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MULTIDIMENSIONAL HOUSE PRICE PREDICTION WITH SOTA RNNs

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Abstract. This paper introduces insights into the Turkish real estate market, which can be generalized globally. It primarily aims to find the best forecasting algorithms for the housing price index and compare their prediction performance over three, six, nine, and twelve months ahead by using recurrent neural networks (RNN) with a comparison of out-of-sample predicting power of econometrical models. For these purposes, we employ three RNN architectures in twenty-four settings, revealing that certain RNN architectures are the best predictors in forecasting the Turkish real housing price index. The RNN architectures outperform traditional econometric models; however, the more months forecasted, the lower the prediction power. The lagged values of the price-to-rent ratio, real rents, and the lagged USDTRY values contribute more than the other predictors in forecasting the real housing price index. The outcomes suggest that stocks, real estate investment trusts, and gold are neither complementary nor competing financial instruments since housing is an illiquid asset.

Keywords: housing price index prediction, recurrent neural networks, deep learning.

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1. Introduction

Opportunities for better education and employment trigger migration to metropolitans, causing increased demand and price exuberances in residential real estate. However, housing price booms due to high demand adversely impact the economy. Several factors varying from the economy's overall health and stock market returns to the money supply and interest rates can affect housing prices (Tan et al., 2017). Accordingly, it is crucial to monitor the market trends and forecast index series to identify bubbles, bursts, and turning points in the housing market and analyze the factors that affect house prices for academics, policymakers, investors, analysts, and financial institutions. Numerous studies around the world, including in Turkey, have investigated the existence of real estate price bubbles and examined the long-term relationship between macroeconomic indicators and real estate prices.

There is a recent debate concerning bubble formations in Turkish real estate prices as house price growth exceeds the inflation rate, especially between 2010 and 2017. The term "bubble" implies that overvalued and fragile prices may collapse eventually, affecting governments and the financial markets. In particular, the 2008 global financial crisis illustrated that the bubble's deflation in the real estate market could trigger comprehensive economic deterioration, even becoming the source of a banking crisis due to corruption in the loan standards. Therefore, the government and investors should closely monitor and comprehend housing price dynamics and their features as Turkish real estate market prices are highly volatile and fragile. The primary purpose of the legal authorities is to establish economic stability and monitor and audit financial institutions through specific provisions. The real estate market in Turkey is more alluring due to high house price growth – exceeding growth in income and rents – causing housing to be less affordable for low-income and middle-income groups.

Two definitions of the term bubble stand out among several variations. Garber (2000) defines bubbles as increases in the difference between prices and fundamental values, whereas Case and Shiller (2003) indicate that bubbles occur due to unrealistic expectations of price increases. However, prominent features of the Turkish real estate market, especially between the 2010–2017 period, are the real growth in housing prices exceeding growth in EURTRY, gross domestic product (GDP), gold prices, income, inflation, and net deposit returns, rents, and USDTRY. Especially in İstanbul, Ankara, and İzmir, housing prices tend to exhibit explosive behavior. This situation revives affordability concerns that it is becoming harder to find an affordable

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house, especially in the three metropolitans mentioned above. Similar patterns of housing price surges and affordability concerns have also been observed in other major cities worldwide, indicating that this phenomenon is not unique to Turkey.

Recent studies forecasting Turkish housing prices have generally employed models varying from Autoregressive Integrated Moving Average (ARIMA), Autoregressive Distributed Lag (ARDL) cointegration, Markov regime-switching to Structural Vector Auto-regression (SVAR), and various other models used in time-series analysis. In addition, to the best of the authors' knowledge, there is a niche in the studies examining Turkish real estate market dynamics and forecasting Turkish housing prices through deep learning algorithms.

This study makes twofold original contributions to the literature. Firstly, this research sheds light on the Turkish real estate market dynamics and indicates the future housing price index's forecasting performance by introducing deep learning forecasting algorithms for three, six, nine, and twelve months ahead by considering three different batch sizes and eight learning coefficients, that is, 24 settings (1). This has profound implications for economic policy, enabling more informed decision-making by government officials, central banks and financial institutions. In addition, the improved forecasting performance of these algorithms provides investors and market participants with the tools necessary to anticipate price movements, manage risk, and optimize investment strategies in the volatile Turkish housing market. Second, this study determines the features' contribution to forecasting the housing pricing index among its twenty-one financial, housing-sector-related, and macroeconomic features and their first lags by employing the SHAP (SHapley Additive exPlanations) values with the most comprehensive multidimensional dataset (2) used in the Turkish real estate market. Key financial indicators, such as interest rates and credit availability, are examined for their influence on housing affordability and market demand. Housing sector-related variables, including housing supply metrics and construction activity, are evaluated for their role in price movements. Macroeconomic factors such as GDP growth, inflation rates, and unemployment levels are analyzed to understand their broader impact on the housing market. The results of the study highlight the comprehensive impact of these characteristics on the forecasting model, demonstrating how they collectively influence the prediction of future house price trends and identifying the most predictive variables.

This study is motivated to explore the Turkish housing market characteristics because its location serves as a crossroads for commerce between Asia and Europe, offering significant return potential for foreign investors with increasing nominal prices since 2010. The Turkish residential real estate market exhibited higher returns than deposits, USDTRY, EURTRY, and gold between 2010 and 2017, where construction corporations' NPL ratio increased to 9.81% as of December 2019 (Özgüler et al., 2023). However, the fundamental prices converge to observed prices in the long run, and these figures fuel fears of a bubble presence. This study finds the Turkish housing case worth examining due to unaffordable price levels for white collars, the absence of affordable housing policies for low- and middle-income households, and the increasing sales to foreigners.

Investors, construction companies, and governments benefit from the housing price prediction to impose decisions such as buying a new house, starting construction, and reducing the money supply by raising the interest rate. Therefore, this research aims to forecast the future housing price index in Turkey and, by comparison, reveal the best deep learning model for three, six, nine, and twelve months ahead, and compare their prediction power with the traditional Nonlinear Autoregressive Distributed Lag (NARDL) model. Thus, the outcome aids in allaying fears of purchasing a house at an unreasonably high price in Turkey by dispersing the clouds of vagueness in future house prices. However, the three models employed in this study have relatively lower prediction power for twelve months ahead of the Turkish real housing price index. The second purpose of this research is to determine the best predictors of the real Turkish housing price index between 2003 and 2019 to provide insights for first-time homebuyers. SHAP values indicate that the first lags of the price-to-rent ratio, rent prices, and USDTRY in real terms are the best forecasters of the housing price index for the Turkish experience.

