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Fluctuations in the european housing market: forecasting the house price index change with time-series models

Avrupa konut piyasasındaki dalgalanmalar: zaman serisi modelleriyle konut fiyat endeksi deęişiminin tahmini

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Fluctuations in the European Housing Market: Forecasting the House Price Index Change with Time-Series Models

Highlights

- ❖ House price index is analyzed for 27 European countries (2013-2024).
- ❖ Additive Damped Trend, ARIMA, Exponential Smoothing, Holt Linear Trend are used for forecasting.
- ❖ Dickey-Fuller test applied for stationarity; transformations performed if necessary.
- ❖ The House Price index growth rate of European countries has been forecasted for 2025 and 2026.

Graphical Abstract

The figure illustrates the structural flow of the time series forecasting process, encompassing the stages from data collection to the final forecast.

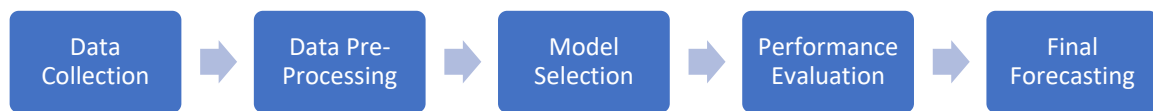


Figure. The process of time series forecasting

Aim

To analyze and forecast house price index changes in 27 European countries using various time-series forecasting models, evaluating their accuracy based on Mean Squared Error (MSE).

Design & Methodology

House price index change data from Q4 2013 to Q3 2024 are analyzed for 27 European countries. Data stationarity is assessed using the Dickey-Fuller test. Four forecasting models are tested, and the best-performing model for each country is selected based on MSE. The models used are Additive Damped Trend, ARIMA, Exponential Smoothing, and Holt Linear Trend.

Originality

This study offers a comparative analysis of multiple time-series forecasting models, optimizing parameter selection for each country and providing a robust methodological framework for housing market predictions.

Findings

The ARIMA model provided the most accurate forecasts for 9 out of 27 countries, while the Holt Linear Trend model is optimal for 7 countries. It is emphasized that each country might be modeled with a different forecasting model.

Conclusion

Accurate forecasting of house price indices is crucial for informed policymaking and investment strategies. The study emphasizes the necessity of adaptive forecasting techniques to accommodate economic fluctuations and market dynamics in housing sectors across the European Countries.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Fluctuations in the European Housing Market: Forecasting the House Price Index Change with Time-Series Models

Araştırma Makalesi / Research Article

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ABSTRACT

This study presents a comparative analysis of a time series models for forecasting changes in the Housing Price Index (HPI) in 27 European countries. Accurate HPI forecasting is essential for the development of effective policies and investment strategies. The study uses quarterly data from Q4 2013 to Q3 2024. Methodologically, the stationarity of the data is tested using the Dickey–Fuller test and differencing is applied to non-stationary series. The ARIMA, Holt Linear Trend, Additive Damped Trend and Exponential Smoothing models are evaluated based on the lowest mean squared error (MSE) value for each country. The findings confirmed the heterogeneous structure of the European housing market, showing that no single model is suitable for all countries. The ARIMA model provided the most accurate results for nine countries, while the Holt Linear Trend and Additive Damped Trend models performed best in seven countries each. Forecasts for the period 2025–2026 are generated based on these results. This study highlights the importance of adopting country-specific and adaptable forecasting approaches to accommodate the varying dynamics of European housing markets.

Anahtar Kelimeler: House Price Index Change, Time Series Forecasting, ARIMA, Housing Market Dynamics.

Avrupa Konut Piyasasındaki Dalgalanmalar: Zaman Serisi Modelleriyle Konut Fiyat Endeksi Değişiminin Tahmini

ÖZ

Bu çalışma, 27 Avrupa ülkesinde Konut Fiyat Endeksi değişikliklerini tahmin etmek için zaman serisi modellerinin karşılaştırmalı bir analizini sunmaktadır. Doğru Konut Fiyat Endeksi tahmini, etkili politikalar ve yatırım stratejileri geliştirmek için gereklidir. Çalışma, 2013 yılının 4. çeyreğinden 2024 yılının 3. çeyreğine kadar olan veriler kullanmaktadır. Metodolojik olarak, verilerin durağanlığı Dickey–Fuller testi ile test edilmiş ve durağan olmayan serilere fark alma uygulanmıştır. ARIMA, Holt Doğrusal Trend, Katkılı Sönümlü Trend ve Üstel Düzeltme modelleri, her ülke için en düşük ortalama karesel hata (MSE) değerine göre değerlendirilmiştir. Bulgular, Avrupa konut piyasasının heterojen yapısını doğrulamış ve tek bir modelin tüm ülkeler için uygun olmadığını göstermiştir. ARIMA modeli dokuz ülke için en doğru sonuçları verirken, Holt Doğrusal Trend ve Holt-Winters Sönümlü Trend modelleri yedi ülkede en iyi performansı gösterdi. 2025–2026 dönemi için tahminler bu sonuçlara dayalı olarak oluşturulmuştur. Bu çalışma, Avrupa konut piyasalarının değişen dinamiklerine uyum sağlamak için ülkeye özgü ve uyarlanabilir tahmin yaklaşımlarının benimsenmesinin önemini vurgulamaktadır.

