Prediction of US GDP Growth Rate Based on ARIMA and ETS

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Abstract. Based on the demand for predicting the quarterly year-on-year growth rate of the US GDP, this paper conducts time series prediction research using the ARIMA model and the ETS model. The background of research stems from the fact that GDP, as a core indicator for measuring a country's economic strength, its accurate prediction is of vital importance to policymaking and market decision-making. This paper captures the characteristics of data autocorrelation and differential stabilization by constructing the ARIMA model and combines the dynamic modeling ability of the ETS model for horizontal, trend and seasonal components to compare and analyze the performance of the two methods in the prediction of GDP growth rate. The research results show that both models can effectively depict the dynamic characteristics of GDP growth. However, the ARIMA model demonstrates higher prediction accuracy on MSE and BIC by effectively identifying the data structure. The significance of this study lies in providing methodological references for macroeconomic forecasting, verifying the complementarity of the two classical models in GDP growth rate prediction, and contributing to enhancing the robustness of economic forecasting and the efficiency of policy response.

Keywords: ETS; ARIMA; time series; quarterly GDP growth rate.

1. Introduction

As the world’s largest economy, fluctuations in US output generate significant spillover effects on global trade, finance, and capital flows [1]. Improving prediction accuracy therefore provides international markets with more stable expectations and reduces uncertainty. Moreover, GDP forecasts serve as a critical reference for macroeconomic policymaking, enabling timely fiscal and monetary adjustments to prevent overheating or recession [2]. Accurate forecasts also enhance the applicability of econometric models and provide quantitative bases for evaluating policy effectiveness [3]. Finally, financial institutions benefit from reliable GDP forecasts by optimizing asset allocation and risk management, thereby mitigating systemic risks caused by macroeconomic volatility [4]. Hence, enhancing GDP forecast accuracy not only strengthens US economic stability but also contributes to global economic resilience.

In recent decades, numerous studies have investigated the forecasting of GDP growth rates using time series and econometric approaches. For instance, Nelsonexamined the predictive performance of early econometric models for U.S. output [5]. Khalaf, Saphores, and Bilodeau applied ARIMA models to U.S. GDP and analyzed structural breaks in growth dynamics [6]. More recently, Marcellino, Stock, and Watson compared alternative autoregressive forecasting strategies [7]. And Akin and Arslan evaluated the relative accuracy of ARIMA, VAR, and Bayesian VAR models in predicting U.S. GDP growth [8]. Although these studies provide valuable insights, the literature still shows limitations when comparing alternative models, particularly in the context of economic shocks and structural changes after the COVID-19 pandemic. To address this gap, this paper employs two widely used time series approaches-the Autoregressive Integrated Moving Average (ARIMA) model and the Exponential Smoothing State Space Model (ETS)-to forecast U.S. quarterly year-over-year GDP growth and evaluates their comparative performance. The changes in the growth rate of the US GDP have significant spillover effects on global trade and financial markets. The ARIMA and ETS models can enhance the accuracy of predicting inflection points and help countries deal with the risks of imported inflation or recession in advance.

2. Data

The quarterly growth rate of real GDP in the United States used in this article is derived from the official release of the Bureau of Economic Analysis of the United States (https://www.bea.gov/). The quarterly growth rate of real GDP in the United States is a core and authoritative indicator for measuring the dynamics of the US economy, released quarterly by the Bureau of Economic Analysis (BEA) of the United States. This indicator is calculated based on the year-on-year growth rate (compared to the same quarter of the previous year), reflecting the quarterly trend of economic output after excluding price factors. Compared with the annual growth rate, quarterly data can more sensitively capture short-term economic fluctuations and provide high-frequency basis for policymaking and market analysis. Considering data integrity and research continuity, all quarterly data from the first quarter of 1984 to the second quarter of 2025 (a total of 166 observations) were selected. This data series inherently possesses temporal continuity and requires no additional processing, fully covering the economic cycle fluctuations over 40 years. The dynamic evolution of the quarterly growth rate of the real GDP of the United States during the sample period is shown in Fig. 1.

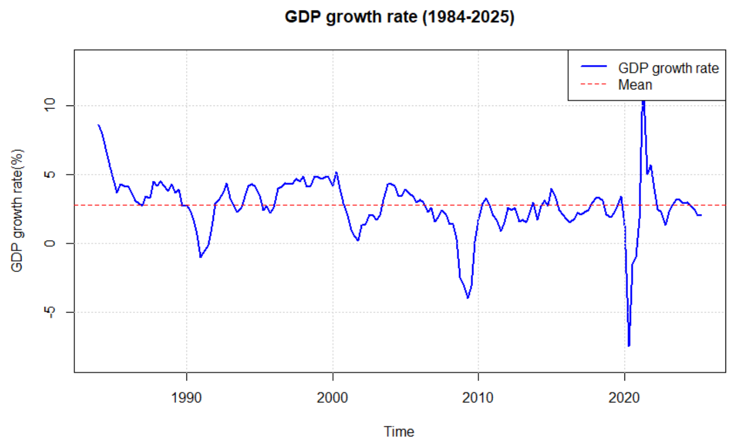

Fig 1. GDP growth rate

Among them, the data changes in the four quarters from June 2020 to June 2021 are abnormal. It is speculated that this might be the impact of the COVID-19 pandemic on the US economy. The year-on-year growth of 2.0% in the second quarter of 2025 is the same as 2% in the first quarter. It is speculated that the economy has entered a plateau period. The endogenous growth momentum has stabilized, and the economy has transitioned from sharp fluctuations after the pandemic to a medium and low-speed stable stage. This stability is reflected in the quarterly data, that is, maintaining the same growth rate for two consecutive quarters. The following Table 1 shows some statistics about the data.

