



Publisher

<http://jssidoi.org/esc/home>

TURKEY'S HOUSING MARKET: SALES, PRICES, AND THEIR LINKS TO INTEREST RATES, EXCHANGE RATES, AND COSTS (2013–2023)

Bahman Peyravi¹, Mehmet Recai Uygur^{2*}, Gediminas Blaževičius³, Mehmet Emre Çamlıbel⁴

¹*Kauno Kolegija / Higher Education Institution, Lithuania*

^{2*,4}*Vilnius Business College, Lithuania*

³*Vilnius Gediminas Technical University (VILNIUS TECH), Lithuania*

E-mails; ¹bahman.peyravi@go.kauko.lt; ^{2*}mehmet.uygur@kolegija.lt (Corresponding Author);
³gediminas.blazevicius@vilniustech.lt; ⁴emre.camlibel@kolegija.lt

Received 18 January 2026; accepted 28 March 2026; published 30 June 2026

Abstract. This paper demonstrates that the relationships between sales (total and mortgage-backed) and the housing price index (RPPI) in the Turkish housing market operate within a regime-sensitive and time-dependent structure. Using monthly official data (CBRT, TÜİK) from the 2013–2023 period, a multi-layered econometric design was applied: exploratory correlations and rolling windows; VAR/VECM and Granger causality; ARDL (Bounds) for short-long term separation; Markov-Switching and Bai-Perron for regime/break detection; and finally, SARIMAX for short-term forecasting. Findings are grouped into three axes. (i) Credit-interest rate channel: ARDL long-term coefficients show that a 1-point increase in interest rates affects total sales $\approx -1.8\%$ and mortgage sales $\approx -8.2\%$ at the equilibrium level; error correction speeds are strong at $|\phi| \approx 0.60\text{--}0.70$. Granger tests reveal that interest rates predict both mortgage and total sales, with feedback from sales to interest rates. (ii) Price-cost/inflation channel: The RPPI is found to interact with the CPI and construction costs with short lags and in both directions; regime analysis shows that the CPI $\rightarrow$ RPPI link dominates in 2022, while the cost $\rightarrow$ RPPI link dominates in 2023. (iii) Regimes and breaks: Markov-Switching reveals the distinctiveness of high-credit regimes in mortgage sales (2019-08 $\rightarrow$ 2020-08; 2021-11 $\rightarrow$ 2022-06) and the high inflation regime in RPPI (2021-10 $\rightarrow$ 2023-12); Bai-Perron breaks historically confirm these episodes. In the forecasting layer, SARIMAX provides applicable short-term accuracy with sMAPE $\approx 5\%$ for RPPI and $\approx 14\%$ for sales. The results show that a policy reading based on single-period average coefficients is insufficient; instead, a regime-sensitive framework that jointly considers credit-price-supply channels and is calibrated with exogenous macro scenarios is necessary.

Keywords: housing market; real estate; regime change; ARDL–Bounds; VAR/VECM; Granger causality; Markov-Switching; Bai-Perron; SARIMAX; housing price index; mortgage sales

Reference to this paper should be made as follows: Peyravi, B., Uygur, M. R. Blaževičius, G., Çamlıbel, M. E. 2026. Turkey's housing market: sales, prices, and their links to interest rates, exchange rates, and costs (2013–2023). *Entrepreneurship and Sustainability Issues*, 13(4), 232–249. <http://doi.org/10.9770/p7382684759>

JEL Classifications: C22, E43, R31

1. Introduction

The housing market is both the social memory and the financial lifeline of an economy: it carries household wealth, sets the pace of credit, and transmits cost shocks and inflation waves across the country through its prices, sales volume, and permit dynamics.

In Turkey over the past decade, this rhythm has been observed to accelerate at times and undergo sharp regime shifts at others. The official housing price index (RPPI) has been compiled monthly by the Central Bank of the Republic of Turkey since 2012; global comparisons document that real housing price increases showed an

extraordinary surge in Turkey in 2022. Construction costs reached triple-digit annual rates in the same year, leaving the supply side facing headwinds. These official series also form the backbone of the data universe used in this study (CBRT, 2025; BIS, 2024; TÜİK, 2022, 2025). Recent Turkey-focused studies also emphasize that mortgage conditions, housing inflation, regional convergence, and affordability pressures jointly shape post-2018 market dynamics (Yildirim & İvrendi, 2021; Kırca & Canbay, 2022; Özgüler, Büyükkara & Küçüközmen, 2023; Canöz & Kalkavan, 2024). The theoretical and empirical literature on the macroeconomic importance of such fluctuations focuses on the mortgageable asset nature of housing. Groundbreaking studies showing that the feedback mechanism between credit and prices intensifies financial cycles through collateral constraints emphasize that housing is not only a consumption or shelter item, but also a key vector of money-credit transmission (Kiyotaki & Moore, 1997; Iacoviello, 2005; Yildirim & Yildirim, 2025). The impact of external shifts based on credit supply regulation on housing prices is particularly evident during periods of mortgage market expansion (Favara & Imbs, 2015; Akgündüz et al., 2023). The interaction between household debt and the economic cycle reveals that increasing indebtedness can cast a significant negative shadow over growth and employment in subsequent years (Mian, Sufi, & Verner, 2017; Kayakus, Terzioglu & Yetiz, 2022). On the supply side, geography and regulatory intensity are persistent determinants of housing supply elasticity; this necessitates evaluating permit/occupancy and cost dynamics alongside prices and sales (Saiz, 2010; Sayin, Elburz & Duran, 2022; Gunduz, Çakir, & Cepni, 2025; Nasiboglu et al., 2025; Goekler, 2025).

In the case of Turkey, the intertwining of post-2020 credit conditions, exchange rate volatility, inflationary pressures, and divergences in construction costs suggests that economic relationships do not operate at the same pace over time. Indeed, the emphasis placed in recent years by international institutions (e.g., BIS) on borrower-based macroprudential frameworks to mitigate financial stability risks in housing markets also indicates that parameters cannot be captured by average effects from a single smoothed period (BIS, 2023). Recent evidence also shows that macroprudential tightening shapes housing-market expectations themselves, which further strengthens the case for regime-sensitive analysis (Kuang et al., 2026). In such periods, both Markov-switching approaches (Hamilton, 1989) that directly model regime shifts and Bai-Perron class structural break tests (Bai & Perron, 1998) that detect time-independent breaks are indispensable tools.

This article reinterprets the relationship between sales (total and mortgaged) and prices (RPPI) in the Turkish housing market within a regime-sensitive and dynamic framework through interest rates, exchange rates, inflation, costs, and permit/occupancy indicators. Our empirical strategy is built on a five-part architecture: (i) correlation and robustness in rolling windows; (ii) multiple dynamic interactions via VAR/VECM and Granger causality (Sims, 1980; Johansen, 1991); (iii) Short-long term separation via the ARDL-bounds test (Pesaran, Shin, & Smith, 2001); (iv) Regime/break detection via Markov-Switching and Bai-Perron (Hamilton, 1989; Bai & Perron, 1998); (v) Short-term forecasting with SARIMAX and the predictive power of exogenous macro variables. This composite approach allows us to test not only the signs and magnitudes of the coefficients, but also in which period they changed; it also allows us to test the question of “who predicts whom” under regime conditions.

Our data pool consists of monthly indicators compiled from official institutions: RPPI (CBRT), housing sales/mortgage sales, construction cost index, and permits/occupancy (TÜİK), in addition to mortgage interest rates, CPI, and USD/TRY exchange rate. The scope and methodology of the RPPI are detailed by the CBRT; housing sales, cost, and permit indicators are regularly published in TÜİK bulletins. This allows for the simultaneous monitoring of credit and income channels on the demand side, as well as cost and permit bottlenecks on the supply side. (CBRT, 2025; TÜİK, 2025).

Within this framework, the article aims to make three concrete contributions. First, it quantitatively identifies regime-specific coefficients and causality patterns by distinguishing between normal and crisis regimes in the Turkish housing market in a data-driven manner. Second, it cross-checks ARDL and VECM results with periods indicated by structural breaks and Markov regimes in terms of econometric consistency, thus enabling short-term shocks and long-term co-movements (cointegration) to be read within the same picture. Third, it conditions the short-term predictive power with SARIMAX estimates on external macro scenarios; it makes the possible reflections of interest rate/exchange rate/inflation paths used in policy discussions on sales and prices visible in a numerical language. Methodologically, we base the established nature of the references we use on seminal

studies in the top quartile (Q1) journals of economics literature (Sims, 1980; Johansen, 1991; Pesaran et al., 2001; Hamilton, 1989; Bai & Perron, 1998; Iacoviello, 2005; Saiz, 2010; Favara & Imbs, 2015).

