 Olympics.

Bengaluru has HPI CAGR of 6.1 percent. The city's diversified service economy, sustained IT leadership, and steady migration flows might have underpinned consistent demand. Other metros such as Mumbai, Chennai, Pune, and Kolkata remained clustered in the 4–6 percent range, reflecting a more moderate trajectory. Moderate growth in Mumbai might be due to already high property prices, affordability ceilings, pushing demand outward to peripheral zones like Thane and Navi Mumbai. Chennai's growth has been supported probably due to its dual industrial and services base, while Pune remains buoyant due to its IT and education clusters. Kolkata had a CAGR of 5.07 percent, in line with cities such as Chennai and Pune.

Collectively, Tier I cities highlight the contrasting dynamics of mature housing markets. Delhi exemplifies how affordability, liveability deficits, and better opportunities in the vicinity impact housing prices in a city. Similarly, Mumbai, another mature housing market, sees relatively lower growth in the housing index. Hyderabad and Ahmedabad, in contrast, demonstrate the possible catalytic role of infrastructure and emerging job markets. Other Tier 1 cities such as Bengaluru, Chennai, Kolkata, and Pune have HPI CAGR ranging from 4-6 percent, which might be considered typical for a Tier 1 city.

3.4.2.2 Tier II Cities: Hubs with Uneven Momentum

The housing price dynamics in Tier II cities between 2013 and 2024 reveal a strikingly uneven trajectory compared to Tier I metros. While the majority of Tier II markets recorded moderate growth in the 4–6 percent CAGR range, several cities significantly outperformed, registering growth rates above 6 percent. Patna, Bhubaneswar, Visakhapatnam, Surat, Meerut, Thiruvananthapuram, Ranchi, and Guwahati emerged as frontrunners, highlighting the transformative impact of targeted infrastructure investment, sectoral diversification, and institutional anchors. In contrast, Navi Mumbai (HPI CAGR: 1.71) stands out as a notable under-performer, recording one of the weakest growth profiles despite a pipeline of mega-infrastructure projects. This divergence underscores the heterogeneity of India's second-tier housing markets and the differentiated pathways through which urban development shapes residential property appreciation.

Patna recorded the highest CAGR among Tier II cities (7.3 percent), probably driven by transformative infrastructure interventions such as the metro rail Phase I, JP Ganga Path expressway, and new bridges like the Danapur–Bihta and Kacchi Dargah–Bidupur links. These projects have expanded city's connectivity and extended its urban footprint, creating new demand corridors. Patna might have also benefited from the availability of affordable houses and an expanding middle class looking to occupy these spaces. Another aspect of this trend could be economic diversification into IT, education, and manufacturing, particularly in Bihta, reinforcing its housing market.

Bhubaneswar similarly posted robust growth (6.7 percent CAGR), sustained by its positioning as a successful Smart city. Road development, traffic modernisation, and urban infrastructure improvements have enhanced liveability, while the presence of large IT firms (Infosys, Wipro, TCS) and educational institutions (IIT, AIIMS, KIIT) provide durable anchors of housing demand. Infrastructure commitments such as the proposed metro rail, ring roads, and airport expansion are expected to consolidate these gains further, positioning Bhubaneswar as a stable yet high-growth Tier II housing market.

Visakhapatnam (6.6 percent CAGR) demonstrates how coastal and port-based cities can achieve sustained housing price growth when aligned with IT and industrial expansion. The city's Fintech Valley and IT hubs, combined with global-scale commitments such as Google's $6 billion data centre, have created a robust growth ecosystem. The Visakhapatnam Metropolitan Region Development Authority's (VMRDA) PPP-based township projects, strategically located along metro and IT corridors, might have further diversified the urban geography of housing demand, while its natural coastal appeal adds to the city's investment attractiveness.

Surat, with a CAGR of 6.5 percent, continues to consolidate its role as India's industrial powerhouse. Anchored in textiles, diamonds, and petrochemicals, the city has created employment-led demand that supports housing price appreciation. The Smart City Mission has reinforced governance, urban mobility, and sustainability measures, while relatively affordable property prices compared to Tier I metros make Surat a preferred destination for investors seeking higher returns.

Other outperformers such as Meerut (6.4 percent CAGR) illustrate the transformative role of transit-oriented development (TOD). Its integration into the Namo Bharat RRTS corridor, coupled with major infrastructure linkages such as the Delhi–Meerut Expressway and the Eastern Dedicated Freight Corridor, has generated momentum in real estate development. Similarly, Thiruvananthapuram (6.1 percent CAGR) has benefitted from IT expansion through Technopark, the largest IT park in India by built-up area, and the institutional stability offered by ISRO's space research facilities and aerospace clusters. Ranchi (6.5 percent CAGR) and Guwahati (6.5 percent CAGR) highlight the role of state capitals as housing growth nodes. While Ranchi's growth is supported by public-sector expansion and rising investments in education and healthcare, Guwahati's Smart City Mission projects, improved connectivity across the Brahmaputra, and institutional anchors such as IIT and AIIMS have positioned it as the gateway to the Northeast.

In contrast to these out-performers, Navi Mumbai represents an anomaly. Despite headline projects such as the Mumbai Trans Harbour Link (MTHL), Navi Mumbai Metro, and the upcoming international airport, the city recorded only 1.7 percent CAGR growth over the period. Several factors might explain this weak performance: persistent delays in project delivery, uneven distribution of infrastructure benefits, and speculative supply that often outpaced real end-user demand. On the other hand, micro-markets such as Panvel and Kharghar did witness sharp localised appreciation. By 2025, sales volumes in Navi Mumbai had declined by 17 percent year-on-year, and new launches dropped by 56 percent, reflecting a deeper structural imbalance. The case of Navi Mumbai underscores that infrastructure alone is insufficient to sustain housing demand without robust demand absorption mechanisms, affordability measures, and balanced supply pipelines.

The majority, 23 out of 32 Tier II cities, including Jaipur, Lucknow, Indore, Coimbatore, Vadodara, and Dehradun clustered within the 2–6 percent CAGR range. Taken together, Tier II cities reveal sharper divergences in housing market performance than Tier I metros. Cities where infrastructure investment, diversified economic bases, and institutional anchors converge such as Patna, Bhubaneswar, and Visakhapatnam, record sustained and outsized growth. By contrast, markets characterised by speculative excess and inventory overhang, such as Navi Mumbai, lag despite their infrastructure headlines. In summary, Tier II cities are likely to absorb the next wave of India's urban expansion, making it imperative to align housing finance, transit-oriented planning, and inventory management to prevent speculative overbuilding while maintaining affordability.

3.4.2.3 Tier III Cities: Emerging Growth Poles

Between 2013 and 2024, Tier III cities recorded housing price growth largely in the 3–5.5 percent CAGR range, consistent with their positioning as peripheral nodes in India's urban hierarchy. Yet this aggregate conceals striking divergence: some Tier III markets have outperformed established metros, while others have stagnated despite being situated within high-growth corridors. Three cities New Town Kolkata (6.2 percent), Greater Noida (6.5 percent), and Gandhinagar (7.7 percent) stand out as clear out-performers, while Bhiwadi (0.7 percent) had significantly low HPI CAGR growth.