Table 1. Descriptive Statistics

	mean	SD	max	min	kurtosis	skewness
GDP Growth Rate	2.77	2.05	12.2	-7.5	9.75	-0.59

The long-term mean stability (2.77%) reflects the resilience of the US economy, but high volatility (SD=2.05%) and a left-skewed peak (kurtosis 9.75) expose its high sensitivity to external shocks. For instance, events such as the 2008 financial crisis and the 2020 pandemic both led to a sharp drop in growth rates and a long recovery period. The Kurtosis is 9.75, which is much greater than 3. It indicates that the data follows a Leptokurtic distribution, meaning that while the growth rate is concentrated around the mean, the frequency of extreme values (especially negative growth) is much higher than that of the normal distribution. This is consistent with the characteristics of the US economy, which is highly dependent on the financial system and vulnerable to external shocks - black swan events such as financial crises and trade wars can trigger systemic risks, leading to a sharp drop-in growth rate. The Skewness is -0.59 (negative skewness). A distribution showing a Negative Skewness means that the probability of negative growth is higher than expected in a normal distribution. Although the average remains positive, the left-skewed feature warns that the US economy is facing a relatively high tail risk of "growth stagnation - recession", and it is necessary to be vigilant against cyclical downward pressure. The Standard deviation is 2.05%. This indicates that the degree of dispersion of the quarterly growth rate around the mean is moderately high. Compared with European economies (such as Germany, where the standard deviation of GDP growth is approximately 1.8%), the US economy is more affected by factors such as financial markets and consumption cycles and is more volatile.

3. Method

3.1. ARIMA

The time series characteristics of the quarterly GDP growth rate are in line with the ARIMA premise. Box, Jenkins and Reinsel introduced the theories and methods of time series analysis systematically, especially the AR, MA, ARMA and ARIMA models [9]. After seasonal adjustment, the growth rate sequence shows no obvious trend or seasonality, only random fluctuations, which meets the ARIMA's requirement for a "stationary sequence". Economic growth has an Inertia Effect, meaning that the growth rate of the previous quarter will have a continuous impact on the next quarter. This autocorrelation can be captured by ARIMA's autoregressive term (AR). Research by institutions such as the IMF and the World Bank shows that ARIMA has a lower error rate in short-term (1-4 quarters) GDP predictions than traditional econometric models (such as VAR), especially when predicting inflection points (such as the start of a recession). The specific formula is as follows.

$$Y_t = c + \sum_{i=1}^{p} \varphi_i Y_{t-i} + \sum_{i=1}^{q} \theta_t \epsilon_{t-i} + \epsilon_t \tag{1}$$

In this formula, Y_t is the US GDP Growth Rate this paper studies. φ_1 to φ_p are the parameters of the AR model. These parameters are used to describe the relationship between the current value and the value of the past p time points. θ_1 to θ_q are the parameters of the AR model. These parameters are used to describe the relationship between the current value and the error at q time points in the past.ϵ_t is the error term at time t. c is a constant term.

3.2. ETS

The ETS model comprises three core components that collectively describe dynamics in the time-series. Hyndman, Koehler, Ord, & Snyder explains the additive/multiplicative trends and seasonal processing of the ETS model, as well as the calculation of the prediction intervals [10]. Errors capture random, unexplained fluctuations in the data—variations not attributable to underlying trends or seasonal patterns. They represent noise or irregular shocks (e.g., unexpected economic events). Trend defines the long-term directional movement of the series over time. It can take forms like additive growth or multiplicative scaling (exponential change), depending on the model variant. Seasonality reflects periodic, recurs patterns that repeat at fixed intervals, this component accounts for regular, predictable variations driven by seasonal factors.