We focus on the following research questions:

Do interest rates, exchange rates, inflation, and costs have significantly different effects on sales and housing prices depending on the regime?

During periods of expansion/tightening of credit conditions, does the answer to the question “who predicts whom?” (Granger causality) change?

Is there a long-term relationship (cointegration) between sales/prices and key macro-financial variables; if so, what are the short-term adjustment speeds?

To what extent do short-term forecasts based on external macro indicators improve with models that incorporate regime/break information?

The rest of the article proceeds as follows: The next section discusses the international literature on housing-credit-price dynamics and the Turkish context, along with academic findings. The data and methods section then presents the details of the econometric architecture summarized above. The findings section reports regime/break detection, dynamic interactions, and short-long term decompositions in an integrated manner. Finally, the discussion and conclusion sections address policy implications—particularly recommendations regarding interest rates, the calibration of the macroprudential framework, and the stimulation of the supply side (BIS, 2023).

2. Literature Review

The housing market is both a mirror and an accelerator of the financial cycle. In theoretical terms, the interaction between credit constraints and asset prices explains how shocks are amplified and made persistent. Kiyotaki and Moore's (1997) collateral-constrained general equilibrium model shows that, because durable assets serve as both production inputs and collateral for debt, balance sheet-price feedbacks create a powerful transmission channel. Extending this framework to monetary economics, Iacoviello (2005) quantifies housing's role as a “financial accelerator” by documenting that demand shocks are markedly amplified, while supply shocks are partially dampened due to the nominal structure of debt, using a New Keynesian DSGE model incorporating the nominal debt-collateral link. Empirical evidence on the causal link between housing market expansion and credit supply is also supported by studies using bank branch deregulation in the US as an instrumental variable (Favara & Imbs, 2015). In the broader link between credit cycles and growth, multi-country panels have shown that increases in household debt suppress growth and employment in the medium term (Mian, Sufi, & Verner, 2017). Taken together, these findings emphasize that the impact of fluctuations in credit conditions on housing prices and sales is not only strong but also asymmetric and time-sensitive.

The effect of housing prices on household spending operates through two channels: the wealth effect and the easing of the borrowing constraint. The first is that an increase in housing wealth stimulates consumption; the second is that increased collateral value facilitates access to debt. Studies using UK microdata provide convincing empirical evidence for both channels (Campbell & Cocco, 2007). In the US, the 2006–2009 downturn showed that the loss of housing wealth sharply reduced consumption, with marginal consumption propensity being higher in low-income and highly leveraged areas (Mian, Rao & Sufi, 2013). These results indicate that changes in credit and collateral conditions strongly affect macro consumption dynamics through housing.

The design of mortgage contracts is decisive in the transmission power of monetary policy. As the prevalence of variable-rate mortgages increases, the impact of policy interest rate shocks on housing prices and housing investment grows; institutional parameters determining down payment ratios and maximum borrowing capacity also shape the magnitude of the impact (Calza, Monacelli & Stracca, 2013). European Central Bank research supports these findings by documenting at the institutional level how the housing finance architecture confers heterogeneous sensitivity to the monetary transmission mechanism (European Central Bank, 2009). More recent evidence also shows that housing activity measures can be substantially more sensitive to mortgage-rate changes

than house prices, reinforcing the importance of treating mortgage sales as a distinct transmission channel (Časta, 2025).

In an open economy, the pass-through of exchange rate movements to import prices affects the trajectory of construction costs and overall inflation. Multicountry evidence distinguishes between the short- and long-term elasticities of pass-through from exchange rates to import prices, revealing the policy framework's effects on the expenditure-switching channel (Campa & Goldberg, 2005). For the cost-intensive construction sector with a high share of imported inputs, this channel provides an important background explaining why cointegration relationships between housing prices and cost indices may be strong. For Turkey, Kırca and Canbay (2022) likewise show that housing inflation responds to macro-financial variables in a horizon-dependent manner.

On the supply side, persistent determinants are geographical and regulatory constraints. Local land scarcity and topographical barriers limit supply elasticity, determining how much demand shocks are reflected in prices (Saiz, 2010; Yasar & Bulut, 2023; Muddasir & Dondas, 2023).

Multisectoral growth models have shown that the housing cycle is synchronized with the business cycle but is more volatile (Davis & Heathcote, 2005). The cumulative effect of regulatory constraints leads to market prices carrying permanent premiums relative to production costs, thereby transforming regional welfare and settlement patterns (Glaeser & Gyourko, 2018). In a broader macroeconomic context, it has been calculated that supply constraints in high-productivity cities reduce total output levels by distorting labor allocation and diminish long-term growth (Hsieh & Moretti, 2019). This literature methodologically justifies modeling permit/housing flows and the construction cost index alongside housing sales and prices.

The vector autoregression (VAR) approach, which addresses dynamic multivariate relationships without imposing structural constraints, has become standard in the literature (Sims, 1980). Cointegration and error correction models play a critical role in testing level relationships and distinguishing between short- and long-term periods (Engle & Granger, 1987; Johansen, 1991). The ARDL–Bounds approach (Pesaran, Shin, & Smith, 2001), which can be applied even with mixed integration degrees, is widely used in practice because it reduces the sensitivity of pre-tests and performs relatively well with small samples. The direction of causality and the assessment of predictive power are completed within the Granger (1969) framework. This fundamental methodological approach allows for the examination of both short-term and equilibrium relationships between the housing price index and sales with interest rates, exchange rates, inflation, and cost indicators under the same umbrella.

The fact that parameters are not constant over time suggests that relationships can change in sign and magnitude across different periods. Markov-switching structures apply models that allow for probabilistic transitions between regimes, where coefficients and shock variances can jump depending on the regime (Hamilton, 1989). Another line of research is the approach by Bai and Perron (1998; 2003), which tests for multiple structural breaks without prior knowledge of break dates. This allows for the derivation of “normal/crisis” periods from the data and the comparison of coefficients across periods. These two classes provide complementary tools for showing how the impact of credit and cost shocks in the housing market becomes asymmetric during periods of financial tightening and abundance.

The time-varying parameter VAR (TVP-VAR) literature, designed to capture regime shifts over time under the assumption of continuity, allows for modeling the temporal evolution of policy responses and shock propagation. Primiceri (2005) develops a TVP-SVAR framework where coefficients and innovation covariances are jointly time-dependent, enabling reliable estimation of both the temporal evolution of the systematic policy rule and shock volatility. This approach strengthens the empirical trace of the interest rate-housing price interaction, for example, during periods when inflation regimes or credit spreads change.

Answers to the question of who “predicts” whom in the housing market literature also vary depending on the period and institutional context. Studies showing that exogenous expansions in mortgage credit supply push up housing prices through causal designs (Favara & Imbs, 2015) should be considered alongside evidence highlighting the medium-term macro-outcomes of debt accumulation through credit conditions (Mian, Sufi, &

Verner, 2017). These results also require a regime-specific interpretation of Granger causality tests: the credit-price interaction may be directed toward prices in a “plentiful liquidity” regime and toward sales and credit flows in a “tightening/crisis” regime.

Factor models are widely used tools for forecasting and using high-dimensional indicator sets. Dynamic factor models, which summarize common movements in large data sets using a few diffusion indices, provide significant improvements in short-term forecasting (Stock & Watson, 2002), while the information-criterion approach of Bai and Ng (2002) remains a standard tool for determining the number of common factors. Forni, Hallin, Lippi, and Reichlin's (2000) generalized dynamic factor model, on the other hand, has developed a framework based on the dynamic covariance structure of the entire panel and offering one-sided estimation capabilities. BVARs reduced with Bayesian constraints in large-scale systems effectively manage the risk of overfitting, particularly in multivariate macro forecasts (Bańbura, Giannone & Reichlin, 2010). The use of scale-invariant and low-bias indicators is also recommended when comparing forecasts; Hyndman and Koehler (2006) discussed the shortcomings of MAPE-type measures and highlighted MASE. Recent Turkish applications using Bayesian time-varying VARs and deep-learning architectures further show that flexible forecasting frameworks can capture affordability dynamics and nonlinear price movements more effectively in fast-changing environments (Canöz & Kalkavan, 2024; Kütük, 2024).

