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Forecasting the UK House Price Index: A Comparative Study of ETS and SARIMA Models

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Abstract. The increasing house prices in the UK are affected by factors such as the Pandemic, Brexit, inflation, and monetary policy, among other structural economic shifts. This societal phenomenon has led to a pressing housing affordability crisis due to a conflict between the residents' average income and mortgage affordability, which sequentially affects the decisions of UK residents and real estate investors. A widely recognized indicator of house prices is the HPI (House Price Index), which measures the change in prices of residential properties. This research aims to forecast the Housing Price Index in the UK by leveraging the ETS model and the ARIMA model. The first step in this process is to conduct a detailed analysis of the HPI dataset retrieved from the UK Office for National Statistics and HM Land Registry, spanning from 1968 to 2025. As a result, the forecast showcases that the SARIMA(1,1,3)(1,0,0) model with drift is the best for forecasting the UK HPI from 2010 to 2025. This study has provided an excellent statistical forecast model in order to gain a nuanced understanding of future house price index fluctuation within the United Kingdom and hoped that this can provide valuable insights for both local residents and financial institutions, as well as real estate agencies, with regard to risk assessment and investment planning against the structural economic shift.

Keywords: UK Housing Market, Time Series Forecasting, SARIMA Model, Exponential Smoothing, Real Estate Economics

1. Introduction

1.1. Context and motivation

UK housing market is one of the biggest real estate trading market across worldwide. Recent years, global political events such as the Coronavirus pandemic, the United Kingdom's withdrawal from the European Union, and the subsequent period of elevated inflation and monetary policy [1,2] has drastically affect the the UK housing market , causing a significant structural change and market volatility. This can profoundely lead to an consistent increment of investment uncertainty.

Therefore, this highlights the importance of investigation into the UK housing market by utilizing its crucial indicator, which is HPI--an abbreviation for the House Price index. Traditionally, certain economic or financial model could be adopted for the expectation of the house price. However, modern statistical models is useful to function as an independent and exogenous perspective to

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analyze house price market dynamics based on the historical data, providing a backward looking approach compared to other disciplinary such as economic and finance inorder to assist valuable and educated decision making regarding the real estate investment. As of late, while there has been an increasing consideration of the application of network-based and other machine learning approaches in time series forecasting field, such as Graph Neural Networks(GNNs), ANN(Artificial Neural Network) and Extreme Gradient Boosting (XGBoost) [3]. Here, conventional univariate time series models are considered, particularly, this study ratified the SARIMA(Seasonal Autoregressive Integrated Moving Average) model and ETS(Exponential Smoothing Techniques) model. Leveraging SARIMA and ETS models enables a clear dissemination of the expectation of the house price as the incentive behind these two models are linear regression and explicit seasonal components.

Consequently, this study will dissect the forecast performance of proposed models within UK housing market. This will provide an empirical insight into the UK house pricing market fluctuation apttern and the expectation of price index for investors and other relevant stakeholders as comparative experiments of SARIMA and ETS models will be conducted.

1.2. Literature review and research gap

One of the substantial factors that affect the process of house price index forecasting and pattern discovery is data availability dilemma. Different researches incorporate different data source into the analysis of house price index. Although most researchers have encompassed publicly available HPI data sets, which were established by federal and national statistical bureaus with regard to the reliability of original data [3], few researchers opted for data from property agencies' public datasets or other open resources, where the time duration is limited, and a high possibility of missing values is observed, potentially leading to a poor forecast result [4]. This suggests that utilizing data retrieved from unofficial authorities may yield poor forecast accuracy and outcomes. Thus, in this investigation, a legitimate database retrieved from UK national statistic bureau is selected.

Despite the potential original data defect, Auto-Regressive Integrated Moving average(ARIMA) and Error, Trend, Seasonality(ETS) model have been expansively and prevalently employed for future price and indices forecasting, considering its predominant position within the conventional statistical-based time series analysis. This is supported by a wide range of related research.

For instance, a researcher applied the ARIMA modelling technique into the prediction of house prices in Beijing, demonstrating its capability in capturing regional disparities and trend prediction [4]. Meanwhile, another researcher analyzed the performance of ARIMA model for the Malaysia house price index forecast and the results implied that the model appears to generate a favourable forecast result, particularly for short-term predictions [5]. Moreover, researchers in medical field also incorporate the SARIMA and ETS models for forecasting the incidence rate [6]. SARIMA and ETS models possess a wide and cross-disciplinary versatility with regard to time series analysis across field.