The hypothesized research questions in this study are as follows: Which of the three models best forecasts the real Turkish housing price index in the next three, six, nine, and twelve months? What are the best predictors of housing prices in Turkey?

The paper's organization is as follows: The second section briefly informs the literature on forecasting housing and other asset prices through several methodologies and deep learning algorithms. The third section presents the data, and the fourth section introduces the methodology, whereas section five includes empirical findings. Finally, the sixth section provides concluding remarks and offers policy implications.

2. Literature review

Several empirical studies estimate the housing price index through its macroeconomic, financial, and housing-sector-related predictors used in this study. Zhou (2010) aims to determine linear and non-linear long-run linkages among house prices and their macroeconomic fundamentals via Johansen and Augmented Engle-Granger cointegration tests for ten US cities. Dua and Miller (1996) employ several determinants varying from mortgage rates, unemployment rate, and real income to building permits. They find that the Bayesian Vector Auto Regression (BVAR) model forecasts are superior to the unemployment rate and real income; however, the best-performing model includes employment indexes for Connecticut. Engsted and Pedersen (2015) use the price-to-rent ratio to estimate and compare housing returns across eighteen OECD countries by considering the risk premium, finding changes in rental yield estimates, and instabilities between sub-samples. Robstad (2018) studies the effect of monetary policy shocks on Norwegian house prices and household credit responses through SVAR models, indicating significant contemporary effects of monetary policy and modest credit effects on house prices. Besides, this study comments that reducing credit volume as a monetary policy may adversely affect GDP and inflation figures. Chen and Cheng (2017) indicate that real income growth and interest rates are the fundamentals of the price-to-income ratio. Coskun and Umit (2016) find no long-run cointegrating relationship between the real housing price index and its factors, namely the USDTRY exchange rate, BIST100 returns, gold prices, and deposit interest rates. Chang et al. (2010) suggest that their Markov regime-switching model is superior to a linear VAR model in comprehending asset return dynamics. In particular, the impact of a one-time shock to the federal funds rate or the interest rate spread is less significant but longer lasting on US housing market returns than REIT returns.

A variant of the studies focuses on forecasting the housing price index, asset prices, or sales and predicting their future values. Elíasson (2017) fits a demand and supply model in forecasting house prices in Iceland from 1961 to 2014 and examines the bubble existence between 2004–2007. Using linear regression and particle swarm optimization methods, Alfiyatin et al. (2017) determine that physical conditions, concept, and location are the predictors of Malang city house prices. Temur et al. (2019) estimate housing sales for the Turkish experience with ARIMA, LSTM, and a hybrid model, which combines the above-mentioned models. The hybrid model exhibits the best performance with the lowest error rate. Hong et al. (2020) indicate that the Random Forest (RF) method is superior to Ordinary Least Squares-based (OLS-based) models with 72% and 17.5% prediction probabilities, respectively, in the practice of mass appraisal for Gangnam house prices over 2006–2017. Jadevicius and Huston (2015) employ twenty different ARIMA models and select the best modeling results to estimate twelve out-of-sample Lithuanian housing price growth estimates. In addition, the selected ARIMA model forecasts 8% house price growth for 2015. Vatansever et al. (2020) split the data set of five big Turkish cities' similar housing price index trends between 2010–2017: The 2010–2016 period for training the model and 2017 to validate the forecasting performance of the selected models. The results show that an autoregressive (AR) model-based fuzzy clustering approach performs better than AR models in forecasting 71% of the districts. Kalczynski and Zerom (2015) propose a framework to predict short-run electricity prices via financial measures for 2.5, 13, 23, and 38 hours ahead.

Empirical studies use machine learning algorithms to forecast housing prices, predict portfolio assets, and detect banking fraud. Guo et al. (2020) gather data by text mining keywords of Chinese houses for sale on the internet. The research comprises four approaches to evaluate housing price prediction performance, indicating that Random Forest outperforms the others. Phan (2018) compares the prediction results of Melbourne's house prices varying from linear and polynomial regressions, regression trees to support vector machines, and a combination of several other techniques. The study suggests that integrated principal component analysis (PCA) and tuned Support Vector Regression (SVR) models have higher accuracy. Milunovich (2020) discovers that the SVR algorithm generates six of eight top Australian real housing price index forecasts for one, two, four, and eight quarters ahead. Wang et al. (2021) simulate the machine learning models, including XG-Boosting, LG Boosted Machine, deep learning, and several attention models. They suggest their proposed model performs better in two Taiwanese cities. Sharma and Shekhawat (2021) aim to provide a portfolio selection strategy by predicting asset returns and suggest that the prediction accuracy is higher in the given order for predicting next month's portfolio revenue: Jaya-based Spotted Hyena Optimization (J-SHO), integrated Jaya Algorithm (JA), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), Spotted Hyena Optimization (SHO), and Particle Swarm Optimization (PSO). Kolli and Tatavarthi (2020) propose a fraud detection strategy in bank transactions through the deep RNN, which we employ in our research.

Recent studies such as Hill and Trojanek (2022) provide a methodological foundation by demonstrating the superiority of hedonic methods in constructing house price indices. Building on this, Trojanek et al. (2023) apply advanced econometric techniques to identify housing bubbles in Polish cities, finding evidence of pre-2008 bubbles but suggesting more sustainable recent growth. Brzezicka (2021) contributes a theoretical framework for understanding bubble types, proposing a nuanced typology that combines functional and structural approaches. Finally, Brzezicka (2022) introduces a practical tool for real-time bubble detection, emphasizing the importance of timely data in market analysis. Taken together, these studies offer a multifarious approach to understanding, measuring, and forecasting housing market trends that combines methodological advances, empirical analysis, theoretical frameworks, and practical tools. This integrated perspective is critical for policymakers, investors, and researchers seeking to navigate the complexities of housing markets and mitigate the risks associated with speculative bubbles.

Unaffordable prices and house price growth exceeding the inflation rate stimulate discussions over bubbles in the Turkish housing market, especially between 2007 and 2018. However, predicting future house prices makes this study more appealing since most academic studies cannot detect bubble formations in the Turkish real estate market. Zeren and Ergüzel (2015) analyze the housing market in three Turkish metropolitans (İstanbul, Ankara, and İzmir) between 2010 and 2014 and conclude that there were no bubble formations in relevant cities. In the same year, Erol (2015) cannot identify any signals of a bubble in the Turkish housing market between July 2007 and December

2012. In addition, Coskun and Jadevicius (2017) analyze the period from January 2010 to December 2014 to dissect the probability of a housing bubble in the Turkish real estate market by using Case and Shiller's (2003) regressions and the Right Tail Augmented Dickey-Fuller (RTADF) test. The authors found that the Turkish housing market was not in a bubble in the same period. Afsar and Dogan (2018) also conclude that there was no bubble in the Turkish real estate market between January 2010-November 2017. A recent study examines the bubble formations in the Turkish housing market by Coskun et al. (2020), employing two different housing price indexes (CBRT's THPI and REIDIN's RHPI) in two different periods (2010:M1–2014:M12 and 2007:M6–2014:M12). This study finds that house price appreciations in both indexes did not indicate a bubble. However, overvaluations are limited in number, small in magnitude, irregular, non-persistent, and non-explosive in Turkey.