In terms of diagnostic tools, generalized response functions that are insensitive to the order of shocks in structural VARs (Pesaran & Shin, 1998) are practical and order-invariant in application. This allows for the visualization of short-term shock dynamics between housing prices, sales, and financial/cost variables. However, it should be noted that in the presence of regime shifts, the course of responses may differ conditionally on the regime; therefore, it would be more appropriate to interpret the response functions on a period-by-period basis after performing a “regime mapping” using Markov-switching or breakpoint tests.

Data architecture and comparability directly affect the reliability of findings. At the international level, the BIS provides minimal standardization in an area where definitions are heterogeneous by publishing detailed and selected housing price series for approximately 60 countries on a nominal and real basis. Its published methodology notes detail differences in frequency, coverage, price unit, and compilation method (BIS, 2026). Specifically for Turkey, the Central Bank of the Republic of Türkiye's (CBRT) Residential Property Price Index (RPPI) data and methodology notes describe the transition to a quality-adjusted hedonic method since 2016 and the revision of the publication framework. For construction costs, the Turkish Statistical Institute's (TÜİK) Construction Cost Index and permit data, as well as Eurostat's building permits metadata, serve as references for tracking the current pulse of the supply side (CBRT, 2025; TÜİK, 2025; Eurostat, 2025). These official sources support the placement of domestic findings in an international context and robustness checks.

Applying this literature to Turkey requires addressing three axes together. First, the demand/financing axis: policy interest rates, mortgage interest rates, and the expansion-contraction cycles of credit taps; second, the price-cost axis: the long-term relationship between RPPI and the construction cost index and the cost channel of the pass-through from exchange rates to prices; and third, the supply axis: the simultaneous dynamics of permit/occupancy flows with housing sales and prices. VAR/VECM and ARDL models are suitable for decomposing these three axes into short- and long-term components and testing their causal directions; Markov-switching and Bai-Perron class approaches reveal how parameters are rewritten according to periods. Factor models and/or Bayesian large-scale VARs allow high-dimensional indicator sets (interest rates, exchange rates, inflation, costs, permits, external indicators) to be included in the estimation process in a parsimonious manner; estimation comparisons should also be made using scale-insensitive criteria. These guidelines directly inform a research framework that jointly models the variables Sales (Total/Mortgage), Housing Price Index, interest rate-exchange rate-inflation-cost, and permit/occupancy in datasets related to the Turkish housing market. Recent Turkey-specific studies on housing inflation, convergence, and affordability also suggest that national averages can mask important shifts across cities and over time, which makes a regime-sensitive empirical strategy particularly relevant (Yasar & Bulut, 2023; Muddasir & Dondas, 2023; Özgüler et al., 2023; Canöz & Kalkavan, 2024).

Ultimately, international research converges around three common findings. First, credit conditions generate a bidirectional and self-reinforcing interaction with the housing market; second, supply constraints sharpen the transformation of this interaction into prices depending on the spatial and institutional context; and third, these links change over time in a regime-sensitive manner. In practice, it is therefore recommended to (i) test for the existence of cointegration and long-run coefficients, (ii) examine short-run adjustment dynamics and the direction of causality, (iii) disaggregate parameters according to regimes or structural breaks, and (iv) use high-dimensional data sets in a parsimonious manner for estimation. Such a design provides both policy and sector decision-makers with period-sensitive and empirically reliable roadmaps.

3. Method

The method of this study consists of five mutually compatible components designed to read a market (housing) that is dynamic, regime-sensitive, and multi-channel to an extent that cannot be confined within the limits of a single statistical framework, along with its transformations over time. The fundamental principle of the design is to proceed in a pre-data-determined and iterative sequence: first, to discover relationships; then, to test for causality and dynamic interaction; next, to separate short- and long-term components; to identify regimes in which relationships are rewritten according to periods; and finally, to measure predictive power in the short term. Therefore, the method follows a five-layer architecture consisting of (i) discovery and pre-processing, (ii) VAR/VECM and Granger multiple dynamic interaction, (iii) short- and long-term separation with ARDL–Bounds, (iv) regime and break analysis (Markov-switching and Bai-Perron), and (v) short-term forecasting with SARIMAX and evaluation of the predictive power of exogenous variables (Sims, 1980; Johansen, 1991; Hamilton, 1989; Pesaran, Shin & Smith, 2001; Bai & Perron, 1998, 2003).

Data and variables. The data universe compiled at monthly frequency consists of the residential property price index (RPPI), total residential property sales, mortgage sales, residential mortgage interest rate, USD/TRY exchange rate, CPI, and construction cost index, as well as building permit/occupancy indicators. The data coverage is 2012–2023; however, in series where the year-over-year (YoY) transformation is applied, the first 12 months of observation are naturally not used, and the main study period is reduced to 2013–2023. The definition and scope of official indicators are based on the methodological notes of the relevant institutions, thus ensuring consistency between definitions and international comparability (CBRT, 2025; TÜİK, 2025; BIS, 2026).

Pre-processing and transformations. Two types of transformations are used to reduce the risk of spurious correlation and co-trending in time series. The first is the logarithms of level series: $y_t^{tot} = \ln(S_t^{tot})$, $y_t^{mort} = \ln(S_t^{mort})$, $p_t = \ln(RPPI_t)$, $e_t = \ln(USD/TRY_t)$, $c_t = \ln(CPI_t)$, and $m_t = \ln(Cost_t)$. The second is annual change indicators: $\Delta_{12} x_t = 100 \times (\ln x_t - \ln x_{t-12})$ for percentage changes, and for interest rates the annual difference in percentage points is defined as $\Delta_{12} i_t = 100 \times (i_t - i_{t-12})$. During the discovery phase, correlations are reported via YoY transformation; in multivariate models, level-based (VAR/VECM, ARDL) and difference/log-difference-based (SARIMAX) representations are used together. In 2022, symmetric robustification is applied to prevent extreme values in some YoY indicators due to divisive base effects: trimming (winsorizing) at the $\pm 300\%$ limit applies only to the discovery phase; raw transformations are preserved in estimation and causality analyses. Missing observations are very limited; a common sample set is used in multiple models.

Exploration: Pearson/Spearman, rolling correlation, and cross-correlation. In the first layer, simultaneous linear and monotonic relationships between series are visualized using Pearson and Spearman correlations, while regime-sensitive changes in relationships over time are visualized using rolling correlations in 12- and 24-month windows. For the timing (lead-lag) structure, the cross-correlation function (CCF) is calculated within a ± 24 -month range. This step clarifies hypotheses that provide input for subsequent econometric stages—for example, "interest rate shocks appear first in mortgage sales, then in total sales," "exchange rate and CPI increases are reflected in the price index with a 1–2 month lag"—in a data-driven manner.

Multiple dynamic interactions: VAR/VECM, Granger, and IRF. Two blocks are defined in the second layer. Sales block: (y_t, y_t^m, i_t, c_t) ; and price block: (p_t, e_t, c_t, m_t) . First, stationarity classification is performed in each series using ADF and KPSS tests; if most level series show I(1) findings and cointegration signals are observed

at levels, rank- r systems are estimated using the Johansen method (Johansen, 1991). VECM is estimated for cointegrated systems; otherwise, VAR is estimated for differences; the lag length p is determined by selecting an information criterion that considers AIC/HQ/BIC/FPE ratios together (Sims, 1980). To read dynamic responses, impulse response functions are reported over a 24-month horizon; the basic specification is done with Cholesky orthogonalization, while generalized response functions are also used as sensitivity checks to reduce ordering dependence (Pesaran & Shin, 1998). Granger causality tests are conducted bidirectionally through stationary representations (difference or VECM error correction); tests are evaluated in the 1–12 month lag band and at the 5% significance level (Granger, 1969). The purpose of this layer is to answer the question, who predicts whom, in a multivariate dynamic context and with explicit attention to the possibility of cointegration (Engle & Granger, 1987).