Keywords: Ev Fiyat Endeksi Değişimi, Zaman Serisi Tahminleme, ARIMA, Konut Piyasası Dinamikleri.

1. INTRODUCTION

One of the basic needs of people is housing. Housing markets are recognized as being a dynamic and complex system; therefore, it is important to acknowledge that they are susceptible to being influenced by a variety of factors. These include, but are not limited to, the financial market, economic policies, land prices and emergencies [1]. The availability of housing represents a critical component in evaluating the economic vitality of a nation. An increase in the national economy is often accompanied by a migration of population from urban to rural areas, resulting in an escalation of the urban population. Concurrently, the demand for

accommodation experiences an analogous increase. Consequently, as the demand for housing rises, so does its price [2]. It is evident that the accurate estimation of housing prices is instrumental in enabling policymakers to formulate optimal decisions, thereby preventing the occurrence of excessive price increases. The House Price Index (HPI) is a statistical tool used to analyze fluctuations in the transactional prices of residential properties, encompassing both newly constructed and existing properties that are procured by households [3]. The estimation of the HPI is of significant value to a range of stakeholders, from individual investors to mortgage lenders and government policymakers. By

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providing insights into potential market trends and economic conditions, the index enables informed decision-making processes. This facilitates effective real estate planning, supports the decision-making process within financial institutions, and contributes to the formulation of appropriate government policy. Moreover, by identifying future price movements, the index helps stakeholders to mitigate potential risks and foster the growth of sustainable housing markets.

In the literature, housing prices and housing price index have been estimated using different techniques. Random Forest (RF) is used to predict house prices [4]. Moreover, different regression techniques are also used for forecasting house prices [5]. Comparison analysis is applied to different techniques such as using linear regression, RF, and decision trees algorithms. Mean Squared Error (MSE) is used as a Key Performance Indicator (KPI) for comparison [6]. Multiple linear regression and RF regression are utilized to predict house prices in Jabodetabek. The KPIs employed included Mean Absolute Error (MAE), MSE, Root Mean Squared Error, Mean Absolute Percentage Error, and R2 score [7]. On the other hand, hybrid whale algorithm and support vector regressor models are employed to predict HPI in Beijing, Shanghai, Tianjin, and Chongqing [8]. Moreover, a suite of machine learning models is utilized to predict the house price index. These models include RF, XGBoost, LightGBM, a hybrid regression model, and a stacked generalization approach [9]. Furthermore, Root Mean Squared Logarithmic Error is utilized to evaluate the performance of these models. In addition, price forecasting for different products is made using various methods. Prophet, XGBoost, Long Short-Term Memory, and Gated Recurrent Unit (GRU) are used for predicting steel plate price [10]. Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, moving average, and Holt linear methods are employed to estimate the production of cereal products [11]. The multiple trend-corrected exponential smoothing is utilized to forecast the exchange rates of currencies [12]. A hybrid model that employs deep learning methodologies for the prediction of transcription factor binding sites [13] and regression models are used to estimate GPS-Total Electron Content [14].

Although various machine learning and regression techniques have been used in the literature to predict house prices and their index, there is a lack of comparative analysis to determine the most suitable model for each country in Europe, given their diverse and fluctuating economic structures. The heterogeneous nature of European housing markets means that a model successful in one country might not perform equally well in another. This lack of country-specific model validation creates uncertainty in making accurate forecasts, which are vital for both economic planning and investment strategies. This situation constitutes the core problem statement of this study. Therefore, this research aims to answer the central question of which time-series forecasting model provides the most accurate and reliable

predictions for HPI changes across different European countries. The objective of this study is to establish a robust benchmark against which to assess the performance of more contemporary and intricate models in the extant literature.