New Town Kolkata demonstrates how planned urbanisation can create self-sustaining housing demand. Conceived under HIDCO as a greenfield township, it has evolved into a hub for IT, financial services, and social infrastructure. The city's integration with Kolkata's economy through expanding metro lines, together with its recognition as Smart Green city, has ensured steady absorption.

Greater Noida's trajectory reflects its integration into the NCR growth system. High-quality road infrastructure, metro extensions, and its proximity to the upcoming Jewar International Airport have significantly enhanced its attractiveness. The demand in the region can be attributed to diversified base in manufacturing, logistics, and education.

Gandhinagar, recording the strongest CAGR among Tier III cities, illustrates how anchor projects can reposition smaller markets as nationally significant growth nodes. The development of Gujarat International Finance Tec (GIFT) City as India's first International Financial Services Centre has generated sustained premium housing demand, complemented by Gujarat's pro-business policies, expressway linkages to Ahmedabad, and metro expansion. Together, these factors have created an ecosystem where housing markets benefit directly from global capital flows and policy-backed institutional anchors.

On the other hand, Bhiwadi underscores the limits of peripheral urbanisation when driven primarily by speculative supply. Despite its location along the Delhi–Mumbai Industrial Corridor and proximity to NCR, the city has failed to generate sustained end-user demand. Oversupply, limited amenities, and weak liveability indicators have probably resulted in negligible price growth.

The majority of Tier III markets (6 out of 10 cities) include Pimpri-Chinchwad, Panvel, Thane, Vasai–Virar, and Howrah clustered in the 3-5.5 percent range. These cities benefit from commuter linkages to Tier I metros and incremental industrial or service-sector activity, but their housing markets remain moderate. This shows Tier III cities closer to metros will likely act as pressure valves for metropolitan cores, making integrated metropolitan peripheral planning essential to ensure balanced and sustainable growth. Taken together, Tier III cities illustrate the polarised outcomes of India's peripheral growth. When supported by planned urbanisation, anchor institutions, and policy stability, smaller cities such as Gandhinagar and Greater Noida can outperform mature metros. Conversely, markets such as Bhiwadi reveal the fragility of peripheral real estate systems when growth is speculative rather than demand driven.

3.4.3. Housing Prices and Urban Liveability

While the preceding discussion on Tier I, II, and III cities highlights the differentiated momentum of housing prices across India's urban hierarchy, it is equally important to situate these trajectories within the broader frame of urban liveability. The Housing Price Index (HPI) captures the market's response to structural and policy conditions, whereas the Ease of Living Index (EoLI) reflects institutional, environmental, and social endowments that shape long-term urban sustainability. An integrated reading of these datasets (for 35 cities) will help in understanding how liveability is related to growth in housing prices.

3.4.3.1 Brief Background about Ease of Living Index

The Ease of Living Index is structured across four pillars: Quality of Life, Economic Ability, Sustainability, and the Citizen Perception Survey (CPS). Taken together, these provide a comprehensive framework for assessing the liability of a region. The methodology adopted for assessing the Ease of Living Index is provided in Figure 10.

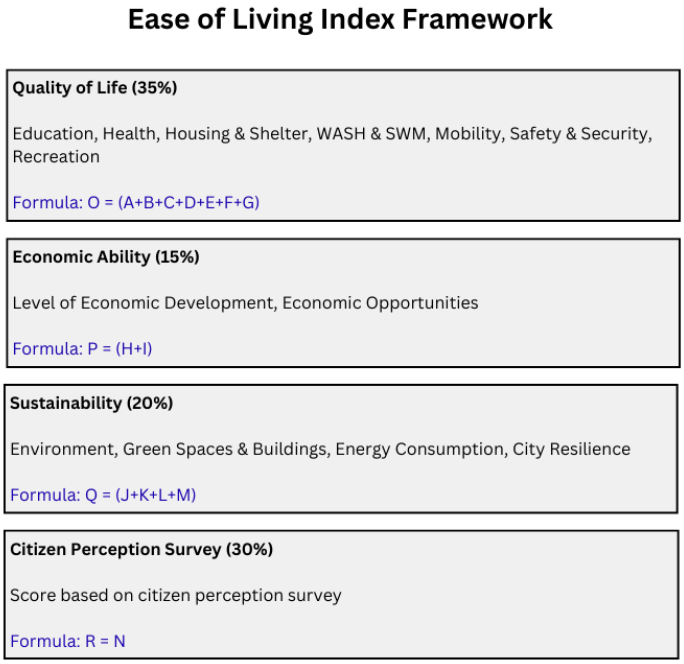

Figure 10 Ease of Living Index Methodology (Adopted from Ease of Living Report, MoHUA 2020)

3.4.3.2 Correlation Patterns Between HPI and Liveability Pillars

At the aggregate level (Table 8), correlations between HPI CAGR and the four EoLI pillars are weak and, in some cases, negative, underscoring that housing markets are often forward-looking and do not mechanically mirror current liveability conditions. Among the four pillars, Economic ability shows a modestly positive relationship with HPI, suggesting that cities with expanding economic opportunities are better able to sustain demand-side pressures in housing. The strongest relationship, however, emerges from the Citizen Perception Survey, where positive resident sentiment aligns more consistently with higher price growth.

Table 8 Correlation between CAGR, HPI and Liveability Index Pillars

Liveability Index Pillars	Correlation with the CAGR of HPI
Quality of Life	-0.07
Economic Ability	0.07
Sustainability	-0.06
Citizen Perception Survey (CPS)	0.25

The correlation analysis of Liveability dimensions (Table 9) reveals two distinct patterns. First, there is a high correlation between composite Ease of Living indicator and the individual pillars, which is expected since the aggregate Ease of Living score is a weighted average of these components. By contrast, the three underlying pillars, Quality of Life, Economic Ability, and Sustainability are not highly correlated with one another. This suggests that they capture distinct dimensions of urban liveability and are therefore better analysed separately rather than treated as interchangeable measures.

Table 9 Correlation Plot of Liveability Dimensions

	Quality of Life	Economic Ability	Sustainability	Ease of Living (without CPS)
Quality of Life	1.00	0.37	0.47	0.74
Economic Ability	0.37	1.00	0.40	0.85
Sustainability	0.47	0.40	1.00	0.72
Ease of Living (without CPS)	0.74	0.85	0.72	1.00

Building on these aggregate and spatial correlations, a pillar-level analysis was conducted to unpack the heterogeneity across cities. This assessment considered (i) variation in EoLI pillar scores by tier of city (Tier I, II, III), and (ii) their association with HPI CAGR. The results highlight that while some dimensions of liveability show intuitive linkages with housing market trends, others diverge reflecting the forward-looking and often speculative nature of real estate markets in India.