Short- and long-term distinction: ARDL–Bounds and UECM. In the third layer, ARDL class models are established for sales with two dependent variables (total and mortgage):

$$\begin{aligned} \ln S_t^{(k)} = & \alpha_0 + \sum_{j=1}^p \alpha_j \ln S_{t-j}^{(k)} \\ & + \sum_{l=0}^{q_1} \beta_l i_{t-l} + \sum_{l=0}^{q_2} \gamma_l \ln(\text{USD/TRY})_{t-l} \\ & + \sum_{l=0}^{q_3} \delta_l \ln(\text{Cost})_{t-l} + u_t, \quad k \in \{\text{tot}, \text{mort}\}. \end{aligned}$$

The lag orders are selected using AIC in the grid (p, q_1, q_2, q_3) , with $p \leq 8$ and $q_k \leq 6$; the model is transformed into UECM form and the Pesaran–Shin–Smith bounds test (Case 3: constant, trendless) is applied (Pesaran et al., 2001). When the bounds test supports cointegration, the long-run coefficients are reported using the equation $\theta = -\beta/\varphi$ (where φ is the coefficient of the level term) and the error-correction speed $\varphi < 0$; the short-run effects are the coefficients of the terms marked Δ . The purpose of the ARDL layer is to disentangle how interest rates, exchange rates, and costs affect sales both immediately and at the equilibrium level.

Regime and break analysis: Markov-switching and Bai-Perron. The fourth layer tests the hypothesis that parameters are not constant over time using the data. With Markov-switching (MS) models, structures where regime-specific means and variances can jump are estimated in univariate annual change series; $k = 2$ –3 regime candidates are compared using BIC, and smoothed probabilities are converted into episodes using the threshold $\pi \geq 0.6$ (Hamilton, 1989). In parallel, the Bai-Perron multiple break framework is applied with BIC minimization for a piecewise constant indicator model with at most two breaks (at least 12 months long) (Bai & Perron, 1998, 2003). Based on the obtained segments, regime-conditional OLS regressions are estimated with HC1 robust standard errors; the statistical significance of coefficient differences is tested using Wald tests in an interaction-term combined model. This layer quantitatively reveals, for example, why and to what extent the interest rate $\rightarrow$ mortgage sales relationship strengthened during periods of credit expansion, and why the CPI and cost $\rightarrow$ price relationship changed in sign and magnitude during shock years such as 2022 and 2023 (Hamilton, 1989; Bai & Perron, 1998, 2003).

Short-term forecasting: SARIMAX. In the fifth layer, short-term forecasts for Total Sales and RPPI are generated using univariate SARIMAX models (season 12). The external variable set (i_t , $\ln \text{USD/TRY}_t$, $\ln \text{CPI}_t$, $\ln \text{Cost}_t$) is fed into the model with z-score standardization on the training sample; selection is made using AIC on the grids (p, d, q) and $(P, D, Q, 12)$. The test horizon is 12 months; log-RMSE and sMAPE in the original scale are used as evaluation criteria (Hyndman & Koehler, 2006). The coefficients of the selected models are interpreted as a consistency check for the partial effects of the external variables; however, these coefficients are conditional relationships, not causal. Since the default forecast will be limited to carryover of the last value when external variable paths are not provided, the use of interest rate, exchange rate, inflation, and cost scenarios in policy applications is essential.

Specification, validation, and significance. The significance threshold for all tests is 5%; sensitivity to alternative thresholds (e.g., 1%) is considered. Order sensitivity in VAR/VECM IRFs is controlled using generalized responses (Pesaran & Shin, 1998). In the ARDL–Bounds test, the results are re-estimated with alternative deterministic components (Case 3) and lag bounds (8/6) to check for stability. In regime analysis, k -regime selection is performed using BIC; probability profiles and segment durations are reported for $k=2/3$. HC1 is used for sensitivity to heteroscedasticity in regime-conditional OLS outputs; the risk of multicollinearity

(especially the CPI-cost-exchange rate triad) is monitored using standardized beta coefficients and stepwise specifications.

Causality and interpretation principles. Granger causality is a conceptualization for forecasting purposes; it does not imply structural causality (Granger, 1969). VAR/VECM shocks can only be considered structural under the selected specification; therefore, final policy implications are based on overlapping findings from a multiple-model approach, including regime and break specifications. When cointegration is present, the VECM representation is reported along with short-run adjustment speeds (ϕ) and long-run level relationships (β) (Engle & Granger, 1987; Johansen, 1991).

Software and reproducibility. The analyses were conducted in an open-source scientific computing environment. All transformations, model selection rules, windows (12/24-month rolling; ± 24 lag CCF), IRF horizon (24 months), ARDL and SARIMAX grids, and significance thresholds were pre-specified. Version control notes for the code and outputs have been archived in a reproducible workflow.

Limitations. Although data was obtained solely from official sources, annual change indicators are highly volatile during intense shock periods such as 2022–2023; therefore, trimming in the exploratory phase is for visualization and correlation purposes only. Regime-conditional regressions are subject to high uncertainty in short segments ($N \approx 12$); therefore, while Wald tests and standardized betas provide information on "direction and magnitude," robustness using more flexible frameworks such as MS-regression or TVP-VAR is recommended for definitive structural results (Hamilton, 1989; Primiceri, 2005).

4. Findings

The rhythm of the housing market is far from a simple rise-and-fall curve; the patterns we observe in the data show that relationships are rewritten over time, with the effects of some channels, which remain subdued during normal times, becoming pronounced during years of shock and credit expansion. We present the findings in a comprehensive flow, ranging from the discovery phase to multiple dynamic models, from long-short term distinctions to regime and break analysis and short-term forecasting performance. All analyses are monthly frequency and based on official statistics; the sample covers the period 2013–2023 (the first 12 months are excluded due to initial losses required by the annual change transformation).

4.1. Correlations, timing, and resilience

The table below (Table 1) shows the prominent simultaneous relationships based on year-over-year (YoY) changes. The meaning of the correlations is indicative: the sensitivity of mortgage sales to interest rate changes is negative and very strong; the residential property price index (RPPI) and inflation/costs are both positive and high.

Table 1. Static correlations (YoY)
(Pearson r / Spearman ρ ; $N \approx 120$ –143 months; $p < 0.01$ unless otherwise stated)

Target (YoY)	Driver (YoY)	Pearson r	Spearman ρ	Comment
Mortgage Sales	Interest Rate (pp)	−0.786	−0.870	Very strong negative
Total Sales	Interest Rate (pp)	−0.420	−0.515	Moderately strong negative
Total Sales	Building Permit	+0.398	+0.123 ($p \approx 0.10$)	Medium, moving together
RPPI	CPI	+0.942	+0.398	Very strong positive (Pearson)
RPPI	Construction Cost	+0.918	+0.412	Very strong positive
RPPI	USD/TRY	+0.740	+0.445	Strong positive

Source: created by authors

The timing structure (which variable leads) was tested using the cross-correlation function (CCF). Table 2 reports the "best lag" where the highest absolute correlation is observed within a ± 24 -month band. The finding that the RPPI adjusts with a 1–2 month lag relative to CPI and costs, while the interest rate effect appears simultaneously in sales, is consistently repeated.

Table 2. Best lag (± 24 months) and correlation (YoY)

Target (YoY)	Driver (YoY)	Best lag (months)	Correlation	Comment
Total Sales	Interest Rate (pp)	0	-0.420	Strong negative correlation
Mortgage Sales	Interest Rate (pp)	0	-0.674	Simultaneous very strong negative
RPPI	USD/TRY	+2	+0.781	Exchange rate 2 months ahead
RPPI	CPI	+1	+0.951	Inflation 1 month ahead
RPPI	Cost	+2	+0.943	Cost 2 months ahead
Total Sales	Building Permit	0	+0.513	Simultaneous movement

Source: created by authors

Interim reading. While mortgage sales react instantly to interest rate changes, price dynamics "catch up" with cost and inflation shocks with short lags. This intuition has been tested more systematically in the following multi-dynamic framework (VAR/VECM).

4.2. Multivariate dynamic interaction: VAR/VECM, IRF, and Granger

Following stationarity tests on level series and lag selection, both blocks were specified as VECMs. Findings for the sales block (ln Total Sales, ln Mortgage Sales, i, ln CPI) and the price block (ln RPPI, ln USD/TRY, ln CPI, ln Cost) are summarized in Table 3.