Compared to these conventional approach, the utilization of Machine Learning methods and other Neural Network approaches is implemented by a bulk of modern researchers. Researchers not only adopt conventional statistical forecast models, such as ARIMA and STL with ETS, but also apply neural network methods like LSTM in analyzing the UK housing market dynamics [3]. In addition, multiple time series, machine learning, and deep learning models like Random Forest and Extreme Gradient Boosting (XGBoost), are used to predict the US housing Price Index in global research, along with robust prediction outcomes, and model fitness is evaluated by statistical performance metrics and information criteria [7]. While these studies highlight the potential of different

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approaches, few have directly compared traditional statistical models, such as ETS and SARIMA, in the recent UK housing market. Hence, this study will employ the ETS and SARIMA models to examine the performance of traditional linear statistical methods within the UK housing market context.

1.3. Research objectives

This study was set out with the aim of comparing time series forecasting models, particularly ETS and SARIMA, to not just identify and predict patterns in the UK House Price Index but also evaluate the model performance and best fit to the data. Specificially, model accuracy and fitness will be evaluated using multiple performance metrics including RMSE, MAE, MAPE, and MASE. In addition, this will be graded on the basis of information criteria, including AIC and BIC. The most suitable model will be determined through a comparative analysis based on both performance metrics and information criteria. Meanwhile, a national-quality monthly dataset spanning from 2010 to 2025 will be used to ensure the relevance to recent market conditions.

The analysis also aims at offering practical guidance for all stakeholders such as inside market participants and outside policymakers through detailed analysis on UK HPI pattern. Finally, the study will outline gaps for future work and offer recommendations for related stakeholders, which including home buyers, real estate investors, policymakers and financial institutions. The ultimate goal is to strengthen their connection to real-world market conditions and improve executive decision-making.

2. Methodology

2.1. Data collection and preparation

2.1.1. Data sources and characteristics

The UK House Price Index (HPI) dataset is retrieved from the official gov.uk website. This is compiled by HM Land Registry, the Land and Property Services Northern Ireland, the Office for National Statistics (ONS) and the Registers of Scotland. The dataset is a monthly time series from 1968 to 2025, providing 689 monthly observations, which offers a rich historical perspective on housing price indices dynamics. The ONS applies a hedonic regression model for computation, which help controls various differences in property price characteristics. As a result, the index reflects pure price changes. In addition, the dataset meets the highest national standards of accuracy and reliability, ensuring a rigorous bedrock for analysis.

2.1.2. Data preprocessing

A univariate time series analysis will be utilised to examine the temporal dynamics of a single variable. While the original dataset follows a panel structure comprising both temporal and cross-sectional dimensions, this study isolates national-level trends by extracting House Price Index (HPI) observations specific to the 'United_Kingdom' within the 'Region_name' category. The final dataset consists of 690 monthly UK HPI observations, the series is entirely continuous with no missing values reported. Since the full dataset spans a long period, a window function in R is implemented for restricting the data between January 2010 and September 2025. This narrower and refined window ensures a more reliable basis for forecasting. Otherwise, incorporating historical data would introduce noise and distort prediction accuracy, especially when structural breaks are present.

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2.2. Modelling framework

Exponential Smoothing state space(ETS) and Seasonal ARIMA(SARIMA) are employed in this study as foundational time series models. These serve as the statistical modelling threshold for predictive performance.

Firstly, the Exponential Smoothing (ETS) model is employed. These models constitute a list of time series models formulated within a state space framework, comprising level components: a trend component (T), seasonal component (S) and error term (E). The ets() function in the R forecast package automatically selects the optimal ETS model specification based on information criteria minimization, including AIC, AICc, and BIC [8,9].

Secondly, the ARIMA model. The ARIMA is an acronym for Autoregressive (AR), Integrated (I), and Moving Average (MA). This linear regression model can be presented as ARIMA (p, d, q), where p represents the order of the autoregressive, d stands for the degree of first-order differencing, and q represents the order of the moving average. In addition, to address the explicit seasonal pattern in the housing price index data, a Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model is introduced. The SARIMA model is the extension of the standard ARIMA model by incorporating seasonal lags. The core structure of SARIMA is SARIMA (p, d, q)(P, D, Q)m, where the former parentheses represent the same coefficients as the ARIMA model. The latter (P, D, Q) represent the seasonal part of the model, and m specifies the annual seasonal length over the time period. The auto.arima() function in the R forecast package selects the best model based on the minimization of information criteria and parsimony.