3.4.3.3 Relationship between HPI and Quality of Life

Quality of Life scores (Figure 11) for different cities range from 43.65 to 60.84, with Tier I cities generally clustered toward the upper end (51.22–60.84). Within this group, however, Delhi (51.22) and Hyderabad (51.28) perform below their Tier I peers. In Delhi, the shortfall is likely attributable to persistent environmental stress, particularly air pollution, while Hyderabad's score reflects its transitional status as a rapidly developing urban centre. Tier II cities occupy a broad and evenly distributed range (43.65–60.33), while Tier III cities exhibit a narrower band, concentrated around 55.

When considered against housing price performance, no significant relationship emerges between Quality of Life and HPI CAGR. Cities with relatively high Quality of Life scores do not necessarily record stronger or weaker housing price growth, reaffirming the weak aggregate correlation. This outcome suggests that while Quality of Life indicators capture important dimensions of urban well-being, they are not systematically capitalised into real estate markets, which remain more responsive to forward-looking factors such as economic opportunity and infrastructure expansion.

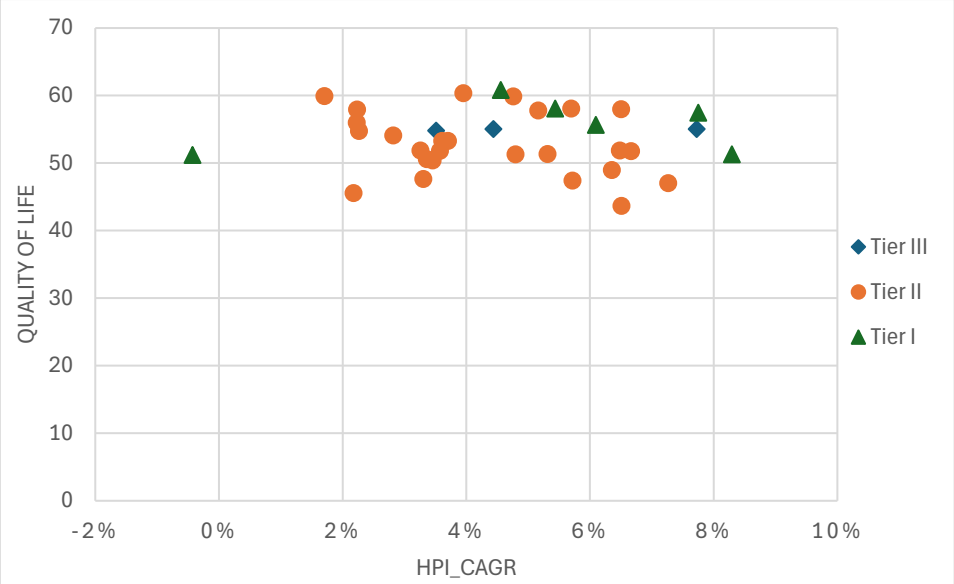

Figure 11 Quality of Life vs HPI_CAGR

3.4.3.4 Relationship between HPI and Economic Ability

Economic Ability scores (Figure 12) exhibit a widespread (6.88 to 78.82), with Bengaluru (78.82) standing out as an outlier at the upper end. The mean of economic ability scores is 23.78, and the median is 17.25. Tier I cities generally occupy higher scores (30.05–78.82), though Hyderabad (30.05) and Chennai (34.16) fall significantly below their peers. The mean of economic ability scores for Tier I cities is 48.47, and the median is 48.54. Tier II cities are distributed across a much lower band (6.88–32.5). The mean of economic ability scores for Tier II cities is 17.12, and the median is 14.06. The Tier III cities occupy an intermediate range (15.12–40.52), though the limited sample size restricts broader generalisation.

When linked to housing price dynamics, a clearer pattern emerges compared to other liveability pillars. Cities with Economic Ability scores greater than 40 consistently record HPI CAGR above 4%, underscoring the role of stronger economic fundamentals in sustaining housing demand. Conversely, cities with weaker economic capacity (<30) tend to have lower growth in housing prices.

Notable anomalies further illustrate the forward-looking nature of real estate markets. Hyderabad, with a relatively low Economic Ability score (30.05), records the highest HPI CAGR (8.3%), driven by a confluence of factors: the city's IT and pharmaceutical sector growth, affordability advantages from historically undervalued housing stock, large-scale infrastructure investment, governance stability, and speculative investor as well as NRI demand. Similarly, Gandhinagar (15.12; 7.73%) combines low current economic strength with high price growth, buoyed by its positioning as the site of GIFT City, planned infrastructure projects, proximity to Ahmedabad, and the leverage of a low starting price base.

These patterns underscore that the Economic Ability index, being largely backward-looking (income levels, GDP per capita), does not fully capture policy announcements, speculative expectations, or infrastructure commitments that can catalyse housing price growth. In

practice, real estate markets price in future potential rather than present economic capacity, and demand is often amplified by investor sentiment and state-led development agendas.

The proximity effect is also evident, with Economic Ability showing a negative correlation with distance from Tier I hubs (–0.36). This reinforces the role of major metros as anchors of regional economic opportunity, diffusing their advantages to nearby cities more rapidly than to distant counterparts.

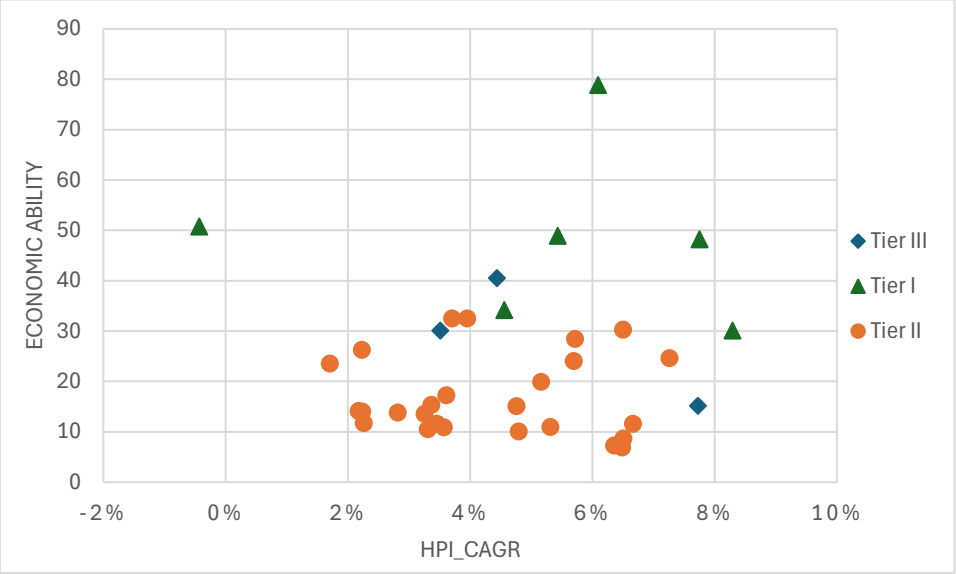

Figure 12 Economic Ability vs HPI_CAGR

3.4.3.5 Relationship between HPI and Sustainability

Sustainability scores (Figure 13) range from 45.69 (Kochi) to 75.74 (Pune), with mean score of 56.30, and a median score of 56.08. The Tier I cities generally perform better (56.02–75.74, Mean: 61.95, Median: 59.33) compared to Tier II (45.69–63.77, Mean: 54.88, Median: 55.03) and Tier III (51.99–65.09, Mean: 57.33, Median: 54.90) counterparts. Pune stands out with the highest score (75.74), reflecting relatively strong performance across sustainability indicators, while Kochi anchors the lower end.