To achieve this, the study first compares the performance of these models when applied to the HPI quarterly change data of 27 European nations. It then identifies the most suitable model and its specific parameters for each country, analyzing what these variations imply about their respective housing market dynamics. Before deciding on the forecasting model for each country, the stationarity of the data is checked with the Dickey-Fuller test, and non-stationary data are made stationary using the Difference methods. The parameter optimization of each model is performed for each country and the model with the smallest MSE value is used as the forecasting model for that country. Finally, based on the most accurate models identified for each nation, the study projects the trends for HPI changes for the years 2025 and 2026.

This study takes a structured approach to addressing the presented research problem. In the 'Materials and Methods' section of the article, the time series stationarity of 27 European countries is analyzed first using the Dickey-Fuller test. Non-stationary data are then transformed using the differencing method. The Additive Damped Trend, ARIMA, Exponential Smoothing, and Holt Linear Trend models are then applied to the data for each country to determine the model and parameters with the lowest MSE. The Diebold-Mariano (DM) test is then used to verify the statistical significance of the forecast performances of the two models, yielding the lowest MSE values for each country. In the 'Results & Discussion' section, HPI change forecasts for the period 2025–2026 are produced using the models that yielded the lowest MSE values for each country. These estimates are analyzed in comparison with the European Union average, revealing the heterogeneous structure and diverging dynamics that suggest European housing markets do not operate as a single entity.

2. MATERIALS & METHODS

2.1. Data

The percentage of HPI change data of 27 different European countries is used. The data set is created as quarters and includes price index changes between the 2013 4th Quarter and 2024 3rd Quarter [3]. The percentage change in the data set indicates the extent to which it has changed in comparison with the previous quarter. Average house price index changes for 27 European Union countries are shown in Figure 1. The housing price changes within the European countries demonstrate considerable fluctuations between 2013 and 2024, indicative of underlying economic conditions and policy shifts. From late 2013 to 2016, housing prices exhibited a consistent upward trajectory, reaching approximately 4% annual growth, likely attributable to

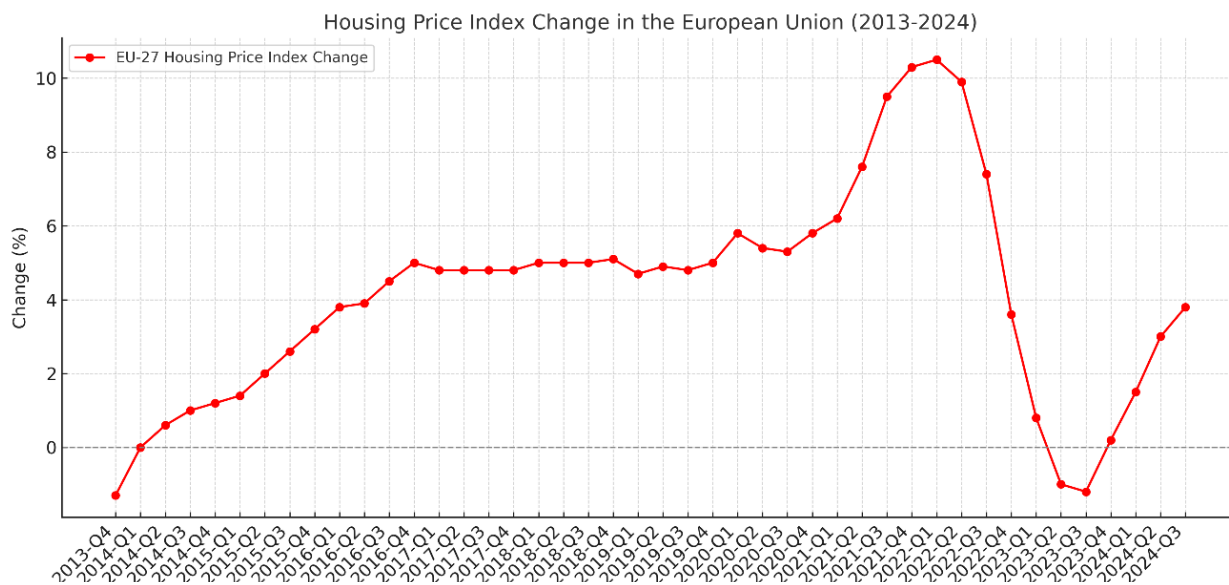


Figure 1. Average house price index values for 27 countries

economic recovery and increasing demand. A period of relatively stable market conditions, characterized by annual growth rates of around 4-5%, ensued from 2017 to 2019. However, the subsequent surge in housing prices, which exceeded 10% annual growth at its peak, occurred from 2020 to 2022. This is attributable to pandemic-related economic stimuli, historically low interest rates, and heightened demand for residential properties. In contrast, 2023 witnessed a substantial downturn, with housing price growth rates declining to almost zero, likely influenced by rising interest rates, inflationary pressures, and weakening housing demand. However, by early 2024, a partial recovery is observed, suggesting potential stabilization in the market.