On the other hand, Cagli (2019) analyzes the bubble formations in 2010–2017 and concludes a bubble in the Turkish housing market. Iskenderoglu and Akdag (2019) also examine and find a bubble in Turkey during the 2010–2018 period. Duran and Özdoğan (2020) investigate the dynamics behind the housing prices in various Turkish regions by several alternative tests: Vector-Autoregressions, Unit Root Analysis, Cholesky Forecast Error Variance Decompositions, Impulse-Response Functions, Panel Regressions, Lagrange Multiplier Spatial Dependence Tests and Granger Causality Tests. The authors investigate that housing price appreciations were heterogeneous across regions, and the role of speculative behavior in housing prices was quite important between the 2010–2016 period. Coskun and Pitros (2022) also find bubble formations from 2013 to 2017. The peak/last year of the bubble was 2017, whereas the bubble burst occurred in 2018 in the Turkish housing market.

Forecasting the house price index in Turkey offers significant benefits to various stakeholders due to the unique characteristics of the Turkish real estate market. For government officials and central banks, accurate forecasts enable more effective economic policy formulation and regulatory measures, helping to control inflation and stabilize the market. Financial institutions use these forecasts to better assess the risks associated with mortgage lending and real estate investments, thereby improving their risk management strategies. Investors and real estate developers gain critical insight into future market conditions, allowing them to optimize investment decisions and development strategies.

3. Data and preliminary analysis

We employ an extensive data set of predictors, including 21 different financial, housing-sector-related, macroeconomic observations, their first lags, and an autoregressive component to predict the Turkish housing price index and rental prices in real terms between 2003:M01 and 2019M12. The mainspring for selecting 204 observations is data availability; the time interval for the Real Estate Investment and Development Information Network (REIDIN) TR7 Housing Price Index and REIDIN TR7 rental prices in real terms starts from 2003:M01. TR7 connotes seven Turkish metropolitans, namely Adana, Ankara, Antalya, Bursa, İzmir, İstanbul, and Kocaeli. This study does not include later periods because there was disequilibrium in housing and rent prices due to the COVID-19 epidemic and fluctuations in mortgage rates. According to Turkish Statistical Institute statistics[1], İzmir is the third most populous Turkish metropolitan, with an approximately 4.4 million population in 2019. The 2020 earthquake in İzmir caused a deterioration in house prices and the economy.

The data set includes 21 variables affecting both supply and demand sides of real estate prices. The motives for selecting the data used in this study are as follows: First, the consumer's price index (CPI) directly influences the real housing price index since Goodhart and Hofmann (2008) shows the relationship between inflation, as measured by CPI, and various asset prices, including housing, and how CPI influences real housing price indices for 17 developed economies. The real GDP and growth rate are also added as the construction sector is the driving force of GDP for the Turkish experience offered by Erol and Unal (2015) indicating the causal relationship between construction investments and economic growth in Turkey from 1998 to 2014. As Bentolila and Saint-Paul (2003) investigated the dynamics of labor's share of income, considering factors such as industrial production and wage levels, including minimum wages for OECD countries; industrial production index and real gross minimum wage are included as an indicator of income. Household debt-to-GDP ratio, price-income ratio and price-rent ratio are also added to include indicators of housing affordability as Andrews et al. (2011) analyses various indicators of housing affordability, including these three ratios, across OECD countries, offering a comprehensive perspective on how these metrics reflect housing affordability. Glindro et al. (2011) discusses the factors influencing house prices and compares housing investments with other alternative investment instruments such as stock markets, currency exchange rates (including the US dollar), gold prices, and real estate indices, providing a comprehensive analysis of how these variables interact in investment decision-making. For this reason, BIST100, USDTRY foreign exchange rate, gold prices and XMGYO index as alternative investment instruments are also considered in the data set. The impact of various demand-side factors, including homeownership rates, unemployment rates, credit volumes, rental prices, and mortgage rates, on house prices, offering a detailed examination of how these economic indicators influence the housing market, is also considered in the data set (Girouard et al., 2006). Malpezzi and Maclennan (2001) and Gyourko and Saiz (2006) offer supply-side predictors such

[1] https://data.tuik.gov.tr/Kategori/GetKategori?p=Nufus-ve-Demografi-109 (accessed on 2 March 2022).

Table 1. Variable definition

Variable	Source	Frequency	Details
lncpi	TURKSTAT*	Monthly	Consumer's Price Index
lnrealgdp	FRED*	Quarterly**	Real Gross Domestic Product
growthrate	TURKSTAT*	Quarterly**	GDP Growth Rate (%)
lnipi	CBRT EDDS Data Central*	Monthly	Industrial Production Index
lnrealgrosminimumwage	Ministry of Labor and Social Security	Monthly	Real Gross Minimum Monthly Wage
lnhouseholddebttogdp	BIS*	Quarterly**	Household Debt to GDP
lnunemployment	TURKSTAT*	Monthly	Unemployment Rate
creditgrowthrate	BRSA*	Quarterly**	Credit Growth Rate
lnrealcreditvolume	BRSA*	Quarterly**	Real Credit Volume
lnyouthunemployment	TURKSTAT*	Quarterly**	Unemployment Rate for Young Population
lnbist100	CBRT EVDS Data Central*	Monthly	BIST100 Index Closing Prices
lnrealgoldtry	CBRT EVDS Data Central*	Monthly	Real Republican Gold Sale Price (TRY / Piece)
lnrealusdtry	CBRT EVDS Data Central*	Monthly	Real USDTRY Exchange Rate
lnxmgyo	Bloomberg	Monthly	XMGYO Index Closing Prices
lnbpkm2	TURKSTAT*	Monthly	Building Permits per km^2
lnhomeownershiprate	EUROSTAT	Yearly**	Home Ownership Rate (%)
lnpricetorent	REIDIN	Monthly	Rate of Average Price to Rent per m^2
lnrealconstructioncosts	CBRT EVDS Data Central*	Monthly***	Real Construction Cost Index (2005 = 100)
lnrealhpi	REIDIN	Monthly	Real TR7 Housing Price Index
lnrealrent	REIDIN	Monthly	Average Real Rent per m^2
lnpricetoincome	REIDIN & TURKSTAT*	Monthly	Median House Prices / Median Income
mir	CBRT EVDS Data Central*	Monthly	Average Mortgage Rates

Notes: The term "ln" before variable names represent the natural logarithm.