However, when examined against HPI CAGR, no clear or consistent relationship is observed. Pune, despite leading on sustainability, records only moderate price growth (5.44%), whereas Kochi, the lowest scorer, posts a slightly higher CAGR of 5.72%. Similarly, Hyderabad, which has the highest HPI CAGR (8.3%), holds only a middling sustainability score (58.69). Delhi exemplifies the opposite mismatch - a moderate sustainability score (56.02) paired with the lowest HPI CAGR (–0.43%).

Even within similar growth bands, divergences are evident. Ahmedabad (64.22) and Gandhinagar (51.99) record almost identical HPI CAGR values (~7.7%) despite a wide gap in sustainability scores. Likewise, Indore (61.62) and Navi Mumbai (61.85) are nearly identical in terms of sustainability but diverge significantly in HPI CAGR (4.76% vs. 1.71%). These inconsistencies highlight that current housing markets are not systematically pricing sustainability attributes.

This disconnect can be partly explained by the composition of the sustainability index, which includes four indicators: environment, green spaces and buildings, energy consumption, and city resilience. Of these, the latter three are relatively recent policy and planning concerns that have yet to become salient in homebuyer decision-making or investor valuation. Limited public awareness, coupled with the lagged benefits of sustainability initiatives, means that such factors are not yet fully capitalised into real estate markets. Over time, however, as regulatory frameworks mature and awareness deepens, sustainability scores may emerge as a stronger determinant of housing price growth.

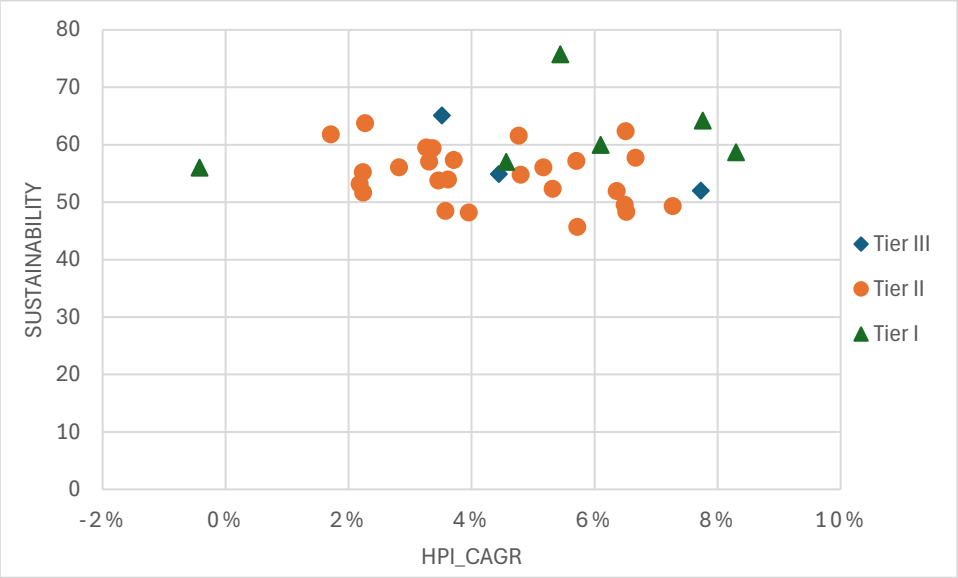

Figure 13 Sustainability vs HPI CAGR

3.4.3.5 Relationship between HPI and Ease of Living (without CPS)

The Ease of Living (excluding CPS) scores (Figure 14) range from 26.23 to 43.3, with Tier I cities occupying the upper band (34.19–43.3). Within this group, Ahmedabad (40.18), Pune (42.81), and Bengaluru (43.3) perform particularly well, each scoring above 40. Tier II cities are distributed across a wider range (26.23–37.31), while Tier III cities are clustered more narrowly (31.92–36.7).

In relation to housing price dynamics, the expected direct association between liveability and HPI CAGR is only partially observed. All cities with an Ease of Living score above 38 are exclusively Tier I, record CAGR values of at least 5.4%, suggesting that higher living standards in large metros are generally associated with stronger price growth. However, the pattern is undermined by notable anomalies. Guwahati, despite having the lowest Ease of Living score (26.23), posts a high CAGR of 6.51%, while Navi Mumbai, with a relatively high score (36.88), records one of the weakest growth rates (1.71%). Similarly, within the mid-range of scores (28.7–34.6), HPI CAGR varies widely (2.18% to 7.73%) without displaying a consistent trend.

These inconsistencies highlight two issues. First, Ease of Living scores may not fully capture the forward-looking drivers of real estate markets, such as infrastructure expansion, speculative investment, and affordability advantages. Second, the relatively small dataset limits the ability to detect stable patterns, particularly in intermediate bands.

Importantly, this pillar exhibits the strongest proximity effect (–0.42) among all dimensions, indicating that adjacency to Tier I hubs is a decisive factor in shaping Ease of Living outcomes. This suggests that while the Ease of Living index provides a valuable snapshot of present urban conditions, its relationship with housing prices is mediated by both spatial spillovers and market expectations rather than by current liveability alone.