3. Result

3.1. Exploratory data analysis

Preliminary time series analysis reveals several attributes of the UK House Price Index. The figure 1 represents a long-term trajectory for the UK house price index from 1968 to 2025, which is generated by R's autoplot() function. It is evident that a clear and persistent upward trend can be observed over time, evidenced by the dashed grey fitted line. The trend indicates a substantial appreciation in UK house prices over roughly fifty-years.

Regarding the fluctuation pattern, a significant downward shift is evident in the early 2010s, consistent with the 2008 UK mortgage crisis and global financial crisis [10]. Meanwhile, the HPI appears to particularly accelerate since 2020 as the trend slope exceed historical averages. Notably, a stochastic fluctuation occurred after a steep increase during the pandemic, indicating a high uncertainty in recent observations.

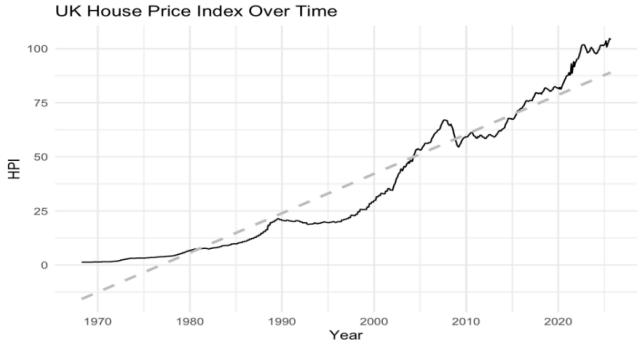


Figure 1. UK HPI over time (photo credit: origin)

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Figure 2 displays the Auto-correlation Function (ACF), where the maximum 12 months lag identifies a positive relationship of seasonal cycle. The high correlation coefficient($r > 0.75$) and the slow decaying trend are indication of the non-stationarity. Since all spikes significantly surpass the critical value line, the null hypothesis of white noise is rejected under default significance level, confirming that the presence of significant autocorrelation within the data set.

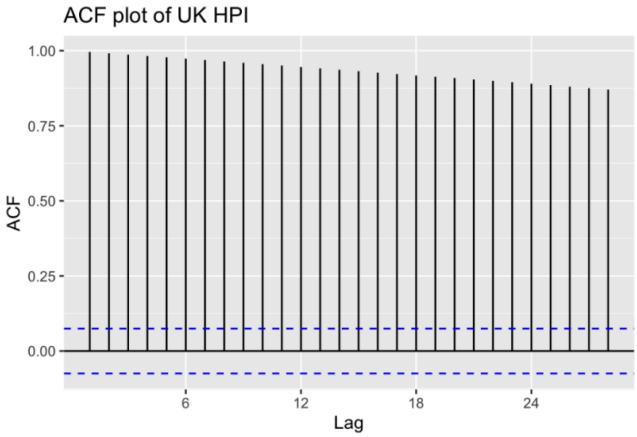


Figure 2. ACF plot of UK HPI (photo credit: origin)

3.2. Time series decomposition

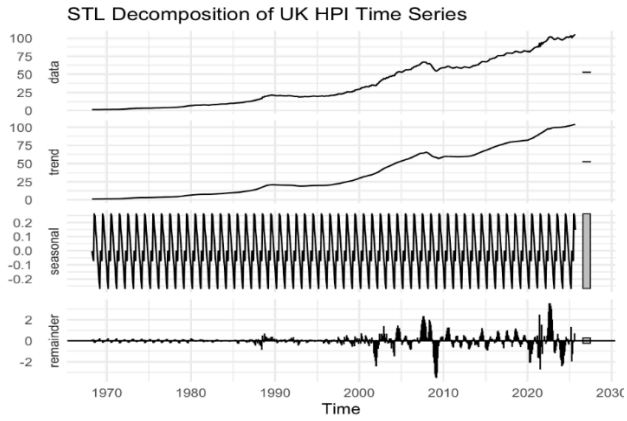


Figure 3. STL decomposition of UK HPI time series (photo credit: origin)

As multiple signals overlap for UK HPI, the time series was decomposed using the STL (Seasonal and Trend decomposition using Loess) method, which applies locally weighted regression to isolate the trend, seasonality, and remainder components. Figure 3 highlights a upward trend and cyclical variations influenced by macroeconomic conditions. In addition, the extracted seasonal component exhibits homoscedasticity, maintaining a uniform amplitude that suggests a highly predictable annual cycle in the UK housing market.