*TURKSTAT, FRED, CBRT, BIS, and BRSA connote Turkish Statistical Institute, Federal Reserve Economic Data, Central Bank of the Republic of Turkey, Bank of International Settlements and Banking Regulation and Supervision Agency, respectively.

**The quarterly and yearly series were transformed into monthly series using the cubic spline interpolation method.

***2003 and 2004 series of the lnrealconstructioncosts are calculated by taking the first difference of the Construction Cost Index (2003 = 100) series and transforming the differences backward from 2005-01 of the Turkish Statistical Institute's Construction Cost Index (2005 = 100) series up to 2003-01.

as building permits per km^2, and real construction costs for housing prices; and an autoregressive component.

This paper has several data sources for the quarterly and monthly time series varying from the Bank for International Settlements (BIS), Banking Regulation and Supervision Agency (BRSA), Bloomberg, Central Bank of Republic of Turkey's (CBRT) EDDS Data Central, EUROSTAT, Federal Reserve Economic Data (FRED), Ministry of Labor and Social Security, Turkish Statistical Institute (TURKSTAT), and REIDIN. Table 1 presents the details of the variables included in this study.

This study employs seasonally adjusted time series through the X13 ARIMA-SEATS approach. However, the X13 ARIMA-SEATS approach cannot identify seasonality for eleven series: BIST100 index closing prices, credit growth rate, growth rate, gross domestic product, homeownership rate, price-to-income ratio, real credit volume, gold prices, real USDTRY exchange rate, XMGYO index closing prices, and mortgage rates.

We employ the cubic spline interpolation method to obtain the monthly values for the quarterly series. The rest of the series has a monthly frequency. The series has natural logarithmic forms except for growth rate, credit growth rate, and mortgage rates.

Table 2 presents the descriptive statistics of the variables employed in the study.

As presented in Table 2, eleven variables are leptokurtic, and the rest are platykurtic. Besides, thirteen of the series' distributions have a long-left tail. The standard deviation-to-mean (coefficient of variation) statistics illustrate some disparity for real gold prices that these series are highly volatile compared to the rest of the financial series. In addition, neither of the series contains a normal distribution.

This study employs seven different unit root tests: Augmented Dickey-Fuller[2] (ADF), Phillips-Perron[3] (PP), Kwiatkowski-Phillips-Schmidt-Shin[4] (KPSS), Dickey-Fuller-GLS[5] (DF-GLS), Elliott, Rothenberg, and Stock[6] (ERS) point

[2] Table S1 with MacKinnon (1996) in online supplementary material.
[3] Table S2 with Phillips and Perron (1988) in online supplementary material.
[4] Table S3 with Kwiatkowski et al. (1992) in online supplementary material.
[5] Table S4 with Elliot et al. (1996) in online supplementary material.
[6] Table S5 with Elliot et al. (1996) in online supplementary material.

Table 2. Descriptive statistics

Variable	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	J-B	J-B (p)	N
lncpi	5.27	5.24	6.09	4.55	0.41	0.15	2.05	8.48	0.01	204
lngdp	0.60	0.61	0.98	0.13	0.24	–0.06	1.95	9.48	0.01	204
growthrate	1.28	1.41	6.09	–5.63	1.96	–0.73	4.37	34.18	0.00	204
lnipi	4.37	4.37	4.80	3.86	0.26	0.04	1.70	14.32	0.00	204
lnrealgrossminimumwage	1.46	1.44	1.78	0.91	0.19	–0.73	4.51	37.43	0.00	204
lnrealhouseholddebttogdp	2.46	2.70	2.98	0.64	0.61	–1.59	4.62	108.29	0.00	204
lnunemployment	2.31	2.29	2.65	2.06	0.14	0.72	2.85	17.86	0.00	204
creditgrowthrate	0.01	0.01	0.08	–0.09	0.02	–0.16	8.65	271.93	0.00	204
lnrealcreditvolume	1.01	1.10	1.93	0.10	0.63	–0.08	1.45	20.70	0.00	204
lnyouthunemployment	3.00	2.97	3.28	2.83	0.11	0.86	3.09	25.26	0.00	204
lnbist100	10.86	11.03	11.69	9.16	0.59	–0.97	3.27	32.31	0.00	204
lnrealgoldtry	–1.14	–1.01	–0.43	–1.87	0.42	–0.25	1.77	15.00	0.00	204
lnrealusdtry	–4.56	–4.56	–4.04	–4.88	0.19	0.45	2.31	10.99	0.00	204
lnxmgyo	10.30	10.42	10.80	9.03	0.38	–1.51	4.56	98.59	0.00	204
lnbpkm2	2.88	2.93	4.93	1.05	0.53	–0.42	4.52	25.55	0.00	204
lnhomeownershiprate	4.10	4.10	4.11	4.07	0.01	–1.04	2.90	36.81	0.00	204
lnpricetorent	2.89	2.88	3.18	2.74	0.11	0.70	3.06	16.51	0.00	204
lnrealconstructioncosts	1.42	1.41	1.55	1.34	0.05	0.65	2.62	15.48	0.00	204
lnrealhpi	1.89	1.96	2.07	1.65	0.13	–0.49	1.91	18.17	0.00	204
lnrealrent	1.23	1.22	1.44	1.02	0.11	0.15	1.96	10.05	0.01	204
lnpricetoincome	0.49	0.49	0.57	0.31	0.04	–1.59	8.49	341.95	0.00	204
mir	0.17	0.14	0.54	0.08	0.08	2.14	8.34	397.21	0.00	204

Notes: Std. Dev. and J-B represent standard deviation and Jarque-Bera, respectively.

optimal, Ng-Perron modified[7], and Zivot-Andrews[8] (ZA) unit root tests. The tables[9] present the evaluation of the unit root test results and test statistics (see tables in online supplementary material).

The unit root test results show that those six variables are integrated into order zero, and 14 are integrated into order one. In addition, the natural logarithm of household debt to gross domestic product ratio and the natural logarithm of gross domestic product in real terms are integrated into order two, i.e., I (2).