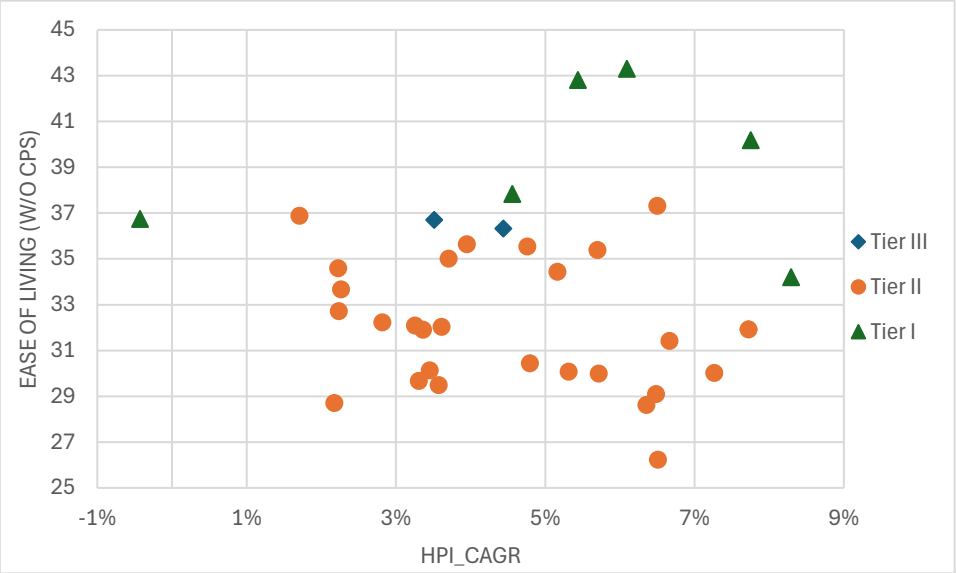

Figure 14 Ease of Living (w/o CPS) vs HPI_CAGR

3.4.3.6 Relationship between HPI and Citizen Perception Survey (CPS)

The CPS scores (Figure 15) range from 64.2 to 94.8, with a mean score of 76.87 and a median score of 77.6. The CPS score for Tier I cities is clustered between 69.4 and 82.6, with a mean 76.87 and a median 78.1. Within this group, Delhi (69.4) register at the lower end, reflecting specific local constraints such as pollution and stressed infrastructure. Tier II cities display the widest spread, ranging from Nashik (64.2) to Bhubaneswar (94.8), while the majority fall within a relatively stable band of 70.0–82.4. The mean and median for Tier II cities are 77.19 and 77.55 respectively. Tier III cities record a narrower range (68.2–81.1), but their outcomes appear more strongly conditioned by proximity to Tier I hubs, which shapes perceptions of service availability and employment access.

When examined against housing market performance, CPS is the pillar that most consistently aligns with HPI CAGR. Cities such as Ahmedabad (82.3; 7.75%), Bhubaneswar (94.8; 6.66%), Surat (81.4; 6.5%), and Gandhinagar (81.1; 7.73%) combine strong CPS scores with robust housing price growth, suggesting that resident sentiment functions as a forward-looking signal of market momentum.

At the same time, anomalies highlight the complexity of this relationship. Hyderabad, for example, records one of the lower CPS scores (70.7) yet has the highest observed HPI CAGR (8.3%). Conversely, Jaipur (87.1) and Navi Mumbai (82.4) post relatively high CPS scores but experience subdued growth in HPI (3.31% and 1.71%, respectively), pointing to potential reasons such as saturation effects, affordability constraints, better opportunities elsewhere, lack of jobs, excessive supply etc.

Overall, CPS emerges as the most reliable explanatory pillar for HPI variation, though its predictive strength is moderated by city-specific contexts and structural dynamics. Importantly, the proximity effect is most evident in Tier III cities, where adjacency to Tier I hubs (e.g., Gandhinagar near Ahmedabad, Navi Mumbai near Mumbai) reinforces positive resident perceptions through infrastructure spillovers and integration with larger economic systems.

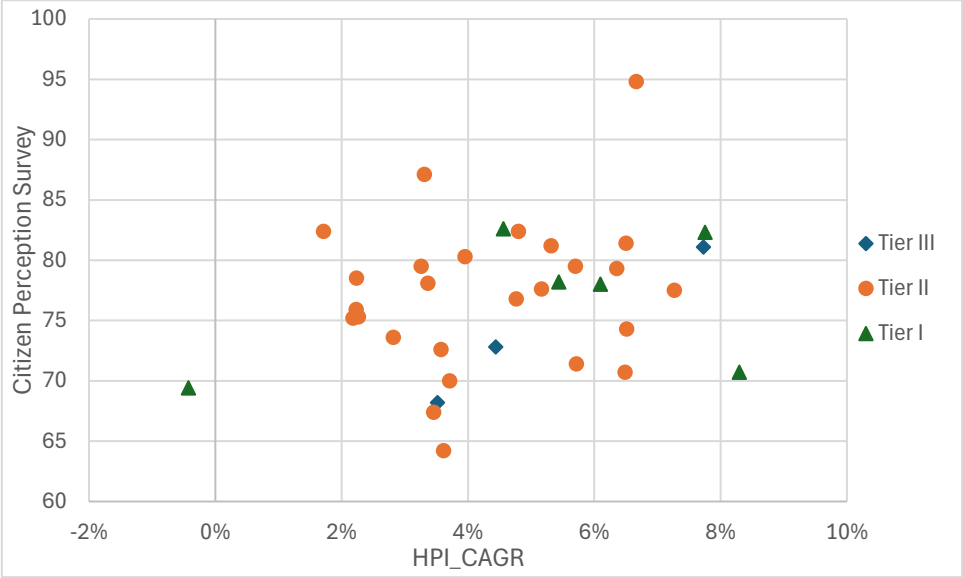

Figure 15 Citizen Perception Survey vs HPI_CAGR

3.4.4. Housing Prices and the Smart Cities Mission

The Smart Cities Mission (SCM), launched in 2015, sought to promote sustainable and citizen-centric urban development through targeted investments in infrastructure, technology, and governance reforms. Given the overlap between designated Smart Cities and the 50 cities covered in this dataset, it is instructive to examine whether participation in the mission has influenced housing price trajectories.

Across the study period (2013–2024), Smart Cities recorded stronger housing price appreciation than their non-participant counterparts. The mean HPI CAGR of Smart Cities was 4.85 percent compared to 4.04 percent for non-Smart Cities, while the median values similarly diverged at 4.98 percent and 3.98 percent, respectively (Figure 16). This suggests that the mission has been broadly associated with stronger real estate momentum, although the effect is heterogeneous across regions.

Figure 16 Mean and median HPI CAGR: Smart vs. Non-Smart Cities (2013–2024)

The distribution of growth rates further underscores this divergence (Figure 17). Of the 14 cities with HPI CAGR above 6 percent, 12 are Smart Cities. In contrast, among the 22 cities with growth rates below 4 percent, only 12 belong to the mission. This pattern indicates that high-performing housing markets are disproportionately concentrated among Smart Cities, reinforcing the catalytic role of targeted urban investment. At the same time, the dataset reveals considerable variation within the Smart City cohort itself. Cities such as Bhubaneswar, Surat, and Visakhapatnam illustrate how effective integration of Smart City initiatives with economic anchors and infrastructure investment has translated into above-average housing price growth. Conversely, cases like Navi Mumbai and Jaipur highlight that designation alone is insufficient; persistent project delays, affordability ceilings, and speculative overhangs can mute or even offset the expected benefits.

The overall range of HPI CAGR values is wider for Smart Cities than for non-Smart Cities, reflecting both their greater number in the dataset and the diversity of their underlying economic and governance contexts. While the general trend tilts toward stronger performance, outliers such as Bhiwadi (0.69 percent) remind us that speculative, poorly anchored markets can underperform even within the Smart City framework.

Taken together, the analysis suggests that the Smart Cities Mission has contributed to rise in housing prices, particularly in Tier II and Tier III cities where incremental improvements in infrastructure and liveability represent a step-change in urban capacity. However, the uneven outcomes also underscore the conditional nature of this impact. The mission amplifies growth most effectively when it is embedded within broader economic diversification, institutional strength, and efficient project execution rather than functioning as a stand-alone driver of housing demand.