2.2. Data Pre-processing

Before commencing the analysis of the data sets, the stationarity of the data is subjected to analysis. The deterministic properties of the series are determined by the presence or absence of constant, trend, and seasonal components. The stochastic properties of a series are primarily linked to the stationarity or lack thereof of the variables. Nevertheless, when performing time series analysis, it is of paramount importance to ascertain whether the analyzed series are stationary [15]. Therefore, the Dickey-Fuller test is employed to ascertain whether the countries and their average house price index values are stationary or not. The Dickey-Fuller test can be defined as a statistical test that is utilized with a view to ascertaining whether a given autoregressive (AR) time series model incorporates a unit root. The alternative hypothesis to be evaluated is subject to variation depending on the specific version of the test that is employed; however, it is generally considered to include either stationarity or trend stationarity [16].

Non-stationary data are attempted to be made stationary by differencing operations. A variety of transformation methods have been proposed in the literature to address the issue of stationarity in the time series; however,

selecting the appropriate method for a specific application within a particular time series is not a simple task. It is essential to analyze the characteristics and expected benefits of each method, taking into consideration initial data assumptions and specific features of the method [17]. Table 1 summarizes the stationarity analyses of the data. In the table, “NS” represents a non-stationary type, and “S” represents a stationary type. Moreover, “DC” shows the number of difference operations (Differencing Count).

The 'Initial p-value' represents the result p-value of the Dickey-Fuller test in Table 1. The 'Final p-value' value denotes the p-value after the transformation of non-stationary data into a stationary form. The 'DC' column indicates the number of data points to which the data has been shifted. The critical p-value for the stationarity test is determined as 0.05. The stationarity test results indicate that the time series of most of the countries examined at the beginning are non-stationary. To make the non-stationary series stationary, the difference method is applied. For certain countries, such as Lithuania (2 differences), Austria (2 differences), and Croatia (2 differences), a higher degree of difference is required; however for most countries, a single difference is sufficient. The initial stationarity of the time series is observed in Cyprus, Latvia, Luxembourg, Hungary, Malta, the Netherlands, Romania, Sweden, Iceland, and Norway, for which no transformation is necessary. The results indicate that appropriate transformation techniques should be applied to make the time series of European countries as a whole and many countries stationary. In particular, the stationarities of the time series stand out as a critical step in understanding the variability of economic indicators over time and developing accurate forecasting models.

Prior to the initiation of the analytical process, the dataset undergoes a process of normalization. The principal objective of this procedure is to ensure the production of

data of the highest quality, thereby preparing it for integration into any learning algorithm.

Table 1. The stationarity analyses of the data

Country	Initial p-value	Stationary Type	Final p-value	DC
Belgium	0.357	NS	0.000	1
Bulgaria	0.654	NS	0.001	1
Czechia	0.119	NS	0.000	2
Denmark	0.089	NS	0.001	1
Germany	0.140	NS	0.000	1
Estonia	0.094	NS	0.000	1
Ireland	0.286	NS	0.000	1
Spain	0.228	NS	0.007	1
France	0.089	NS	0.008	1
Croatia	0.796	NS	0.001	2
Italy	0.274	NS	0.000	1
Cyprus	0.001	S		
Latvia	0.001	S		
Lithuania	0.253	NS	0.003	2
Luxembourg	0.008	S		
Hungary	0.014	S		
Malta	0.000	S		
Netherlands	0.019	S		
Austria	0.167	NS	0.000	2
Poland	0.574	NS	0.000	1
Portugal	0.051	NS	0.000	1
Romania	0.003	S		
Slovenia	0.215	NS	0.000	1
Slovakia	0.292	NS	0.000	1
Finland	0.521	NS	0.000	1
Sweden	0.035	S		
Iceland	0.025	S		
Norway	0.005	S		
Average Value of European Union	0.369	NS	0.000	2

Given the potential for time series data to encompass a broad spectrum of values, it is imperative to scale it to a range that is commensurate with that of the learning algorithm, thereby facilitating an expedited learning process [18]. Min-Max scaling strategy is used. Furthermore, the initial 80% of each country's data is allocated for training purposes, with the remaining 20% designated for testing. The MSE data of the models is derived from the test data.