Data preprocessing

Standard data preprocessing typically involves cleaning the dataset by handling missing values, removing duplicates, and correcting inconsistencies resulting from unit roots, followed by transforming the data through the normalization of features. This process often includes feature engineering to create new relevant variables, dimensionality reduction to focus on the most important features, and splitting the data into training and test sets to prepare for model development and evaluation. We used three steps in the data preprocessing procedure.

In this first step, all variables have been brought to their stationary forms by eliminating unit roots. This process, typically accomplished by differencing or leveling, ensures that the time series data used in the model are free of non-stationary patterns (containing unit roots). By working with stationary variables, we can avoid spurious relationships and obtain more reliable statistical inference in our deep recurrent neural networks.

Second, it is important to note that we use normalized variables between 0 and 1 for the analysis part of this research. This normalization process is a standard preprocessing step in deep recurrent neural networks. By scaling all input features to a common range, we ensure that each variable contributes proportionally to the model's learning process, preventing features with larger magnitudes from dominating those with smaller scales. This approach increases the stability of the deep recurrent neural networks during training and often leads to faster convergence and improved model performance.

Third, we performed a missing value analysis to fill in the appropriate form, but the data set does not contain any missing values that could lead to an underfitting problem in our deep learning procedure. While this lack of missing data is generally beneficial for data quality, it could potentially limit the model's ability to generalize to real-world scenarios where missing values are common.

[7] Table S6 with Ng and Perron (2001) in online supplementary material.

[8] Table S7a, Table S7b, and Table S7c with Zivot and Andrews (2002) in online supplementary material.

[9] Table S8 in online supplementary material.

4. Methodology

The methodology of this study is based on time series forecasting analysis through state-of-the-art deep recurrent neural networks (RNN). Sorting architectures of RNNs from basic to complex are Elman, gated recurrent unit (GRU), and long short-term memory (LSTM). Bai et al. (2018) conducted a comparative analysis of RNNs (including LSTMs and GRUs) and alternative models such as CNNs. Their research showed that RNNs can be more effective for certain types of sequential tasks, although they noted that relative performance can vary depending on the specific dataset and the complexity of the task at hand. Greff et al. (2016) conducted a comprehensive empirical study comparing different variants of LSTMs. Their results consistently showed that LSTM and GRU architectures outperformed other RNN variants across a range of sequence modeling tasks. This study provides a strong rationale for including LSTM or GRU in a model selection. These studies provide evidence-based support for the use of the RNN family, LSTM, and GRU architectures in sequence modeling tasks, which could strengthen the rationale for your model selection.

Elman (1990) introduces the simplest RNN architecture: an input layer fed by predetermined features, a context layer, one or more hidden layers, and an output layer. In such an Elman network, every layer has one or more neurons that use a non-linear function of their weighted sum of inputs to transfer information from one layer to the next with the formula given below:

$$h_t = \sigma_h\left(W_h x_t + U_h h_{t-1} + b_h\right), \tag{1}$$

where: t denotes the order of the sequence; x_t are features; σ_h activation function transforms h_t, which are the hidden layers in Equation (1). The following equation calculates the output:

$$y_t = \sigma_y\left(W_y h_t + b_y\right), \tag{2}$$

where: y_t is the output determined b bias unit added to W_y weighted of the input inherited from the previously hidden layer, which is rescaled by σ_y activation function in Equation (2).

Elman RNNs have a distinct advantage in forecasting tasks, particularly in predicting the house price index, due to their ability to dynamically learn temporal dependencies within the input data. Unlike traditional forecasting methods that rely on a fixed set of lagged observations, Elman RNNs can adapt to and learn varying temporal patterns based on the specific context of the data.

The second RNN architecture for time series forecasting is the Gated Recurrent Unit (GRU), invented by Cho et al. (2014) to overcome the gradient vanishing problem. GRU has three main components: the update gate, the reset gate, and the current memory gate. The formula of the update gate is as follows:

$$z_t = \sigma_g\left(W_z x_t + U_z h_{t-1} + b_z\right), \tag{3}$$

where: z_t denotes the update gate determined by σ_g sigmoid activation function, which includes W_z weighted inputs; while h_{t-1} is inherited and U_z a weighted part from the previous hidden state; b_z is the bias unit of the update gate in Equation (3). In addition to the update gate, GRU has a reset gate regulating how much of one's previous information should be forgotten. The reset gate is a combination of the input gate and the forget gate as in the Long Short-Term Memory (LSTM) architecture; however, we will explain it later. The formula of the reset gate is as below:

$$r_t = \sigma_g\left(W_r x_t + U_r h_{t-1} + b_r\right), \tag{4}$$

where: r_t shows the reset gate determined by σ_g sigmoid activation function again, which includes W_r weighted inputs. In Equation (4), h_{t-1} is passed part with U_r weights, W_r are weights of inputs, b_r is again the bias unit of the reset gate. Cho et al. (2014) offer two-staged final equations to estimate the output. The first stage is the candidate activation function denoted by $\widehat{h_t}$, and the second stage is a construction of hidden states denoted by h_t as follows:

$$\widehat{h_t} = \Phi_h\left(W_h x_t + U_h\left(r_t \odot h_{t-1}\right) + b_h\right); \tag{5}$$

$$h_t = z_t \odot \widehat{h_t} + \left(1 - z_t\right) \odot h_{t-1}, \tag{6}$$

where: Φ_h is the hyperbolic tangent activation function in Equation (5), while the operator $\odot$ denotes the element-wise product in Equation (6).

GRU RNNs offer significant advantages in forecasting house price indices due to their ability to efficiently process and store memories of sequential data. By maintaining an internal state that captures information from previous inputs, GRUs can effectively plan and predict based on historical housing market trends. Crucially, GRUs excel at mitigating the vanishing gradient problem, a common problem in training deep neural networks, especially those dealing with long sequences. This ability allows GRUs to effectively capture and exploit longer-term dependencies in time series data. In the context of the housing market, this means that GRUs can potentially identify and exploit long-term cyclical patterns, multi-year trends, and the lasting effects of major economic events on house prices.