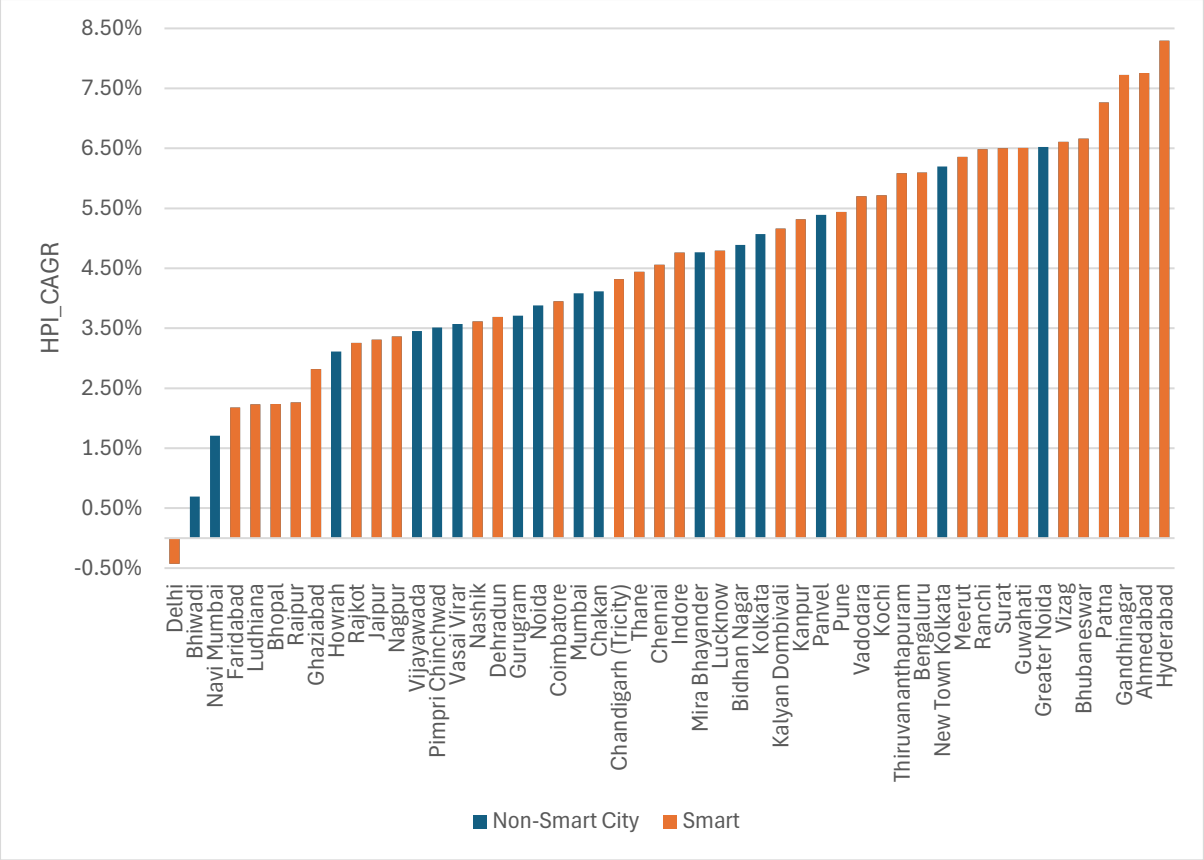

Figure 17 HPI CAGR distribution for Smart and Non-Smart Cities

3.4.5. Housing Prices and Airport Connectivity

Air connectivity is often posited as a catalyst for urban growth, enhancing mobility, trade, and regional integration. To test this proposition, the 50-city dataset was disaggregated by airport status: international, domestic, under construction, and none.

The results reveal a visible airport premium, albeit with important qualifications. Cities with international airports recorded the highest housing price growth (mean CAGR 4.87 percent; median 4.80 percent), followed by those with domestic airports (4.54 percent and 4.50 percent). Cities without airports averaged 4.29 percent growth, while those with airports under construction trailed at 4.04 percent. These differences are modest in magnitude but consistent in direction: both mean and median values rank international > domestic > none > under construction. The relatively high standard deviations for the "no airport" and "under construction" groups reflect their small sample size and more volatile outcomes (Table 10; Figure 18).

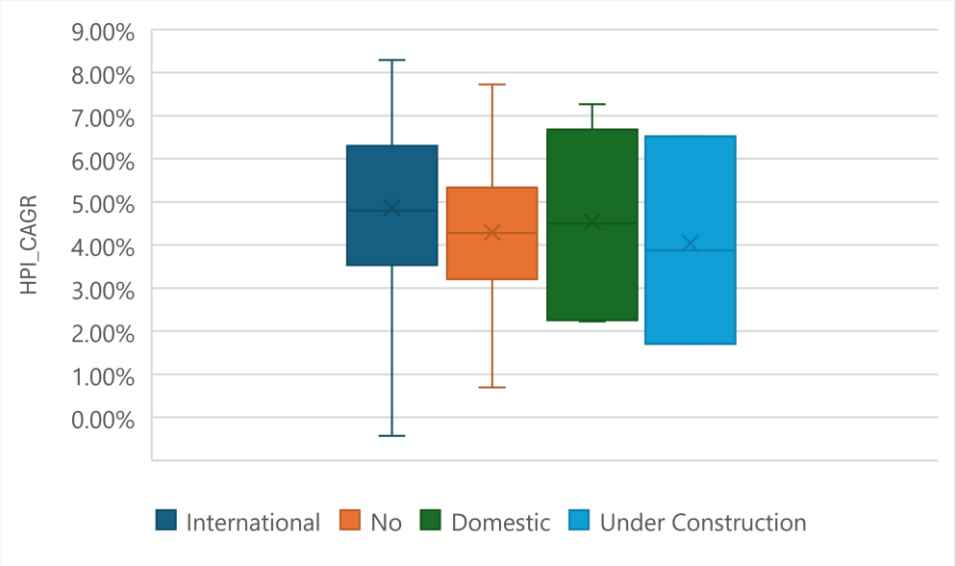

Figure 18 Mean and median HPI CAGR by airport category

Table 10 HPI CAGR by airport category (international, domestic, under construction, none)

Airport Categories	Airport Class	Average of HPI_CAGR	Median of HPI_CAGR	Std. Dev. of HPI_CAGR	Count of Cities
International	1	4.87%	4.80%	1.87%	25
Domestic	2	4.54%	4.50%	2.15%	6
Under Construction	3	4.04%	3.88%	2.41%	3
No	4	4.29%	4.28%	1.73%	16

The tier-wise breakdown underscores this pattern. All Tier I cities are served by international airports, embedding them firmly in national and global networks. Tier II cities display greater heterogeneity: 17 with international airports, six with domestic facilities, one with an airport under construction (Navi Mumbai), and eight without airports. Importantly, the latter group—including Faridabad, Ghaziabad, Gurugram, Meerut, Noida, Vasai–Virar, Kalyan–Dombivli, and Mira Bhayander are all proximate to Delhi or Mumbai. Their integration into metropolitan systems compensates for the absence of local airports, allowing them to sustain moderate housing price growth (Figure 19). Tier III cities remain largely disconnected from aviation infrastructure; Greater Noida is the sole case with an airport under construction.