Full mathematical formulation integrates these elements to generate forecasts, balancing historical patterns with stochastic error terms. The year-on-year growth rate of quarterly GDP in the United States has a typical trend + error structure, which precisely aligns with the core components of ETS. The GDP growth rate often shows a long-term trend (such as the high growth during the post-war "golden age" and the slowdown after 2000). The additive/damped trend component of ETS can capture this directional change. Short-term fluctuations (such as the impact of the epidemic, policy adjustments) are random disturbances. The error term of ETS can absorb these unpredictable shocks and prevent the model from overfitting. Although the year-on-year growth rate has eliminated seasonality (such as turning quarter-on-quarter to year-on-year), if the original data contains seasonal patterns (such as peak consumption seasons), the seasonality component of ETS can further optimize the prediction accuracy. The specific formula is as follows.

$$l_t = \alpha y_t + (1-\alpha)(l_{t-1} + \emptyset b_{t-1}) \quad (2)$$

$$b_t = \emptyset b_{t-1} + \beta(l_t - l_{t-1}) \quad (3)$$

$$\hat{y}_{t+h|t} = l_t + b_t(\emptyset + \emptyset^2 + \cdots + \emptyset^h) \quad (4)$$

l_t is the level, reflecting the current position of a sequence. $b_t$is the damped Trend reflecting the rate of trend decay.y_t is an actual observed value. $\hat{y}_{t+h|t}$is the predicted value of step h ahead of time. α is the control parameters for the horizontal update speed, $\alpha \in [0,1]$. B is the control parameters for the speed of trend updates, $\beta \in [0,1]$. $\emptyset$ is the key parameters for controlling the rate of trend decay, $\emptyset \in [0,1]$.

4. Results

In this study, this paper uses data from 1984 to 2025 as the training set and data from 2023 to 2024 as the test set. The parameters obtained by fitting training set data are shown in Table 2 below.

Table 2. Parameter Fitting Results

	Parameter 1	Parameter 2	Parameter 3
ARIMA	0	1	3
ETS	A	Ad	N

As shown in Table 2, this paper selects the ARIMA (0,1,3) and ETS (A, Ad, N) models respectively. For ARIMA (0, 1, 3), p=0 signifies no autoregressive component, meaning the model does not utilize past observed values to forecast the current value. d=1 indicates that differencing is required to achieve stationarity, implying the presence of non-stationary trends (or seasonality) in the data that can be removed via a single difference operation. q=3 denotes a moving average component with an order of 3, meaning the model incorporates three error terms to predict the current value. For the ETS (A, Ad, N) model, the first letter “A” represents an additive error component, where random fluctuations are added to the level rather than multiplied. The second letter “Ad” stands for a damped additive trend, indicating that the trend component decays exponentially over time (unlike a standard additive trend, which grows linearly indefinitely). The third letter “N” confirms the absence of a seasonal component.The fitting results for both ARIMA and ETS are presented in Fig. 2.

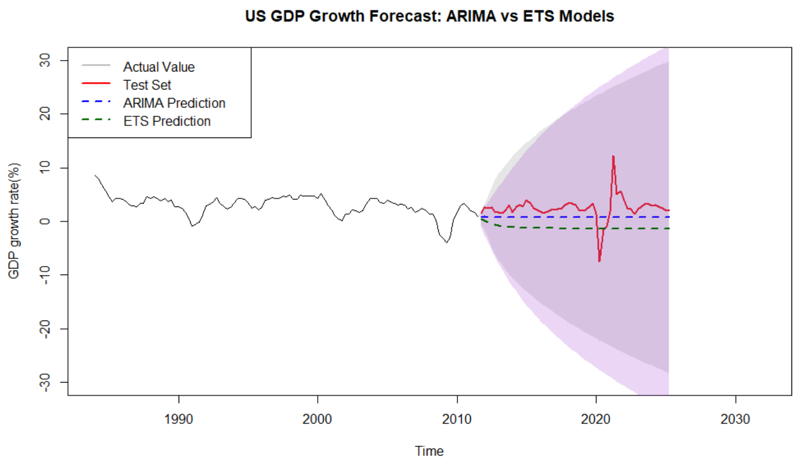

Fig 2. ARIMA vs ETS

By comparing two lines in Fig. 2, both showed a "stabilizing" trend during the forecast period, reflecting a common judgment that "long-term economic growth is stabilizing". The fluctuation range of ARIMA is smaller (with straighter lines), and ETS may cause minor numerical deviations due to model characteristics (such as exponentially smoothed weight distribution), but the overall trend shows no obvious differentiation. In order to compare the predictive performance of the two models more accurately, this article calculated the MSE and BIC of the two models respectively (See Table 3).

Table 3. Comparison Results

Model	MSE	BIC
ARIMA	7.38	239.66
ETS	17.83	489.17

Obviously, both the MSE and BIC of the ARIMA model are smaller than those of the ETS model, indicating that the ARIMA model is superior to the ETS model in predicting the US GDP Growth Rate.

5. Conclusion

This study addresses the forecasting of the U.S. quarterly year-on-year GDP growth by employing two classical time series approaches: the ARIMA and ETS models. Given that GDP serves as a key indicator of a nation’s economic performance, accurate prediction is essential for informed policymaking and market decision-making. The ARIMA model is applied to capture autocorrelation structures and stabilize the series through differencing, whereas the ETS model exploits state-space decomposition to model level, trend, and seasonal components dynamically. Comparative analysis reveals that both models effectively represent the dynamic behavior of GDP growth. The ARIMA model exhibits superior performance in terms of mean squared error (MSE) and Bayesian information criterion (BIC) by precisely identifying underlying data patterns. This research provides methodological guidance for macroeconomic forecasting, illustrates the strengths of ARIMA and ETS model in GDP prediction.

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