The third architecture used in this study is the long short-term memory (LSTM) offered first by Hochreiter and Schmidhuber (1997). Initialization of input vector x_t into the LSTM unit is followed by first, the forget gate is demonstrated as follows:

$$f_t = \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right), \tag{7}$$

where: f_t indicates the forget gate determined by σ_g sigmoid activation function; W_f and U_f are the weights of inputs and the previous inherits (h_{t-1}) respectively while b_f is bias unit of the forget gate in Equation (7). Equation (8) presents the input gate formula:

$$i_t = \sigma_g\left(W_i x_t + U_i h_{t-1} + b_i\right), \tag{8}$$

where: i_t shows the input gate again transformed by a σ_g sigmoid activation function with W_i and U_i weighted of inputs and the remains from the previous cell (h_{t-1}) and with a bias unit of b_i in Equation (8). Output gate, which has a σ_g sigmoid activation is as below:

$$o_t = \sigma_g\left(W_o x_t + U_o h_{t-1} + b_o\right), \tag{9}$$

where: o_t is the output gate containing W_o weights of the inputs and U_o weights of inherit h_{t-1} accompanied by b_o bias unit in Equation (9). An LSTM unit separately consists of a cell input activation vector and cell state vector. However, cell state can be easily regarded as the recalculation of cell inputs determined by the input gate and the previous cell state determined by the forget gate. These two are as follows:

$$\tilde{c}_t = \sigma_c\left(W_c x_t + U_c h_{t-1} + b_c\right); \tag{10}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \tag{11}$$

where: $\tilde{c}_t$ is the cell input activation determined by now a hyperbolic tangent σ_c activation function fed by W_c weighted of inputs x_t and U_c weighted of inherits h_{t-1} plus b_c bias unit in Equation (10). Recalculation of the cell input activation is in c_t which includes the previous cell state (c_{t-1}) element-wise product of the forget gate (f_t) plus the cell input activation vector element-wise product of the input gate (i_t) in Equation (11). The operator is again an element-wise product called Hadamard product. Using connected forget and input gates is another option. These decisions are made jointly rather than independently, determining what to leave out and what new information to add. The most crucial factor that maintains the deepness of LSTM units is the hidden state as below:

$$h_t = o_t \odot \sigma_h c_t, \tag{12}$$

where: h_t is the hidden state of the LSTM unit in Equation (12); o_t is the output gate with a σ_h hyperbolic tangent function similar to Equation (10).

LSTM RNNs, due to their enhanced memory capabilities and ability to overcome the limitations of traditional RNNs, provide significant advantages in forecasting house price indices. By retaining critical information over an extended time series, LSTMs can more effectively capture and exploit long-term patterns in housing market data. Real estate markets are often influenced by a complex interplay of factors that can have both immediate and delayed effects on prices. LSTMs can potentially capture these intricate relationships, taking into account both current market conditions and long-term economic trends that may affect housing prices. LSTMs can learn to prioritize and remember significant events or trends that have a lasting impact on prices while giving less weight to short-term fluctuations that may not be indicative of long-term trends. For example, an LSTM could learn to retain information about major changes in interest rates or significant shifts in housing supply that could affect prices for years to come.

This study tests all RNN architectures by subjecting them to the same hyperparameter setting. By systematically evaluating all combinations, the grid search[10] ensures that the chosen hyperparameters are well-tuned for the specific task, thus improving the reliability and generalization of the RNN models used in the study. Accordingly, the first learning coefficient was determined as follows: λ = {0.0001, 0.0003, 0.001, 0.003}. In addition, the research carries out each stage with different batch sizes in the following order: *Batch Size* = {16,32,64}. Thus, a combination set of λ and Batch Size has emerged in 12 settings. The learning rate range and batch sizes employed in this study align with established practices in the literature. Smith (2017) demonstrated the effectiveness of cyclic learning rate schedules, including values comparable to ours, across diverse deep-learning applications. Our selected learning rates are carefully chosen to expedite convergence without sacrificing model stability. Concerning batch size, Masters and Luschi (2018) inform our approach. While smaller batch sizes (16–32) often enhance generalization, larger ones (64) can expedite training with minimal performance degradation. We train the three aforementioned network structures according to the hyper-parameters specified in these 12 settings. All network structures have 50 cells in the hidden layer. In addition, the activation function was determined as a hyperbolic tangent in all cells. Epoch hyper-parameter, which shows how often the data passes over, is fixed at 200 for each network infrastructure stated above.

The application of advanced forecasting methods with well-designed settings improves the accuracy and reliability of predictions, making them a powerful tool for navigating the complexities of the Turkish housing market and achieving more informed and strategic outcomes for all involved parties.

5. Empirical findings

At first, our study generates the feature set with the variables listed in Table 2 and their lagged values, including the output and the natural logarithm of the real housing price index.

Figure 1 shows the effect of each feature on the predicted output. The lagged values of the natural logarithm of the price-to-rent ratio were the most effective features. In contrast, the natural logarithm of rent prices in real terms was the most effective one for predicting positive output values, according to Figure 1. In addition, SHAP values reveal that the lagged values of USDTRY contributed more than the other predictors in forecasting the real housing price index.

The second part predicts the output with the feature set in different settings for three, six, nine, and twelve months. As mentioned before, the empirical approach calculates 12 possible combinations of batch sizes and learning rates;

[10] Grid search is a widely used method in hyperparameter optimization as it exhaustively searches through a manually specified subset of the hyperparameter space.

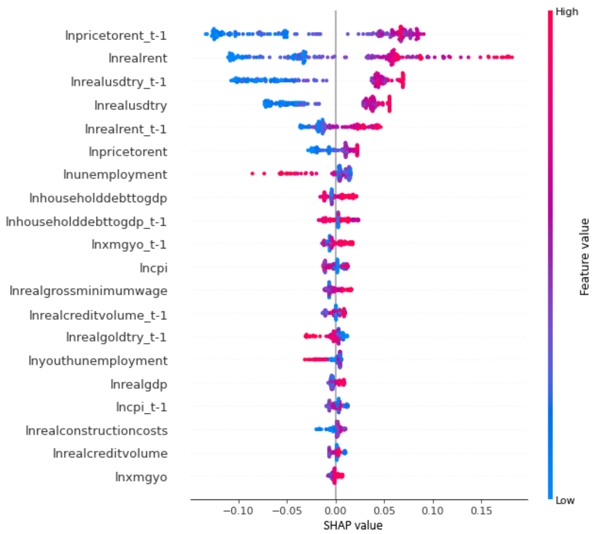

Figure 1. SHAP values of the feature set

however, Table 3 reports the minimum mean squared errors (MSE) and mean average errors (MAE). While reporting these results, if a setting achieved a different minimum MSE among all MSEs or MAE among all MAEs, these two settings were also given in Table 3.

We achieved different minimums in three months ahead of forecasting utilizing GRU and LSTM with 5-layered and Elman with 3-layered. The outcome suggests six months ahead of forecasting using GRU with 4-layered, LSTM with 3-layered, and Elman with 1-layered. Again, GRU with 4-layered, LSTM with 3-layered for nine months ahead prediction, and GRU with 1-layered, LSTM with 3-layered for twelve months ahead prediction were also found to have different minimums among all MSEs and MAEs, as illustrated in Table 3.