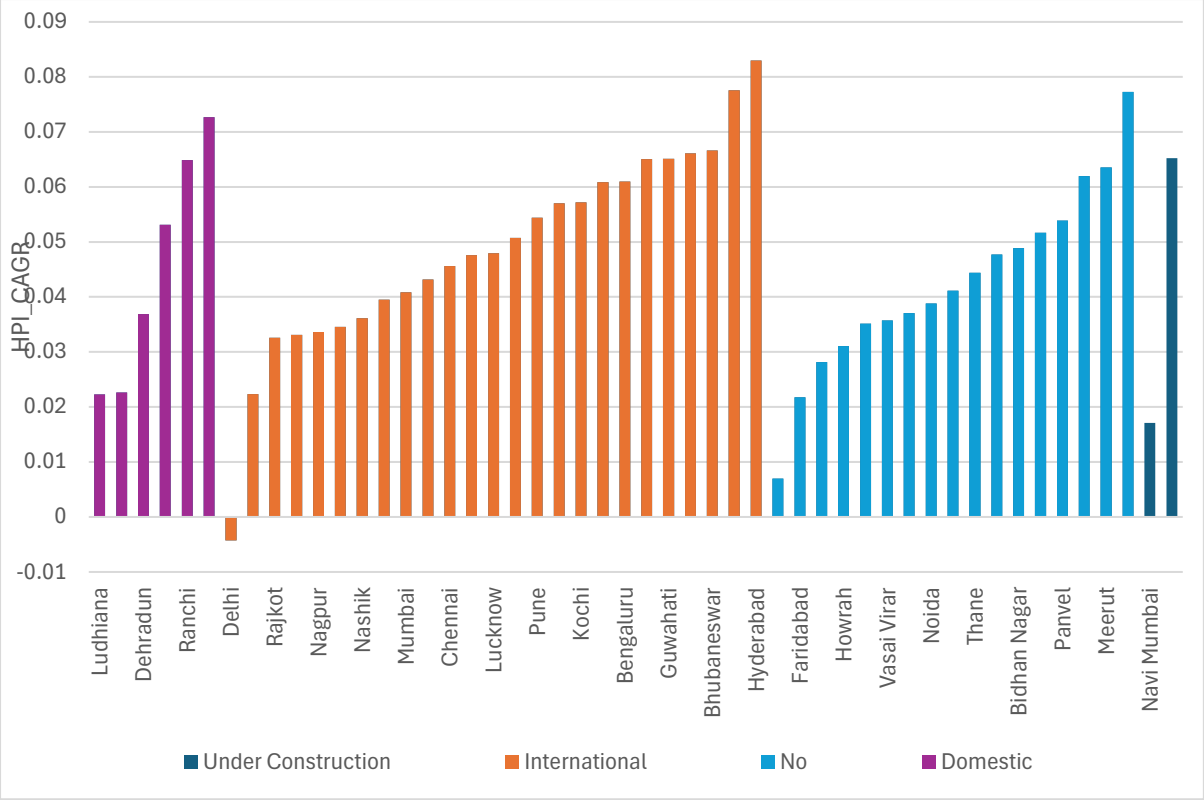

Figure 19 Tier-wise distribution of airport connectivity among cities

While averages suggest a premium for airport-connected cities, the scatter distribution does not reveal systematic clustering across the HPI spectrum (Figure 20). This indicates that airports are enabling rather than determinative factors. In cities with diversified economies and robust infrastructure pipelines such as Ahmedabad, Hyderabad, or Pune airports reinforce existing growth trajectories. Elsewhere, proximity to Tier I hubs substitutes effectively for local airports.

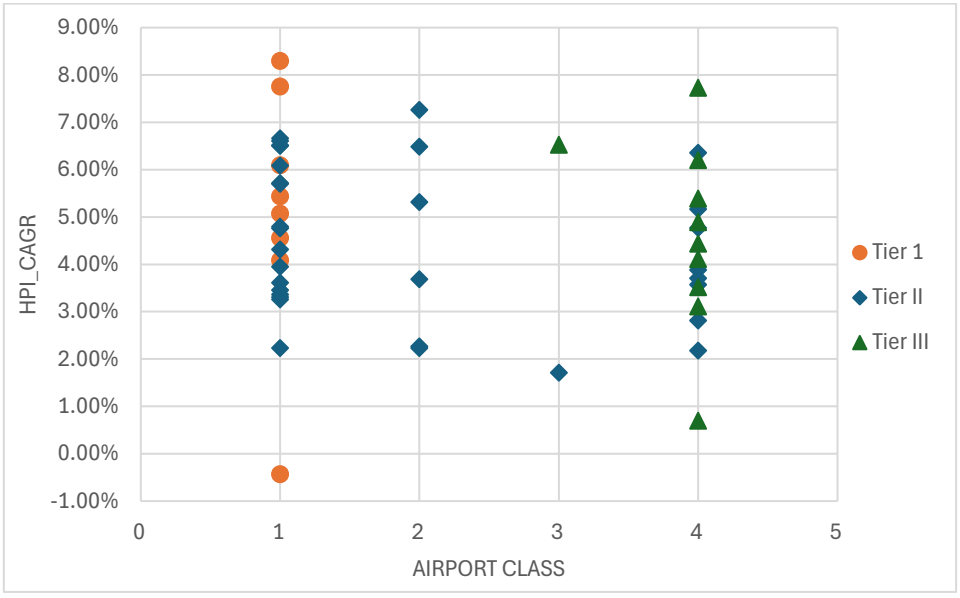

Figure 20 Scatterplot of HPI CAGR across airport classes (1–4)

In sum, the evidence suggests that airport connectivity enhances housing market performance, but its impact is contingent on broader economic and spatial dynamics. International airports confer the strongest premium, yet the effect is uneven, conditional, and most effective when embedded within diversified economic structures and metropolitan linkages.

3.4.6. Housing Prices and Spillover Effects from Tier I Cities

Tier I cities are expected to exert strong spillover effects on their surrounding regions, often shaping housing demand in nearby Tier II and Tier III centres. To test this assumption, 42 Tier II and III cities were grouped into four distance bands from the nearest Tier I hub: G-1 (0–100 km), G-2 (100–300 km), G-3 (300–600 km), and G-4 (600–1100 km).

The results, presented in Table 11, reveal some important anomalies. Cities in the closest band (G-1) recorded the lowest average housing price growth (mean 4.25 percent), whereas cities located 300–600 km away (G-3) recorded the highest average growth (4.79 percent). Even the farthest group (G-4, 600–1100 km) showed healthy appreciation at 4.69 percent. Median values also remain clustered within a narrow range (4.00 to 4.94 percent), confirming the absence of a clear distance gradient.