Table 3. VAR/VECM selection and cointegration summary

System	Selected VAR lag (p)	Johansen rank (r)	Representation	Note
Sales block	12	3	VECM (k_diff=11)	Strong LR links
Price block	12	4	VECM (k_diff=11)	Near-full-rank link

Source: created by authors

Impulse Response Function (IRF) – summary: Interest rate shocks generate a negative response in mortgage and total sales; the intensity is higher in the mortgage channel. Exchange rate/CPI/cost shocks produce positive and significant effects on RPPI; the effect of CPI and cost shocks is particularly pronounced. Granger causality results (Table 4) provide a clear answer to the question "who predicts whom?": interest rates predict sales; there is a strong bidirectional predictive relationship between RPPI and CPI/cost/exchange rate.

Table 4. Granger causality summary (max. 12 months; lowest p-value and lag)

Direction (x $\rightarrow$ y)	Best lag	p-value	N	Comment
Interest $\rightarrow$ Mortgage Sales	11	1.53×10^{-5}	131	Strong forecast
Mortgage Sales $\rightarrow$ Interest	1	1.83×10^{-2}	131	Feedback
Interest $\rightarrow$ Total Sales	12	9.81×10^{-5}	131	Strong forecast
Total Sales $\rightarrow$ Interest	8	1.08×10^{-2}	131	Feedback
USD/TRY $\rightarrow$ RPPI	12	3.26×10^{-4}	142	Exchange rate
RPPI $\rightarrow$ USD/TRY	10	4.42×10^{-10}	142	Two-way
CPI $\rightarrow$ RPPI	12	1.28×10^{-19}	142	Very strong
RPPI $\rightarrow$ CPI	7	3.85×10^{-16}	142	Two-way
Cost $\rightarrow$ RPPI	12	1.54×10^{-25}	142	Very powerful
RPPI $\rightarrow$ Cost	5	2.19×10^{-16}	142	Two-way

Source: created by authors

Interim reading. The "bidirectional" Granger relationship in the sales–interest rate channel implies that credit conditions and sales are co-shaped; the bidirectional link between RPPI and macro price indicators suggests that simultaneous shocks prevail in inflationary regimes.

4.3. Short- and long-term distinction: ARDL–Bounds and ECM

ARDL models reliably provide both long-term coefficients and error-correction rates for sales. The null hypothesis of no cointegration was strongly rejected for both targets (Table 5).

Table 5. ARDL–Bounds tests (Case 3; 2013–2023)

Model	Selected ARDL	F_stat (Bounds)	p (upper/lower)	Decision
log(Total Sales)	(1,4,3,5)	13.77	1.53×10^{-9} / 4.05×10^{-11}	Cointegration exists
log(Mortgage Sales)	(1,2,3,5)	10.92	2.82×10^{-7} / 8.71×10^{-9}	Cointegration exists

Source: created by authors

Long-term coefficients and ECM rates (Table 6) provide a straightforward language for policy interpretation. A 1-point (0.01) increase in interest rates has an approximate effect of -1.8% on long-term Total Sales and approximately -8.2% on Mortgage Sales. The long-term effect of the exchange rate is positive on total sales and weakly negative on mortgage sales. The negative long-term effect of costs on total sales is noteworthy.

Table 6. ARDL long-term coefficients and error-correction rates

Target (log)	Interest Rate (level)	log(USD/TRY)	log(Cost)	ECM speed ϕ (y_{t-1})
Total Sales	−1.768	+0.598	−0.402	−0.675 ($p \approx 6.1 \times 10^{-11}$)
Mortgage Sales	−8.238	−0.119	+0.314	−0.609 ($p \approx 2.2 \times 10^{-9}$)

Source: created by authors

Comment. Long-term interest rate elasticity in the mortgage sales channel is approximately 4–5 times that of total sales. Error correction speeds are high ($|\phi| \approx 0.6$ – 0.7): deviations from equilibrium close at a rate of 60–70% within one month.

Short-term effects (UECM) provide a "shock map." Table 7 summarizes the statistically significant short-run coefficients.

Table 7. Short-term (Δ) significant effects (UECM)

Model	Term	Coefficient	p
Total Sales	$\Delta \log(\text{USD/TRY})_t$	+1.755	0.0039
	$\Delta \log(\text{Cost})_t$	−2.931	0.0074
	$\Delta \text{Interest}_{t-3}$	+3.965	0.0196
Mortgage Sales	$\Delta \text{Interest}_t$	−6.448	0.0007
	$\Delta \log(\text{USD/TRY})_t$	+1.419	0.0525
	$\Delta \log(\text{Cost})_{t-3}$	−2.034	0.0516

Source: created by authors

Interim reading. In the short term, exchange rate shocks immediately boost total sales (forecast demand/substitution), while cost shocks immediately reduce them. As expected, interest rate shocks on mortgage sales produce an immediate negative effect.

4.4. Regime and break analysis: Markov-switching and Bai-Perron

We tested the hypothesis that relationships do not remain constant over time using two complementary tools. We searched for regime-specific mean/variance in Markov-Switching univariate models and multiple breaks at unknown dates in the Bai-Perron framework. Probabilities obtained from MS classification were converted to episodes with a threshold ≥ 0.6 ; in BP, a minimum segment length of 12 months was assumed. Tables 8 and 9 report the Markov-switching regimes and Bai-Perron segments, respectively.

Table 8. Markov-switching regime structures (YoY, best k and regime means)

Series (YoY)	Best k (BIC)	Regime μ (approx.)	Regime episodes (≥ 0.6)
Total Sales	2	$R1 \approx -1.6$; $R2 \approx +25.1$	R2: 2019-11 $\rightarrow$ 2022-05
Mortgage Sales	3	$R_{low} \approx -42.5$; $R_{mid} \approx +14.1$; $R_{high} \approx +151.6$	R_{high} : August 2019 $\rightarrow$ August 2020; November 2021 $\rightarrow$ June 2022
RPPI	3	$R_{low} \approx +11.1$; $R_{mid} \approx +29.7$; $R_{high} \approx +119.7$	R_{high} : October 2021 $\rightarrow$ December 2023

Source: created by authors

Table 9. Bai-Perron (BIC) segments and average YoY

Series	Segment	Period	N	Average YoY (%)
Total Sales	1	2014-01 $\rightarrow$ 2019-10	70	+2.0
	2	November 2019 $\rightarrow$ June 2022	32	+25.1
	3	July 2022 $\rightarrow$ December 2023	18	-16.1
Mortgage Sales	1	January 2014 $\rightarrow$ July 2019	67	-9.1
	2	August 2019 $\rightarrow$ August 2020	13	+213.9
	3	September 2020 $\rightarrow$ December 2023	40	-15.5
RPPI	1	2013-01 $\rightarrow$ 2021-12	108	+15.1
	2	January 2022 $\rightarrow$ December 2022	12	+149.6
	3	January 2023 $\rightarrow$ December 2023	12	+105.6

Source: created by authors

Regime-conditional coefficients (OLS-HC1) are reported in Tables 10, 11, and 12 for total sales, mortgage sales, and RPPI, respectively. The same model was re-estimated on BP segments in different periods. Standardized beta coefficients allowed us to compare the relative strength of the effects.

Table 10. Regime-conditional coefficients: Total Sales (YoY)

Segment	Period	Interest Rate (pp)	USD/TRY (%)	CPI (%)	Cost (%)	Building Permit (%)	Note
1	2013/02–2021/12	-159.8 (p=0.003; β^*) -0.50	+0.26 (p=0.058)	-0.01 (ns)	-0.11 (ns)	+0.062 (p=0.025; $\beta^* \approx +0.25$)	“Normal”
2	2022/01–2022/12	-664.3 (p<1e-7; β^* -0.83)	+0.29 (p=0.10)	-3.93 (p<0.047; β^* -1.32)	+3.81 (p<0.001; β^* +2.07)	+0.277 (p<2e-14; β^* +0.65)	“Crisis-warming”
3	2023/01–2023/12	+235.7 (p<0.001; β^* +1.27)	-0.98 (p=0.001; β^* -1.83)	-3.08 (p<0.001; β^* -2.98)	+3.22 (p<0.001; β^* +5.02)	-0.228 (p<0.001; β^* -0.54)	“Crisis-cooling”

Source: created by authors

Note. The sign change in the interest rate coefficient in 2023 should be interpreted as a regime-specific correlation under high inflation and cost shocks, policy adjustments, and possible multiple connections, rather than as a claim of structural causality.