3.3. Model estimation and forecasting

Adhering to standard time series procedures, the dataset was first evaluated for stationarity and potential outliers. Following these diagnostic checks, a train-test split was implemented using an 80/20 ratio. This sequential partitioning ensures that the model is trained on the earlier portion of the

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UK HPI and validated against the most recent 20% of the data, thereby simulating real-world forecasting conditions.

The ETS (M, A, A) model was implemented via the ets() function in the R forecast package. This specification was selected as the best model for the UK HPI after a comprehensive automated model selection process. The ETS(M, A, A) model yielded an Akaike Information Criterion(AIC) of 692.86 and an AICc of 697.03. The negligible numerical gap between AIC and AICc confirms a good fit. However, the Ljung-Box test yielded a Q* value of 55.481 and a p-value of 0.0002695, which indicates a highly significant difference ($p < 0.001$). This result suggests that the residual witnesses the autocorrelation. This suggests that the ETS framework, while providing a stable baseline, does not fully account for all systematic temporal dependencies. As illustrated in Figure 4, the 36 months forecast via ETS model projects a house price index near 100, with the prediction intervals widening accordingly over time, indicating an increase in uncertainty.

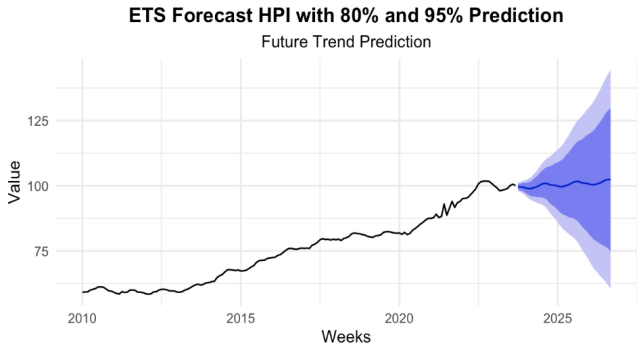


Figure 4. ETS forecast of HPI with 80% and 95% prediction intervals (photo credit: origin)

The auto.arima() function in R's forecast package identified a seasonal ARIMA(1,1,3)(1,0,0) model with drift as the optimal specification, selected through a stepwise search algorithm minimizing the AIC [11]. This specification indicates that: (1) non-seasonal patterns are captured by first-order differencing (d=1) to address trend non-stationarity, one autoregressive term (p=1) modeling price momentum, and three moving average terms (q=3) capturing short-term shocks; (2) seasonal patterns are modeled through one seasonal autoregressive term (P=1) at lag 12, with no seasonal differencing (D=0) or moving average terms (Q=0), reflecting the annual periodicity evident in the data. This model can be written as an equation below: $(1-\varphi_1 B)(1 - \Phi_1 B^{12})(1-B)y_t = c + (1 + \theta_1 B + \theta_2 B^2 + \theta_3 B^3)\varepsilon_t$. An AIC of 332.804 is lower than that of other term combinations. The AIC result obtained from the ETS model (692.86) reveals an improvement in model parsimony towards the given time series, representing a substantial improvement of 360.056 AIC points, which is highly statistically significant ($p < 0.001$). Moreover, the Ljung-Box test resulted in a p-value of 0.1202 ($p > 0.05$). As the null hypothesis was not rejected, it appears that the residuals exhibit no significant autocorrelation and can be treated as white noise.

The absence of significant autocorrelation suggests that the SARIMA model is capable of capturing the underlying systematic patterns in the data. The three-year forecast is generated using the forecast package in R, with the simulation-based prediction intervals to account for parameter uncertainty. As shown in Figure 5, the projected trajectory displays a clear upward trend with a moderate slope and substantially less volatility than the post-2020 historical increase. Overall, the UK HPI is expected to reach approximately 105 by 2028.

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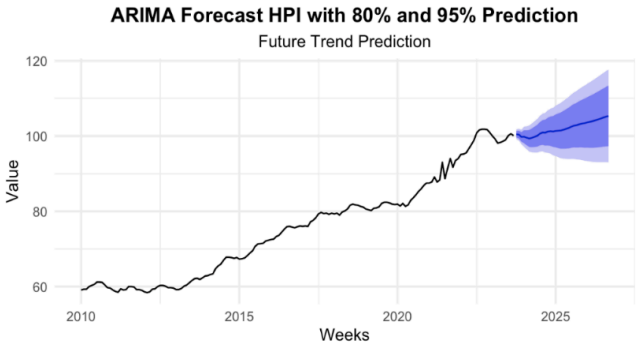


Figure 5. SARIMA forecast of HPI with 80% and 95% prediction intervals (photo credit: origin)

The forecasting framework enables the ETS and SARIMA predictions to be combined into a single visualization using the autolayer function in R (Figure 6). The results indicate that the ETS model underestimates the United Kingdom house price index and produces more conservative projections.