Table 11 Mean and median HPI CAGR across distance bands from Tier I cities (G-1 to G-4)

Category	Count	Mean	Median
G-1	19	4.25%	4.11%
G-2	6	4.51%	4.00%
G-3	13	4.79%	4.80%
G-4	4	4.69%	4.94%

As shown in Figure 21, this pattern contradicts the conventional expectation that proximity to Tier I hubs should automatically translate into stronger housing price growth. Instead, cities in immediate peripheries often face affordability ceilings, traffic congestion, or inventory overhangs that dampen their markets despite geographic advantage. By contrast, several mid-distance cities benefit from new industrial corridors, institutional anchors, or planned township projects, enabling them to outperform closer competitors.

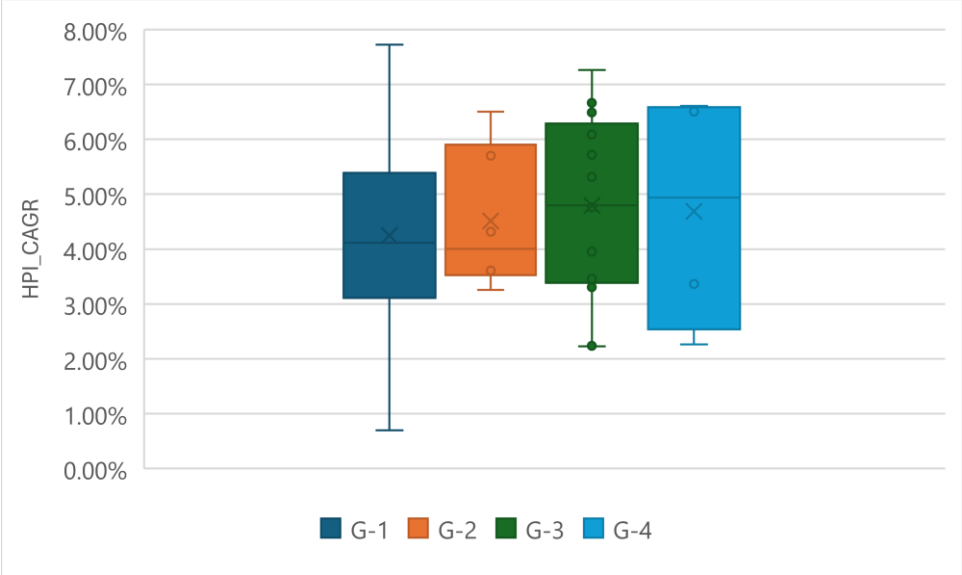

Figure 21 Average HPI CAGR by distance from nearest Tier I city

The scatter distribution in Figure 22 further underlines the anomaly: housing price growth is dispersed across distance bands, with no systematic clustering. Part of this result may reflect data limitations particularly the smaller sample size in G-2 and G-4 but the broader insight is that distance from Tier I hubs is not a reliable predictor of housing market performance.

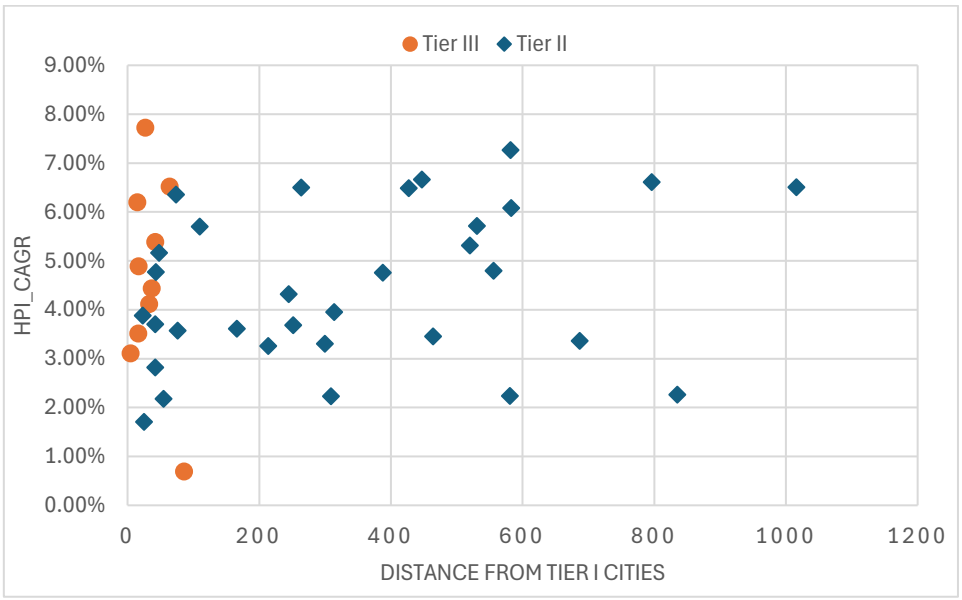

Figure 22 Scatterplot of HPI CAGR for Tier II and III cities by distance from Tier I hubs

In practice, spillover effects from Tier I metros are highly conditional. Cities that combine connectivity with local economic anchors and effective planning whether near or far from a Tier I hub are the ones that record sustained housing price growth. Distance creates opportunity, but it does not guarantee outcomes.

3.5 Summary of Regional Level Analysis

The analysis of Housing Price Index (HPI) growth rate, measured through Compounded Annual Growth Rate (CAGR), in relation to existing tier classifications, the Ease of Living Index and its constituent pillars, Smart City status, airport connectivity, and the distance from the nearest Tier I cities provides important insights into the influence of local factors on housing price dynamics. These findings offer a nuanced understanding of the regional determinants of price movements and serve as an evidence-based foundation for informed decision-making by policymakers, urban planners, and real estate stakeholders.

4. Conclusion, Limitations, and Future Works

The link between economic growth and housing prices has emerged as a key area of study within India's fast-growing urban economy. While regional economic development fosters better employment opportunities and enhances living standards, the pace of urban expansion often drives up housing prices, which can in turn undermine affordability and quality of life. This study explores the dynamics of housing prices in India at both national and regional levels, highlighting the macroeconomic and local factors that influence the Housing Price Index (HPI). The findings provide valuable insights for policymakers. However, the analysis presented in this report has some limitations.

First, the study relies on the HPI as a proxy for actual housing prices and employs its compound annual growth rate (CAGR) as an indicator of price growth. However, because HPI values are adjusted relative to a chosen base year, the values presented might not fully capture the true magnitude of changes in housing prices over time. Future research could complement HPI-based analysis with alternative measures of housing prices, such as transaction-level data, rental market trends, or developer price disclosures, to provide a more accurate picture of price movements. Incorporating longitudinal datasets without base-year adjustments, or triangulating HPI figures with independent housing market indicators, would help validate the findings and capture the true extent of price growth over time.

Second, the study draws upon primary and secondary data sources that are publicly available online to derive its insights. However, the findings have not been validated through expert consultations or direct on-ground observations, which may affect the depth and contextual accuracy of the analysis. Subsequent studies could enrich the analysis by incorporating expert interviews, stakeholder consultations, or field-based observations to validate and contextualise the findings.

Lastly, while the regional analysis is grounded in actual data, the explanations for the observed trends are based on the authors' hypotheses and informed interpretations. These explanations may not fully capture the complex underlying drivers, and further empirical research is required to validate and strengthen this understanding.

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