Table 11. Regime-conditional coefficients: Mortgage Sales (YoY)

Segm ent	Period	Interest Rate (pp)	USD/TRY (%)	CPI (%)	Cost (%)	Building Permit (%)
1	2014/01–2019/07	−851.7 ($p \approx 6.2 \times 10^{-18}$; β^* −0.89)	ns	ns	ns	ns
2	August 2019–July 2020	−3714 ($p=0.064$; β^* −0.37)	−11.89 ($p=0.0015$)	ns	ns	+1.50 ($p \approx 1.3 \times 10^{-10}$)
3	August 2020–December 2023	−395.8 ($p=0.0069$; β^* −0.38)	ns	ns	ns	ns

Source: created by authors

Does the interest rate coefficient differ across regimes? Wald joint test in the interactive model: $\chi^2=101.62$, $p \approx 8.6 \times 10^{-23} \rightarrow$ yes, the interest rate effect is significantly different in the 2019–2020 window.

Table 12. Regime-conditional coefficients: RPPI (YoY)

Segm ent	Period	CPI (%)	Cost (%)	Interest Rate (pp)	USD/TRY (%)
1	2013/01–2021/12	−1.55 ($p=0.00072$)	+1.21 ($p \approx 4.5 \times 10^{-11}$)	−69.1 ($p=0.00036$)	weak/uncertain
2	January 2022–December 2022	+3.30 ($p \approx 1.5 \times 10^{-4}$)	−0.59 (ns)	unstable	unstable
3	2023/01–2023/12	~0 (ns)	+2.04 ($p \approx 7.4 \times 10^{-6}$)	−239.1 ($p \approx 8.6 \times 10^{-4}$)	weak/uncertain

Source: created by authors

Coefficient difference tests (Wald):

– CPI interactions (Seg-2 and Seg-3): $\chi^2=63.93$, $p \approx 1.3 \times 10^{-14} \rightarrow$ significant difference between regimes.

– Cost interactions (Seg-2 and Seg-3): $\chi^2=69.29$, $p \approx 9.0 \times 10^{-16} \rightarrow$ significant difference between regimes.

Interim reading. In normal periods, cost $\rightarrow$ price channel is dominant; in 2022, CPI $\rightarrow$ price relationship comes to the fore; in 2023, cost becomes dominant again. This finding is consistent with the long-term price-cost links indicated by the VAR/VECM and ARDL results.

4.5. Short-term forecast: SARIMAX performance and partial effects of exogenous variables

SARIMAX models measure short-term forecasting power with seasonal differencing and ARMA components alongside exogenous variables. One-step-ahead test performance over the last 12 months is shown in Table 13.

Table 13. SARIMAX model selection and test performance (12 months)

Target (log)	(p,d,q)	(P,D,Q,12)	AIC	RMSE (log)	sMAPE (%)
Total Sales	(0,1,2)	(1,0,0,12)	3.79	0.339	14.07
RPPI	(1,1,0)	(0,0,0,12)	−732.82	0.109	4.85

Source: created by authors

The external coefficients (partial effects) in the selected models are consistent with expectations: in the sales model, interest rate (−0.077; $p \approx 0.011$) and cost (−0.856; $p \approx 0.032$) are negative; CPI (+1.001; $p \approx 0.020$) is positive; USD/TRY is insignificant. In the RPPI model, the USD/TRY coefficient is small but significant (−0.044; $p < 10^{-7}$); CPI and cost are marginally significant; interest rate is insignificant. These coefficients represent conditional relationships; they should be read in conjunction with VAR/VECM-ARDL findings for structural interpretations.

4.6. Synthesis of findings and policy implications

The overall picture converges on three axes. First, the impact of credit conditions (especially interest rates) on sales is strong, immediate, and significantly larger in the mortgage channel; in the long term, interest rate elasticity is 4–5 times greater in mortgage sales than in total sales. Second, on the pricing side, cost and inflation

shocks and exchange rate dynamics are reflected in the RPPI with short lags; CPI dominated in 2022, while costs regained dominance in 2023. Third, these relationships are regime-sensitive: the sign/magnitude of the coefficients may change during credit expansion/shock periods; therefore, single-period average coefficients are insufficient for policy calibration. Regime-conditional readings reveal both the asymmetry of the credit-interest rate response and the year-specific nature of the price-cost link. In short-term forecasting, low error values for RPPI (sMAPE $\approx$ 5%) and reasonable error values for sales (sMAPE $\approx$ 14%) indicate that scenario analyses based on exogenous variables are feasible.

5. Discussion

The findings of this study show that the Turkish housing market is too multi-layered and sensitive to periods to be explained by a single average effect. On one side of the link between sales and prices are credit conditions and interest rates, and on the other side are exchange rates, inflation, and cost dynamics; however, these links do not always operate in the same direction and with the same intensity. When discussing the resonance of the findings with the literature and their relationship to our research questions, it is necessary to consider both the dynamic-multivariate results (VAR/VECM, Granger) and the long-short term decompositions (ARDL–Bounds, UECM) and regime/break diagnoses (Markov-Switching, Bai-Perron) together.

Our first research question was whether the effects of interest rates, exchange rates, inflation, and costs differ significantly depending on the regime. The idea that parameters are not fixed in a non-stationary cycle is a fundamental insight of the Markov-switching and structural break literature (Hamilton, 1989; Bai & Perron, 1998, 2003). The picture we found is fully consistent with this insight: mortgage sales respond strongly and negatively to interest rates during “normal” periods, while the intensity of this response increases markedly during credit expansion episodes (e.g., late 2019–mid-2020); During the price level shock in 2022 and the cooling period in 2023, the magnitude and even the sign of the coefficients can vary in terms of total sales. This fluctuation aligns closely with models that theoretically ground the “financial accelerator” role of housing through the nature of the credit contract and the leverage it carries (Kiyotaki & Moore, 1997; Iacoviello, 2005): collateral values, borrowing capacity, and interest rate dynamics make the reflection of shocks on the market regime-dependent. The finding that the impact of monetary policy on housing increased as the share of variable-rate mortgages and mortgage architecture grew in the European experience (Calza, Monacelli, & Stracca, 2013) bears a meaningful resemblance to the fact that the interest rate elasticity of mortgage sales in Turkey is much higher than that of total sales. Our findings show that this channel operates permanently and strongly in normal periods and exceptionally strongly during credit expansion episodes.

Our second research question was whether the answer to “who predicts whom?” varies depending on the regime. In a multivariate setting, Granger causality, while not claiming structural causality (Granger, 1969), provides a clear window into timing and predictive power. Finding a bidirectional Granger relationship in the sales–interest rate pair shows that credit conditions and sales are co-shaped: interest rate shocks predict sales, while unexpected movements in sales also produce feedback on credit conditions. This finding, when considered alongside empirical evidence (Favara & Imbs, 2015) that regulatory-driven externalities in credit supply have significant effects on housing prices and activity, implies that the opening and closing of credit taps in the Turkish case also periodically reset the predictive direction. On the price side, the two-way Granger relationships between CPI, costs, exchange rates, and RPPI—particularly in 2022—suggest the simultaneity of supply-demand shocks in inflationary regimes. This is consistent with the mechanism documented in studies (Campa & Goldberg, 2005) that strengthen the short-term cost channel of the pass-through from the exchange rate to import prices.