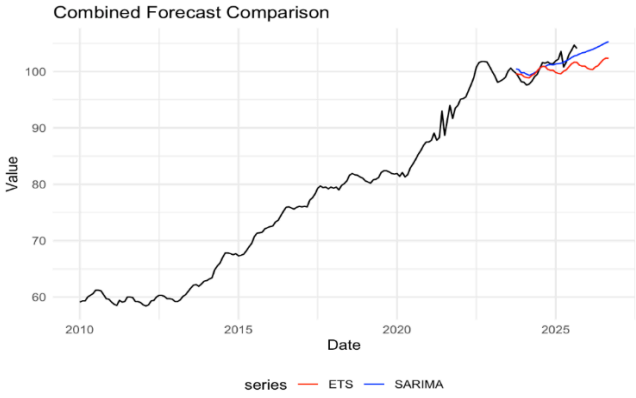


Figure 6. Forecast comparison between ETS and SARIMA (photo credit: origin)

3.4. Model validation and comparison

Table 1. Performance metrics of ETS and SARIMA model (4 decimal)

Model	RMSE	MASE	MAE	MAPE
ETS(training set)	0.6760	0.1192	0.3946	0.4877
ETS (test set)	1.6763	0.4167	1.3788	1.3543
SARIMA(training set)	0.6301	0.1288	0.4262	0.5446
SARIMA(test set)	1.1418	0.2941	0.9732	0.9665

Forecast accuracy is evaluated using RMSE(Root Mean Square Error), MASE(Mean Absolute Scaled Error), MAE(Mean Absolute Error), and MAPE(Mean Absolute Percentage Error) (Table 1), selected for their complementary strengths in assessing different aspects of forecast accuracy. The evaluation is performed on both ETS and SARIMA models using their respective training and test datasets.

The findings demonstrate that the SARIMA framework outperformed the ETS model across both training set and the test set. This signals a high predictive reliability. Therefore, the SARIMA modelling continues to represent a robust threshold in linear statistical forecasting, particularly for

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time series exhibiting both trend and seasonality. However, these models have limitations as certain external factors cannot be captured within statistical-based models, including macroeconomic shocks, policy changes or budget constraints [12].

4. Discussion and limitation

This study has provided an empirical evidence of the robust relevance of traditional statistical models under the era of rising machine learning techniques [3,7]. The seasonal ARIMA(1,1,3)(1,0,0) model with drift delivers a compelling forecast for the UK HPI over January 2010 to September 2025. The superior fitness of the SARIMA framework the model fitness is substantiated via the diagnostic result -- Ljung-Box test compared to ETS model.

Although the SARIMA model can still provide a reliable performance as its ability to capture dynamics through differencing, seasonal patterns, and other non-seasonal ARIMA components [12]. This forecast result can be improved via other machine learning methods or multivariate analysis as linear statistical models may not adequately capture hidden patterns in the UK housing market. Integrating such approaches may yield a improved predictive performance, particularly during structural breaks or when incorporating exogenous variables [13].

Additionally, this study is constrained by the dataset's attributes. The use of monthly observations may neglect higher-frequency dynamics that could be depicted through a daily data. Furthermore, the framework also does not account for regional discrepancy as geographical factor such as the distinction between southern and northern part of United Kingdom could harness the price indices. Finally, while the 2010-2025 period is suitable for examining recent market conditions, it may fail to capture a long-term structural change in the UK housing market due to the lack of historical depth.

Practically, this study provides stakeholders with a robust statistical benchmark for short-term UK house price index trends. However, these forecasts should be integrated with scenario-based analysis and risk management strategies to account for external macroeconomic or geopolitical shocks that purely historical models may not capture.

5. Conclusion

This study aims to find the best model for predicting the UK House price index and discover its volatility pattern via conventional time series analysis approaches. By comparing the result form ETS and SARIMA models. The seasonal ARIMA(1,1,3)(1,0,0) model with drift is considered the most suitable forecasting model. This conclusion is based on a comparison of information criteria and accuracy metrics for reliability. Therefore, this model would relevant stakeholders to make informed and educated decisions not just in the UK but also global housing markets. Moreover, future studies are recommended to investigate the UK house price market through interdisciplinary approaches to gain a nuanced understanding for better decision making.

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