2.3. Model Selection

In this study, an approach is adopted to select the most suitable model for each country's house price index. To this end, a range of time series forecasting models are utilized, including Additive Damped Trend, ARIMA, Exponential Smoothing and Holt Linear Trend. Holt's linear method is a forecasting technique characterized by a constant trend that increases or decreases continuously in the future. Empirical evidence demonstrates, however, that such methods tend to overestimate a propensity that becomes particularly evident in the case of longer forecast horizons [19]. The incorporation of a parameter that 'damps' the trend to a straight line at some point in the future has been demonstrated to result in the effective and widespread utilization of methods incorporating

damped trends in the automatic forecasting of a large amount of series. This is referred to as the Additive Damped Trend [20].

The calculations pertaining to the Holt Linear Method, as illustrated in Equation 1, 2 and 3, involve the estimation of X_t , the level L_t , the trend k_t , and the forecast period represented by T . The level smoothing factor β , and the trend smoothing factor α , are constrained within the interval from zero to one ($0 < \alpha < 1$). In this study, the values of α and β are increased from 0.01 to 1 by 0.01 for each countries house price index data, and the forecast study is carried out. Then, the MSE values are calculated.

$$X_{t+T} = L_{t-1} + k_{t-1} \times T \quad (1)$$

$$L_t = \alpha \times Y_t + (1-\alpha) \times (L_{t-1} + k_{t-1}) \quad (2)$$

$$k_t = \beta \times (L_t - L_{t-1}) + (1-\beta) \times k_{t-1} \quad (3)$$

The equations used in the Additive Damped Trend method are shown in Equation 4, 5 and 6. The notation $X_{(t+h)}$ denotes the estimated value of h time points following time t , whilst L_t represents the level value at time t and k_t denotes the trend value at time t . In contrast to the Holt Linear Method, the trend value undergoes a multiplication process with a damping value j . This coefficient ranges from 0 to 1, with 1 representing the strongest damping effect. In this study, the MSE values are determined for various parameters. To do so, the β values increased from 0.01 to 1 by 0.01 for each of the countries' data. Furthermore, the damping coefficient is calculated by optimizing for each combination of β and α .

$$X_{t+h} = L_t + (j + j^2 + j^3 + \dots + j^h) \times k_{t-1} \quad (4)$$

$$L_t = \alpha \times Y_t + (1-\alpha) \times (L_{t-1} + (j \times k_{t-1})) \quad (5)$$

$$k_t = \beta \times (L_t - L_{t-1}) + (1-\beta) \times k_{t-1} \quad (6)$$

Exponential smoothing techniques are regarded as a group of forecasting methods for specific types of univariate time series data [21]. Exponential smoothing algorithms are predicated on the concept of time series decomposition. The trend component is concerned with the long-term upward or downward movement in the time series; it is important to note that such movement might not always conform to a linear pattern. The seasonal component accounts for fluctuations caused by recurring seasonal factors, which typically occur at regular intervals. Lastly, the error component represents random variations in the data that the model is unable to explain; it is important to note that this component is essential for the process of model evaluation [22].

The exponential smoothing equation is shown in Equation 7. X_t represents the estimated value at time t , $X_{(t-1)}$ represents the estimated value at time $t-1$, and $Y_{(t-1)}$ represents the actual value at time $t-1$. It should also be noted that the value α indicates the smoothing factor of the data determined between 0 and 1. In the

Table 2. Summary of selected models (MSE values are expressed in bold.)