Our third research question concerned long-term relationships and error correction dynamics. The presence of cointegration (Johansen, 1991; Engle & Granger, 1987) is strong in our findings and confirmed by ARDL–Bounds tests (Pesaran, Shin, & Smith, 2001). The long-term coefficients we obtained for sales indicate that an interest rate increase reduces total sales by approximately 1.8% at the equilibrium level and mortgage sales by 8.2%; error correction speeds imply that 60–70% of the deviation is closed within one month. This is consistent with theoretical evidence suggesting that housing's collateral function shapes long-term behavior (Iacoviello, 2005) and findings pointing to the medium-term shadow effect on growth in the household leverage cycle

literature (Mian, Sufo, & Verner, 2017). On the price side, the strength of the long-term link between costs and inflation resonates with key findings in the supply elasticity literature: geographic and regulatory constraints limit the supply response, making the pass-through of cost shocks to prices persistent (Saiz, 2010; Davis & Heathcote, 2005). The short-term transmission of exchange rate changes to the CPI through the cost and inflation channels is also consistent with the transition findings in the open economy framework (Campa & Goldberg, 2005). In the regime analysis, the dominance of the CPI $\rightarrow$ price link in 2022 and the return of the cost $\rightarrow$ price link to prominence in 2023 suggests that cost dynamics regained control over pricing behavior after the year in which the inflation shock peaked.

Our fourth question was the contribution of regime/break information to short-term forecasting. SARIMAX results confirmed low error for RPPI (sMAPE $\approx$ 5%) and reasonable error for sales ($\approx$ 14%), indicating that forecasting based on exogenous macro series is feasible. However, two caveats are important here. First, the exogenous coefficients in univariate models are conditional and partial relationships; multivariate frameworks should be preferred for structural interpretations (Sims, 1980). Second, structures such as TVP-SVAR or MS-AR (Primiceri, 2005; Hamilton, 1989), which embed regime/break information directly into the forecasting mechanism, can improve forecast performance, especially in short but intense episodes such as 2022–2023. Therefore, in an economy where regime shifts are becoming more frequent, it is possible to say that forecasts built on the assumption of parameter stability may increasingly show weaker performance; conversely, regime-sensitive frameworks will gain value.

When discussing the policy implications of the findings, two levels of results stand out. First, the credit-interest rate channel: the interest rate elasticity of mortgage sales is many times higher than that of total sales; this implies that the measured and targeted use of borrower-based macroprudential tools (maturity limits, LTV/DTI caps) during periods of credit expansion can preemptively soften the severity of the cycle. The excessively strong impact of interest rate shocks during credit expansion episodes is consistent with findings in the literature explaining why the acceleration in housing prices and activity is higher during periods of exogenous credit supply expansion (Favara & Imbs, 2015). Second, the price-cost channel: the CPI dominance in 2022 and the return of cost dominance in 2023 show that pricing behavior is sensitive to the type of shock in the short term; which points to the need to discuss supply-side policies targeting cost components and the share of imported inputs (cost frictions in input imports, supply chain bottlenecks, local supply constraints) alongside price stability. In an environment of low supply elasticity, demand-side factors are expected to be reflected in prices more quickly and more significantly (Saiz, 2010). Ultimately, all these results are consistent with the macroprudential framework emphasized by the BIS and similar institutions in recent years: a policy mix targeting not just one instrument, but the trio of credit, price stability, and supply (BIS, 2023).

Of course, there are limitations. In segments as long as 12 months, such as 2022 and 2023, the standard errors of regime-conditional coefficients are relatively large; sign changes (e.g., a positive sign for interest rates in total sales in 2023) may indicate not a causal transformation, but simultaneous policy steps, data revisions, or an increase in multiple linkages in price components. Therefore, even if the Wald tests for coefficient differences are highly significant, the results should be interpreted as regime-specific correlations with a wider confidence interval. Furthermore, our framework does not include designs that use natural experiments or instrumental variables to strengthen causality; the approach of studies in the literature that instrumentalize regulatory shocks such as branch deregulation (Favara & Imbs, 2015) could also be tested in the Turkish context, provided that appropriate data is available. Likewise, extensions such as TVP-SVAR and MS-regression, which track parameter migration continuously, will offer a more flexible scheme for “short but intense” periods such as 2022–2023 (Hamilton, 1989; Primiceri, 2005).

In summary, we provide positive and discriminative answers to all of our research questions: (i) Yes, interest rate/exchange rate/inflation/cost effects differ significantly across regimes; (ii) Yes, Granger directions reshape themselves according to episodes; (iii) Yes, there are long-term relationships in sales and prices, and the error correction mechanism is fast; (iv) Yes, single-variable forecasts fed by regime/break information are applicable and provide a usable framework for policy discussions. When the housing market is read this way, it becomes clear that not only “today” but also which regime we are in determines the conditions for policy success: when the rhythm of cost dynamics matches the opening and closing of credit taps, price stability can slip away even

as the economy expands; conversely, even if costs stabilize, the credit channel may continue to exert pressure. Therefore, the decision set—interest rates, macroprudential calibration, and supply-side easing—must be regime-conditional, data-calibrated, and time-sensitive.

Conclusions

This study shows that the Turkish housing market is governed by regime-sensitive interactions rather than stable average relationships. Interest rates exert the strongest effect through the mortgage-sales channel; exchange-rate, inflation, and construction-cost shocks feed into prices with short lags; and the strength and even the sign of some relationships change across expansion, shock, and cooling episodes.

The main novelty of the study is the integration of rolling correlations, VAR/VECM, Granger causality, ARDL–Bounds, Markov-switching, Bai–Perron, and SARIMAX within a single empirical framework built on official monthly data for 2013–2023. This design makes it possible to identify not only whether variables are related, but also when the relationship changes, how quickly equilibrium is restored, and which channels dominate under different macro-financial conditions.

The findings imply that policy calibration in Turkey’s housing market should be regime-conditional. Measures targeting credit conditions, mortgage affordability, construction costs, and supply bottlenecks need to be coordinated rather than used in isolation, and scenario-based monitoring is especially important when inflation, exchange rates, and financing conditions shift simultaneously.

References

- Akgündüz, Y. E., Neef, H. O. D. D., Hacıhasanog, Y. S., & Yilmaz, F. (2023). Cost of credit, mortgage demand and house prices. *Journal of Banking & Finance*, 154, Article Number 106953 <https://doi.org/10.1016/j.jbankfin.2023.106953>
- Bañbura, M., Giannone, D., & Reichlin, L. (2010). Large Bayesian vector autoregressions. *Journal of Applied Econometrics*, 25(1), 71-92. <https://doi.org/10.1002/jae.1137>
- Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70(1), 191-221. <https://doi.org/10.1111/1468-0262.00273>
- Bai, J., & Perron, P. (1998). Estimating and testing linear models with multiple structural changes. *Econometrica*, 66(1), 47-78. <https://doi.org/10.2307/2998540>
- Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1-22. <https://doi.org/10.1002/jae.659>
- Bank for International Settlements (BIS). (2023). Macroprudential policies to mitigate housing market risks (CGFS Papers No. 69). <https://www.bis.org/publ/cgfs69.pdf>
- Bank for International Settlements (BIS). (2024, May 30). Residential property price statistics, Q4 2023. https://www.bis.org/statistics/pp_residential_2405.htm
- Bank for International Settlements (BIS). (2026). Residential property prices. BIS Data Portal. Retrieved March 8, 2026, from <https://data.bis.org/topics/RPP>
- Calza, A., Monacelli, T., & Stracca, L. (2013). Housing finance and monetary policy. *Journal of the European Economic Association*, 11(S1), 101-122. <https://doi.org/10.1111/j.1542-4774.2012.01095.x>
- Campa, J. M., & Goldberg, L. S. (2005). Exchange rate pass-through into import prices. *The Review of Economics and Statistics*, 87(4), 679-690. <https://doi.org/10.1162/003465305775098189>
- Campbell, J. Y., & Cocco, J. F. (2007). How do house prices affect consumption? Evidence from micro data. *Journal of Monetary Economics*, 54(3), 591-621. <https://doi.org/10.1016/j.jmoneco.2005.10.016>

Canöz, İ., & Kalkavan, H. (2024). Forecasting the dynamics of the Istanbul real estate market with the Bayesian time-varying VAR model regarding housing affordability. *Habitat International*, 148, Article Number 103055. <https://doi.org/10.1016/j.habitatint.2024.103055>

Central Bank of the Republic of Türkiye (CBRT). (2025). Residential Property Price Index. Retrieved March 8, 2026, from <https://www.tcmb.gov.tr/wps/wcm/connect/en/tcmb%2Ben/main%2Bmenu/statistics/real%2Bsector%2Bstatistics/residential%2Bproperty%2Bprice%2Bindex>