Comparing different architectures with their diversified settings, we achieved mixed results for only three months

Table 3. Model results in RNNs

Model	Batch size	λ	MSE	MAE	Model	Batch size	λ	MSE	MAE
3-M-GRU-1-L	32	0.0300	**0.000125**	**0.010958**	9-M-GRU-1-L	16	0.0100	0.000137	0.009727
3-M-GRU-2-L	32	0.1000	***0.000020***	**0.003833**	9-M-GRU-2-L	16	0.1000	**0.000279**	**0.015115**
3-M-GRU-3-L	16	0.0030	**0.000180**	**0.012516**	9-M-GRU-3-L	64	0.0010	0.000499	0.021097
3-M-GRU-4-L	32	0.0030	**0.000147**	**0.010434**	9-M-GRU-4-L	64	0.0100	**0.000235**	**0.013442**
3-M-GRU-5-L	64	0.0030	**0.000055**	0.007185	9-M-GRU-5-L	16	0.0100	**0.000278**	0.014422
3-M-GRU-5-L	32	0.0010	0.000073	**0.006689**	9-M-GRU-5-L	32	0.0100	0.000295	**0.012424**
3-M-LSTM-1-L	16	0.0300	**0.000034**	**0.004091**	9-M-LSTM-1-L	32	0.1000	0.000231	0.013312
3-M-LSTM-2-L	16	0.0030	**0.000123**	**0.007764**	9-M-LSTM-2-L	64	0.0100	***0.000085***	***0.008108***
3-M-LSTM-3-L	32	0.0300	**0.000043**	**0.006244**	9-M-LSTM-3-L	16	0.3000	**0.000419**	0.019105
3-M-LSTM-4-L	16	0.0100	**0.000027**	***0.003798***	9-M-LSTM-3-L	16	0.0010	0.000476	**0.018176**
3-M-LSTM-5-L	32	0.0100	**0.000189**	0.011947	9-M-LSTM-4-L	16	0.0003	0.000195	0.012529
3-M-LSTM-5-L	16	0.0003	0.000190	**0.011041**	9-M-LSTM-5-L	64	0.0010	**0.000437**	**0.015900**
3-M-RNN-1-L	64	0.0100	**0.000083**	**0.006585**	9-M-RNN-1-L	32	0.1000	0.000323	0.017371
3-M-RNN-2-L	32	0.0100	**0.000063**	**0.007075**	9-M-RNN-2-L	64	0.3000	**0.000425**	**0.014459**
3-M-RNN-3-L	64	0.0100	**0.000141**	0.010799	9-M-RNN-3-L	32	0.1000	0.000344	0.013137
3-M-RNN-3-L	16	0.0100	0.000182	**0.010478**	9-M-RNN-4-L	32	0.3000	**0.000350**	**0.013176**
3-M-RNN-4-L	32	0.0030	**0.000136**	**0.010079**	9-M-RNN-5-L	32	0.0030	0.000231	0.013223
3-M-RNN-5-L	64	0.0300	**0.000258**	**0.014376**					
6-M-GRU-1-L	64	0.1000	**0.000038**	**0.005684**	12-M-GRU-1-L	64	0.0100	**0.000619**	0.022336
6-M-GRU-2-L	64	0.0300	**0.000142**	**0.010667**	12-M-GRU-1-L	32	0.0100	0.000629	**0.021216**
6-M-GRU-3-L	64	0.1000	**0.000038**	**0.005625**	12-M-GRU-2-L	64	0.0100	**0.001001**	**0.025994**
6-M-GRU-4-L	16	0.3000	**0.000599**	0.023930	12-M-GRU-3-L	32	0.0010	**0.000586**	**0.018008**
6-M-GRU-4-L	64	0.0010	0.000651	**0.022656**	12-M-GRU-4-L	32	0.3000	**0.001322**	**0.029988**
6-M-GRU-5-L	16	0.0010	**0.000377**	**0.016986**	12-M-GRU-5-L	32	0.0300	**0.000716**	**0.023248**
6-M-LSTM-1-L	32	0.0300	**0.000186**	**0.012249**	12-M-LSTM-1-L	64	0.3000	**0.001335**	**0.030874**
6-M-LSTM-2-L	16	0.0300	**0.000097**	**0.008821**	12-M-LSTM-2-L	16	0.0030	**0.000643**	**0.020171**
6-M-LSTM-3-L	64	0.0300	**0.000354**	0.018456	12-M-LSTM-3-L	16	0.0010	**0.001396**	0.034508
6-M-LSTM-3-L	16	0.0003	0.000547	**0.017199**	12-M-LSTM-3-L	16	0.3000	0.001922	**0.029988**
6-M-LSTM-4-L	32	0.0300	**0.000065**	**0.006507**	12-M-LSTM-4-L	16	0.3000	**0.001964**	**0.030156**
6-M-LSTM-5-L	32	0.0100	**0.000129**	**0.009478**	12-M-LSTM-5-L	16	0.3000	**0.001949**	**0.030057**
6-M-RNN-1-L	32	0.0100	**0.000415**	0.017851	12-M-RNN-1-L	32	0.0100	**0.000877**	**0.024297**
6-M-RNN-1-L	64	0.0300	0.000489	**0.017041**	12-M-RNN-2-L	64	0.0100	**0.000396**	**0.015335**
6-M-RNN-2-L	32	0.1000	**0.000192**	**0.012861**	12-M-RNN-3-L	64	0.0100	***0.000185***	***0.010086***
6-M-RNN-3-L	32	0.0010	**0.000085**	**0.007988**	12-M-RNN-4-L	64	0.0003	**0.000393**	**0.017341**
6-M-RNN-4-L	32	0.0300	***0.000027***	***0.004562***	12-M-RNN-5-L	64	0.3000	**0.001307**	**0.030226**
6-M-RNN-5-L	32	0.1000	**0.000049**	**0.004760**					

Notes: M and L stand for months forecasted ahead and the number of layers, respectively. Bolds indicate the minimums among the settings. ***Italicized*** bold values are the minimums for 3, 6, 9, and 12 months ahead of forecasting.

ahead forecasting: GRU with 2-layered predicted well according to its MSE while LSTM with 4-layered achieved the best predictions with its MAE. For six months ahead prediction, Elman RNN with 4-layered was the best architecture according to the lowest scores of both MSE and MAE in Table 3. LSTM maintained the best prediction again with its 2-layered architecture for nine months ahead of the prediction in Table 3. Twelve months ahead forecasting was obtained well using 3-layered Elman network architecture according to its lowest MSE and MAE.