COUNTRY	Additive Damped Trend (α, β, j)	Exponential Smoothing (α)	Holt Linear Trend (α, β)	ARIMA (p, d, q)	p-value of DM Test
Austria	105.04 (0.1, 0.1, 0.1)	104.38 (0.1)			0.001
Belgium	1.47 (0.48, 0.99, 0.9)		1.79 (0.62, 0.99)		0.069
Bulgaria	7.35 (0.28, 0.1, 0.99)		7.31 (0.28, 0.1)		0.882
Croatia	6.82 (0.52, 0.1, 0.1)	6.82 (0.52)			0.991
Cyprus	2.79 (0.91, 0.99, 0.34)	3.48 (0.99)			0.454
Czechia	99.83 (0.8, 0.99, 0.99)		96.87 (0.81, 0.99)		0.251
Denmark	15.02 (0.99, 0.99, 0.62)			4.89 (2,1,2)	0.011
Estonia	48.31 (0.1, 0.1, 0.1)	48.26 (0.1)			0.121
France	43.65 (0.1, 0.1, 0.1)	43.28 (0.1)			0.004
Germany	56.04 (0.99, 0.99, 0.99)		56.43 (0.99, 0.99)		0.853
Hungary		42.23 (0.1)		16.51 (0,0,2)	0.014
Iceland		52.12 (0.1)		17.03 (2,0,2)	0.103
Ireland			11.60 (0.13, 0.1)	0.33 (4,1,1)	0.016
Italy	0.98 (0.12, 0.2, 0.1)	0.99 (0.12)			0.933
Latvia		34.83 (0.1)		2.29 (4,0,4)	0.005
Lithuania	13.48 (0.1, 0.1, 0.1)	13.39 (0.1)			0.571
Luxembourg	80.86 (0.19, 0.99, 0.99)		73.61 (0.19, 0.99)		0.052
Malta	0.33 (0.3, 0.1, 0.99)		0.33 (0.29, 0.1)		0.971
Netherlands			91.81 (0.99, 0.99)	39.22 (0,0,4)	0.010
Norway	4.11 (0.45, 0.99, 0.85)			2.78 (3,0,4)	0.369
Poland	11.73 (0.13, 0.97, 0.99)		11.52 (0.13, 0.97)		0.052
Portugal		3.94 (0.1)	3.77 (0.1, 0.34)		0.149
Romania			4.08 (0.1, 0.18)	2.94 (3,0,3)	0.281
Slovakia		68.56 (0.1)		65.49 (4,1,3)	0.821
Slovenia	5.04 (0.99, 0.99, 0.97)		5.57 (0.99, 0.97)		0.612
Spain	2.64 (0.2, 0.21, 0.99)		2.61 (0.2, 0.22)		0.749
Sweden	21.06 (0.99, 0.99, 0.81)		35.07 (0.99, 0.48)		0.004
Average Value of European Union		30.01 (0.1)		18.93 (3,2,1)	0.049

present study, the α value was estimated for each cereal product by increasing it by 0.01 between 0.01 and 1, and the mean square error values were calculated.

$$X_t = \alpha x Y_{t-1} + (1-\alpha) x X_{t-1} \tag{7}$$

Time-series forecasting involves the identification of patterns in historical data to facilitate the prediction of subsequent numerical values. The Autoregressive model employs autoregressive techniques to forecast future values, examining the relationships between historical observations of the target variable across different periods. It conceptualizes the target variable as the dependent variable, with previous values designated as independent variables. Correlations between the dependent and independent variables are thus assessed, with the application of pertinent statistical methodologies enabling the construction of a model to predict future values [23].

As outlined in Equation 8, the model under consideration comprises the variable Y_t denoting the value at time t ; the constant c ; the autoregressive parameter β (p); the prediction error α_t at time t ; and the moving average coefficient γ . Within the scope of this study, combinations are generated for p and q values ranging from 0 to 5 for each of the countries' data under

investigation. Moreover, d values are determined according to ADF test results. In the event of the country's time series being stationary at the test value, the d value will be set to 0; otherwise, the difference value will be taken. These combinations are utilized as the parameter values for the ARIMA model. The MSE value is calculated for each model.

$$Y_t = c + \beta_1 x Y_{t-1} + \beta_2 x Y_{t-2} + \dots + \alpha_t - \gamma_1 x \alpha_{t-1} - \gamma_2 x \alpha_{t-2} - \dots \tag{8}$$

These models are applied to data for each country to identify the most appropriate model. Furthermore, parameter optimization is performed for each model, and the parameters and models with the smallest MSE values are employed to estimate the data for each country. The two models with the lowest MSE values for each country, model parameters, and p -values of the Diebold-Mariano (DM) test to understand the statistical difference are shown in Table 2. The DM test is a widely utilized statistical methodology for the purpose of comparing the forecasting performance of two competing forecasting models. The null hypothesis of this test is that two forecasts possess equal predictive accuracy. This hypothesis is tested by analyzing the difference between the loss functions defined based on the models' error terms, the loss differential. The determination of whether

the mean of this loss differential series, typically calculated using metrics such as MSE or MAE, is statistically significantly different from zero is made asymptotically using DM statistics, which is a standard normal distribution. The rejection of the null hypothesis indicates that one of the compared forecasts has statistically superior predictive performance over the other, thus allowing for an empirical choice between the models [24]. The findings indicate that the ARIMA model has been the most frequently preferred, providing the lowest MSE value in nine countries. The Additive Damped Trend method has yielded the most successful results in seven countries. Contrary to prevailing expectations, Holt Linear Trend has demonstrated superior prediction accuracy compared to other models in six countries, and Exponential Smoothing in five countries. When examining the differences in model performance, the lowest prediction error is achieved with the ARIMA model in Ireland (MSE=0.33) and the Holt Linear Trend model in Malta (MSE=0.33). In contrast, the highest prediction errors are observed in Austria (Exponential Smoothing, MSE=104.38) and the Czechia (Holt Linear Trend, MSE=96.87). When considering the mean values across the European Union, the ARIMA model (MSE=18.93) emerged as the most successful model in terms of overall performance, offering the lowest mean squared error value among the available data. The outcomes of the DM test demonstrated that the superiority of the selected model is statistically significant ($p < 0.05$) in numerous countries, including Austria ($p = 0.001$), France ($p = 0.004$), and Denmark ($p = 0.011$).