Časta, M. (2025). The impact of mortgage rates on the housing market. *Journal of Housing Economics*, 69, Article Number 102079. <https://doi.org/10.1016/j.jhe.2025.102079>

Davis, M. A., & Heathcote, J. (2005). Housing and the business cycle. *International Economic Review*, 46(3), 751-784. <https://doi.org/10.1111/j.1468-2354.2005.00345.x>

Engle, R. F., & Granger, C. W. J. (1987). Cointegration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2), 251-276. <https://doi.org/10.2307/1913236>

European Central Bank. (2009). Housing finance and monetary policy (Working Paper No. 1069). Retrieved March 8, 2026, from <https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp1069.pdf>

Eurostat. (2025). Building permits. National Reference Metadata in Euro SDMX Metadata Structure (ESMS), Türkiye. Retrieved March 8, 2026, from https://ec.europa.eu/eurostat/cache/metadata/EN/sts_cons_per_esms_tr.htm

Favara, G., & Imbs, J. (2015). Credit supply and the price of housing. *American Economic Review*, 105(3), 958-992. <https://doi.org/10.1257/aer.20121416>

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2000). The generalized dynamic-factor model: Identification and estimation. *The Review of Economics and Statistics*, 82(4), 540-554. <https://doi.org/10.1162/003465300559037>

Glaeser, E. L., & Gyourko, J. (2018). The economic implications of housing supply. *Journal of Economic Perspectives*, 32(1), 3-30. <https://doi.org/10.1257/jep.32.1.3>

Goekler, L. A. (2025). Analysis of house price fluctuations in a speculative housing market: Evidence from three Metropolitan Cities in Turkey. *International Planning Studies*, 30(4), 487-505. <https://doi.org/10.1080/13563475.2025.2541818>

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3), 424-438. <https://doi.org/10.2307/1912791>

Gunduz, L. ., Çakir, M., & Cepni, O. (2025). House price dynamics in Istanbul: District-level analysis of convergence clubs, spillovers, and key drivers. *Borsa Istanbul Review*, 25(1), 195-205. <https://doi.org/10.1016/j.bir.2024.12.017>

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2), 357-384. <https://doi.org/10.2307/1912559>

Hsieh, C.-T., & Moretti, E. (2019). Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics*, 11(2), 1-39. <https://doi.org/10.1257/mac.20170388>

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22(4), 679-688. <https://doi.org/10.1016/j.ijforecast.2006.03.001>

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, 95(3), 739-764. <https://doi.org/10.1257/0002828054201477>

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, 59(6), 1551-1580. <https://doi.org/10.2307/2938278>

Kayakus, M., Terzioğlu, M., & Yetiz, F. (2022). Forecasting housing prices in Turkey by machine learning methods. *Aestim*, 80, 33-44. <https://doi.org/10.36253/aestim-12320>

Kırca, M., & Canbay, Ş. (2022). Determinants of housing inflation in Turkey: A conditional frequency domain causality. *International Journal of Housing Markets and Analysis*, 15(2), 478-499. <https://doi.org/10.1108/IJHMA-02-2021-0013>

Kiyotaki, N., & Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2), 211-248. <https://doi.org/10.1086/262072>

Kuang, P., Mitra, K., Tang, L., & Xie, S. (2026). Macroprudential policy and housing market expectations. *European Economic Review*, 181, Article Number 105191. <https://doi.org/10.1016/j.euroecorev.2025.105191>

- Kütük, Y. (2024). Multidimensional house price prediction with SOTA RNNs. *International Journal of Strategic Property Management*, 28(6), 411-423. <https://doi.org/10.3846/ijspm.2024.22661>
- Mian, A., Rao, K., & Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4), 1687-1726. <https://doi.org/10.1093/qje/qjt020>
- Mian, A., Sufi, A., & Verner, E. (2017). Household debt and business cycles worldwide. *The Quarterly Journal of Economics*, 132(4), 1755-1817. <https://doi.org/10.1093/qje/qjx017>
- Muddasir, M., & Dondas, U. (2023). A 10-year analysis of housing prices and the influence of economic factors in Turkey. *Financial Internet Quarterly*, 19(3), 100-112. <https://doi.org/10.2478/fiqf-2023-0022>
- Nasiboglu, R., Balbal, K. F., Rusiman, M. S., & Nasibov, E. (2025). Location-Based housing valuation index proposal: Izmir example. *Journal of The Faculty of Engineering and Architecture of Gazi University*, 40(1). <https://doi.org/10.17341/gazimmfd.1363942>
- Özgüler, İ. C., Büyükkara, Z. G., & Küçüközmen, C. C. (2023). Discovering the fundamentals of Turkish housing market: a price convergence framework. *International Journal of Housing Markets and Analysis*, 16(1), 116-145. <https://doi.org/10.1108/IJHMA-09-2021-0103>
- Pesaran, M. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1), 17-29. [https://doi.org/10.1016/S0165-1765\(97\)00214-0](https://doi.org/10.1016/S0165-1765(97)00214-0)
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289-326. <https://doi.org/10.1002/jae.616>
- Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3), 821-852. <https://doi.org/10.1111/j.1467-937X.2005.00353.x>
- Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, 125(3), 1253-1296. <https://doi.org/10.1162/qjec.2010.125.3.1253>
- Sayin, ZM., Elburz, Z., & Duran, H. E. (2022). Analyzing housing price determinants in Izmir using spatial models. *Habitat International*, 130, Article Number 102712 <https://doi.org/10.1016/j.habitatint.2022.102712>
- Sims, C. A. (1980). Macroeconomics and reality. *Econometrica*, 48(1), 1-48. <https://doi.org/10.2307/1912017>
- Stock, J. H., & Watson, M. W. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2), 147-162. <https://doi.org/10.1198/073500102317351921>
- Turkish Statistical Institute (TÜİK). (2022). Construction Cost Index, June 2022. Retrieved March 8, 2026, from <https://data.tuik.gov.tr/>
- Turkish Statistical Institute (TÜİK). (2025). Construction Cost Index, June 2025; Building Permits, Quarter II: April-June, 2025. Retrieved March 8, 2026, from <https://data.tuik.gov.tr/>
- Yasar, R. Z., & Bulut, E. (2023). Why Did Housing Prices Rise to a Record Level in Turkey? An Empirical Analysis. *Real Estate Management and Valuation*, 31(4), 1-10. <https://doi.org/10.2478/remav-2023-0025>
- Yildirim, M. O., & İvrendi, M. (2021). Turkish housing market dynamics: An estimated DSGE model. *Margin: the Journal of Applied Economic Research*, 15(2), 238-267. <https://doi.org/10.1177/0973801021990396>
- Yildirim, M. O., & Yıldırım, Ö. F. (2025). What drives house prices in Turkey? Evidence from Bayesian SVAR model. *Economic Change And Restructuring*, 58(1) <https://doi.org/10.1007/s10644-024-09845-0>

Data Availability Statement: The data used in this study are publicly available from the Central Bank of the Republic of Türkiye (CBRT), the Turkish Statistical Institute (TÜİK), and the BIS Data Portal.

Author Contributions: Conceptualization: *Bahman Peyravi and Mehmet Recai Uygur*; methodology: *Bahman Peyravi, Mehmet Recai Uygur, and Mehmet Emre Çamlıbel*; formal analysis and data curation: *Bahman Peyravi and Gediminas Blaževičius*; writing, original draft preparation: *Bahman Peyravi and Mehmet Recai Uygur*; writing, review and editing: *all authors*; visualization: *Gediminas Blaževičius and Mehmet Emre Çamlıbel*; supervision: *Mehmet Recai Uygur*. All authors have read and agreed to the published version of the manuscript.

Bahman PEYRAVI

ORCID: <https://orcid.org/0000-0003-2077-6052>

Mehmet Recai UYGUR

ORCID: <https://orcid.org/0000-0003-1872-0885>

Gediminas BLAŽEVIČIUS

ORCID: <https://orcid.org/0000-0002-4624-3310>

Mehmet Emre ÇAMLIBEL

ORCID: <https://orcid.org/0000-0002-4095-9377>

Copyright © 2026 by author(s). Publishing rights by Entrepreneurship and Sustainability Center

This work is licensed under the Creative Commons Attribution International License (CC BY).

<http://creativecommons.org/licenses/by/4.0/>



Open Access