We also compare results achieved with the traditional NARDL model, which is the recent advance in time-series forecasting. The traditional NARDL model investigating linear and non-linear relationships among the dependent variable and its predictors (see Table S9 in online supplementary material) did not provide a better forecasting performance than our RNN settings.

6. Conclusions

During an upswing in prices, houses are collateral of credit extensions for further purchases; but once conditions begin to reverse, such exposure can cause the downturns in economic activity, credit, and house prices to become mutually reinforcing (International Monetary Fund, 2006). So, it is crucial to understand, monitor, and forecast the housing market trends before the problems occur. House prices in Turkey may exhibit highly volatile and fragile patterns in different periods, which makes the market riskier for investors and financial institutions. They may trigger more significant problems for first-time buyers and their affordability, making it more critical for policymakers and economic activity. The housing affordability problem has deepened between 2010 and 2017, especially for low-income and middle-income groups, as growth in house and rental prices were the triggering dynamics causing the increase of each other, where price exuberances exceeded growth in income per capita and purchasing power. A recent study (Coskun, 2023) examining housing affordability in Turkey suggests that the housing affordability crisis is mainly driven by credit expansion, rent, and construction costs. However, policymakers have struggled to comprehend the problem's underlying drivers, and they have to pay more attention and understand the housing market dynamics. This paper tries to emphasize the financial, housing-sector related, and macroeconomic variables for determining the forecasters on housing price index and employs time series forecasting analysis to provide an overview to comprehend the dynamics of house prices by using the real Turkish housing price index between 2003 and 2019.

The empirical results suggest that the first lags in price-to-rent ratio, rent, USDTRY foreign exchange rate, and actual values of rent and USDTRY foreign exchange rate in real terms are the best predictors of the Turkish housing price index. The results will contribute to improving the accuracy of house price forecasting and stabilize house prices in the Turkish housing market. These findings also have necessary inferences for investors.

According to our results, a potential first-time buyer purchases real estate by assessing the investment return via rent, price-to-rent ratio, and USDTRY foreign exchange rate dynamics. The price-to-rent ratio and rent levels are key measures for predicting home prices and provide valuable insight into market valuation, demand trends, and economic conditions. A high price-to-rent ratio often signals overvaluation (and price bubbles) and potential market corrections, while a low ratio suggests undervalued opportunities. Rising rents typically indicate strong demand and investor interest, driving home prices higher, while flat or declining rents can indicate market overvaluation or weakening demand. Accurately forecasting home prices using these metrics allows stakeholders to make informed investment decisions, mitigate risk, and proactively respond to market shifts, ultimately optimizing returns and stabilizing the real estate landscape. Especially, the USDTRY foreign exchange rate plays a critical role in predicting housing prices by affecting foreign investment, economic conditions, construction costs, investor sentiment, and housing affordability in the Turkish real estate market. A strong USDTRY can reduce foreign demand, increase construction costs, and reduce affordability, putting downward pressure on prices, while a weak USDTRY increases foreign investment, lowers borrowing costs, and stimulates demand. Changes in the exchange rate also influence investor sentiment, with Turkish real estate often seen as a "safe haven" during periods of both global and local instability, driving speculative price increases. Homeowners can establish the selling price of their home by comparing the one-time purchase price in US dollars to protect the value of their investment, especially during double-digit high inflation periods. In addition, the USDTRY exchange rate directly influences construction costs and, therefore, the initial sale price set by construction companies. Successfully predicting home prices by incorporating USDTRY fluctuations enables stakeholders to better navigate market shifts, anticipate changes in demand, and make informed investment decisions, ultimately optimizing returns and stabilizing the housing market.

The empirical outcome suggests that financial investment tools employed in this study with varying return possibilities other than the USDTRY exchange rate are neither complementary nor competing. Based on future housing and rental price increase expectations due to increases in construction costs and supply constraints, buying a new house in Turkey is still an attractive investment. The findings have significant implications for various stakeholders in the Turkish real estate market. Investors can use these findings to time their investments, policymakers can design more effective housing policies, developers can better plan their projects, first-time buyers can make informed decisions, real estate professionals can provide more valuable advice, economists can improve their models, and international real estate markets can learn from these findings. These implications highlight the interconnectedness of various economic factors in the housing market and underscore the importance of a comprehensive approach to real estate decision-making.

The low contribution impact of price-to-income ratio, household debt-to-GDP ratio, and income indicators, namely gross minimum wage and industrial production index on real housing price index, revive affordability concerns for the Turkish scenario. Our findings underline the imperative for long-run housing policy targets to improve housing affordability by considering these variables. The implications of these findings for the Turkish housing market are profound and multifaceted. The widening gap between income levels and housing costs signals a deepening affordability crisis and underscores the inadequacy of existing policies. This disconnect suggests that non-traditional factors are significantly influencing the market, potentially leading to distortions, widening socio-economic gaps, and increased economic vulnerability. Addressing these complex issues requires a comprehensive approach, including policy reassessment, development of more relevant economic indicators, and implementation of targeted housing initiatives. If left unaddressed, this affordability crisis could have far-reaching consequences, potentially hampering economic growth, limiting labor mobility, and reducing overall quality of life, underscoring the urgency for decisive action to reshape Turkey's housing landscape. Besides, governments cannot improve housing affordability and homeownership rates by extending mortgage loans' maturity to 30 years and implementing variable mortgage interests based on the applicants' creditworthiness. In addition, we recommend socially necessary measures like decreasing disparities in income and wealth and boosting affordable housing availability. Stabilizing house prices is crucial both in the short-term and long-term to address the fundamental issue of housing price affordability. Regulating the profits of construction companies and homeowners through detailed auditing measures appears to be necessary for the stability of housing prices.

On the other hand, the government may manage the supply constraint in metropolitans by granting building permits on rural land and increasing urban transformation activities. The construction companies cannot drive effective financial projections due to the volatile USDTRY exchange rate causing an increase in construction costs. Therefore, building-based renovation is standard in seven metropolitans included in this study instead of urban transformation projects spread over a large area. In addition, first-time homeowners do not prefer new megaprojects on rural lands due to their distance from the city center and traffic problems.

The findings of this paper would help investors, financial institutions, first-time buyers, and the government to create more effective housing policies in Turkey. Especially, for the government side, in addition to macroeconomic indicators, future rises, falls, and turning points in the property prices put into perspective the effects of government policy created to deal with them. Revealing the duration and magnitude of cycles allows for a better understanding of the course of house prices, which, in turn, helps government policymakers take the best stance in reaction to the price changes. Further research might also use this information to build models that connect the housing market and the macroeconomic indicators.

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