3. RESULTS & DISCUSSION

The objective is to calculate the house price index changes between the fourth quarters of 2025 and 2026, utilizing a model that exhibited the lowest MSE value for each country. Moreover, an alternative approach involved the forecasting of the house price index changes between the fourth quarters of 2025 and 2026, employing a model that possessed the lowest MSE value of the European Union average value. As illustrated in Figure 1, the forecasted heterogeneity in housing price appreciation rates across European nations for the 2025.Q1-2026.Q4 period is demonstrated by the deviation of each country's quarterly HPI growth from the EU average growth rate. The chart demonstrates the variation in a country's house price changes in comparison to the European Union average. The price increase difference in each country in each quarter is compared with the European Union average and evaluated as positive or negative. Positive differences indicate that the price increase of the relevant country is higher than the EU average, while negative differences indicate that the price increase is below the average. The analysis of housing price fluctuations within the European Union reveals a multitude of factors influencing these dynamics. These include economic growth rates, demographic trends, interest rates, investor

confidence, and the balance between housing supply and demand. To reveal the statistical validity and inherent uncertainty of the forecasts made for the 2025-2026 period, 95% confidence intervals are also calculated using each country's most successful model. The width of these intervals is directly related to the volatility in each country's historical data and the model's prediction error. For instance, in more predictable markets such as Ireland, where the ARIMA model produced a very low error value of 0.33, and Malta, where the Holt model also yielded an error value of 0.33, the calculated confidence intervals are observed to be relatively narrow. In contrast, in markets with much higher error rates, such as Austria and the Czechia, the confidence intervals are found to be significantly wider. This suggests that housing market forecasts in these countries are subject to higher uncertainty and may be more sensitive to potential external shocks. These findings underscore the critical importance for policymakers and investors to consider the country-specific level of uncertainty when evaluating forecasts.

The data, which demonstrates the deviation of each country's quarterly HPI growth from the EU average, confirms that the European housing landscape is not a monolithic entity but rather a collection of distinct markets with unique trajectories. This finding is consistent with a substantial corpus of academic literature that has long established that European housing markets exhibit limited convergence, often forming clubs of countries with similar dynamics rather than moving in a unified manner [25]. The chart provides a clear visual representation of this multi-speed Europe, where national-level factors supersede a unified regional trend.

The divergence is most starkly illustrated by the outlier cases of Poland and Luxembourg. Poland's projected outperformance, characterized by a consistently higher rate of price appreciation than the EU average, could be explained by strong country-specific fundamentals. A comprehensive investigation of Central and Eastern European markets has identified robust GDP growth, rising household income, and favorable demographics as the primary drivers of house prices in the region [26]. However, Luxembourg's marked underperformance indicates a significant market downturn. This sharp deceleration, where price growth is substantially below the EU average, aligns with established theories on housing market cycles. These theories suggest that extended periods of rapid price growth, often disconnected from fundamentals, are typically followed by a correction or a stagnation phase [27].

Moreover, the extensive heterogeneity exhibited in the graph provides support for the literature on the asymmetric effects of a common monetary policy and the critical role of national regulatory measures. Variations in the structure of national mortgage markets result in the monetary policy of the Eurozone having divergent effects on housing markets across the region. Furthermore, the implementation of national macroprudential policies, such as loan-to-value or debt-to-income limits, has been

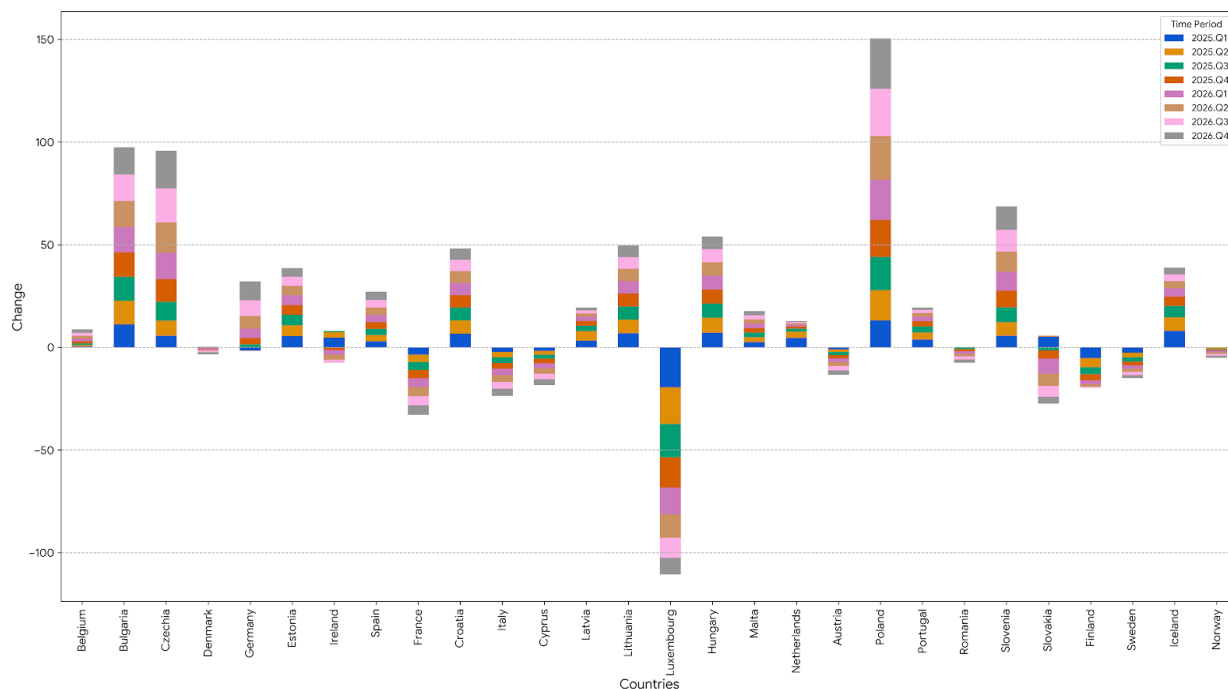


Figure 2. Change in Countries' Data According to European Union Average Data (2025.Q1 – 2026.Q4)

identified as a significant contributing factor to this divergence [28]. Countries that implement stricter regulatory tools are more successful at curbing house price booms [29], explaining why mature markets like Germany and Finland are projected to grow more slowly than the EU average. In essence, the chart provides a visual validation of the argument that national policy choices are a paramount determinant of housing market outcomes within the EU.

4. CONCLUSION

This study employed a comparative analysis of time series models, namely Additive Damped Trend, ARIMA, Exponential Smoothing, and Holt Linear Trend, with the objective of forecasting changes in the HPI across 27 European countries during the period from 2013 to 2024. The results obtained from the study indicate that the European housing market does not behave in a uniform manner; rather, it is comprised of distinct and unique dynamics that are characteristic of each country. Projections for the 2025-2026 period indicate the persistence of this divergence, underscoring the pivotal role of selecting an appropriate model and conducting country-specific analyses for policymakers and investors.

The scope of this study is confined to classical time series models to establish baseline performance. A notable constraint of the study is the exclusion of macroeconomic variables, such as interest rates, GDP growth, and housing policies, from the models. While the impact of these factors on housing prices is acknowledged, future studies utilizing multivariate models that incorporate these variables or modern machine learning methods

could provide more comprehensive and potentially more accurate forecasts. Consequently, the present study is situated as a reference point for comparisons with more complex models. Another crucial point is the strong seasonal patterns that frequently characterize housing market data. The principal objective of this study is to provide fundamental performance analysis employing seasonally adjusted data. Approaches that directly model seasonality, such as Seasonal ARIMA (SARIMA), are not evaluated in this study. In future research, the employment of methods such as SARIMA, which model potential seasonality in housing data, has the potential to enhance forecasting performance. An in-depth examination of this topic would be valuable.

In conclusion, this research demonstrates the heterogeneity of forecasting models in European housing markets, with the optimal model varying across countries. The findings emphasize the necessity for adaptive forecasting techniques that might adapt to economic fluctuations and market dynamics. The limitations of this study present significant opportunities for future research, both in incorporating exogenous variables and modelling complex patterns such as seasonality.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in their work did not require ethical committee approval and/or legal special permission.

CONFLICT OF INTEREST

The author declares that there are no competing interests.

AUTHORS' CONTRIBUTIONS

Mehmet Eren Nalici: Writing - original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization.

İsmet Söylemez: Writing - original draft, Visualization, Validation, Software, Methodology, Formal analysis, Conceptualization, Writing - review & editing.

Ramazan Ünlü: Writing - review & editing, Methodology.

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