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A Comparative Evaluation of ETS and ARIMA Models for Forecasting China's Inflation Rate

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Abstract. This study conducts a comparative evaluation of the Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) models for forecasting China's monthly inflation rate, based on Consumer Price Index (CPI) data from December 2022 to November 2025. Within a univariate forecasting framework, both models are estimated and assessed using out-of-sample accuracy measures, including the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Scaled Error (MASE). The empirical results consistently show that the ARIMA model, specifically the ARIMA (1,0,0) specification, outperforms the ETS model across all evaluation metrics. This advantage reflects ARIMA's effectiveness in capturing short-term persistence and lag dependence in the inflation series, rather than increased structural complexity. In contrast, the automatically selected ETS (A, N, N) model produces smoother forecast trajectories by emphasizing level-based smoothing, which provides a stable representation of underlying inflation behavior but reduces responsiveness to short-lived fluctuations. Overall, the findings highlight the importance of aligning model selection with data characteristics and forecasting objectives. While ARIMA models are better suited for short-term inflation monitoring under low-volatility conditions, ETS models may remain informative for medium- to long-term trend analysis. Limitations related to the short sample period and the univariate framework suggest avenues for future research using extended datasets and multivariate models.

Keywords: Inflation Forecasting, ARIMA Model, Exponential Smoothing (ETS), Model Comparison, China

1. Introduction

Forecasting inflation accurately is important for macroeconomic fine-tuning and policy making. This need is particularly pressing in large, evolving economies like China. One important indication of the broad state of the economy of a country is the inflation rate determined through the rise in prices. There will be fluctuations in the general price level of goods and services when it changes. The purchasing power of residents, macroeconomic stability, and the decision-making process regarding monetary policy are greatly affected by it [1]. As China became one of the world's major economies, the reasons for inflation and its dynamic patterns became increasingly more complicated, which reflects economic transformation and policy adjustments. Forecasting inflation

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will allow the government to formulate macroeconomic control policies more effectively. In addition, it also helps enterprises and other economic entities develop their decision-making and operations.

To study the dynamic features of inflation, academic work often uses time series techniques to price data [2]. The Consumer Price Index (CPI) is generally employed as an indicator of inflation in the respective literature. An analysis of the CPI–based time series will identify the trend and periodicity of price movements and thus can be used to forecast inflation. Economic growth, monetary policy orientation, changes in energy and commodity prices, and the international economic environment are all internal and external influences on China's inflation [1]. The inflation rate is unstable, even though the government is conducting measures to stabilize it. Economic restructuring, external shocks, and market expectations are said to be the causes of inflation and price fluctuations. Changes in prices can fluctuate rapidly or fall faster than their fundamental trend because of special circumstances such as disasters and hoarding. These factors may cause a short-term fluctuation that is needed for systematic analysis of inflation, assessment of the economic operation trend.

Univariate time-series models are very simple forecasting methods. Moreover, they are easy to explain and interpret and work well in short-term forecasting. Nonetheless, it is not empirically clear which of the different univariate approaches is most effective for China. In this study, inflation data is going to be analyzed and forecasted using the very popular time series models ARIMA and ETS (exponential smoothing) models. Both models have a solid theoretical foundation and are both successful empirical ones in the forecasting literature.

The ARIMA model is used to capture temporal dependence in time series data by using autoregressive and moving average components, which are used to model short-term fluctuations in economic indicators. In contrast, the ETS framework, which stands for Error, Trend, and Seasonal, has a state-space formulation. That is, it decomposes a series into these 3 components and uses the exponential smoothing method to capture.

This study compares the forecasting performance of ARIMA and ETS models and assesses their suitability for modeling China's inflation rate. It does so under different assumptions and similarities of data.

Though ARIMA and ETS are often used, there is limited evidence comparing their performance for inflation in China, especially during the post-pandemic economic environment. The study applies both models to new high-frequency data to try to fill this gap. As a result of this, the present study does a systematic comparative analysis of the ARIMA and ETS models of short-term inflation forecasting in China. This study has three objectives: to assess their relative forecasting accuracy based on standard metrics, to evaluate which of them appears suitable given the observed character of China's inflation series, and to guide practitioners and researchers on model selection for Chinese macroeconomic forecasting.

2. Research design and methodology

This part of the text presents the methodology to forecast China's inflation. The three important components include: (1) a description of the data source and data pre-processing steps, (2) theoretical foundations and specification procedure of ARIMA and ETS models, and finally (3) criteria and metrics for evaluation and comparison of models. This systematic procedure guarantees that the empirical analysis can be replicated.

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2.1. Data description

This paper uses the monthly observations of inflation in China. The yearly change in Consumer Price Index (CPI) data for the month reflects the annual change in the representative group of products and services comprising the overall price levels. The National Bureau of Statistics provides the monthly CPI values from December 2022 to November 2025, which creates a total of 36 observations. The sample period is relatively short in length and also quite recent, owing to the after-effects of inflation in China due to the pandemic; however, it might limit the presence of long-term cycles. The data required pre-processing to make it consistent. Missing values dealing (none exists in this series), and It was converted into a regular time series object to be used in R/Python. Derived from the National Bureau of Statistics, CPI data covers December 2022 to November 2025 and gives a total of 36 monthly observations. The chosen period for this paper is relatively limited but quite recent. This period is chosen so that the paper studies the post-COVID inflation pattern in China. However, such a limited period may not help with the identification of long-term cycles. Pre-processing of the data was performed to ensure uniformity. This involved the treatment of missing values (this series had none) and structuring into a regular time series object in R/Python.

2.2. Introduction to the ARIMA model

The Autoregressive Integrated Moving Average (ARIMA) model is classified as a univariate analytical method for time series data. The model practitioners estimate that integrates autoregression (p), differencing (d), and moving average (q). The ARIMA model is widely used in economic forecasting due to its sound theoretical properties and flexibility for capturing different stochastic processes. ARIMA is an acronym for AutoRegressive Integrated Moving Average.

$$\phi(B)(1-B)^d y_t = \theta(B)\epsilon_t \tag{1}$$

This study has B is the backshift operator, $\phi(B)$ is an autoregressive polynomial, $\theta(B)$is a moving average polynomial, and ϵt is a white noise error term [3].

Because the ARIMA model has a strong theoretical foundation and because it is flexible enough to capture a wide range of stochastic processes, it is widely used in economic forecasting.

2.3. Introduction to the ETS model

Besides the ARIMA model, the Exponential Smoothing model is a state space model (ETS – Error-Trend-Seasonality) used for forecasting time series data. The model includes Error, Trend, and Seasonal components, which can take the forms additive (A), multiplicative (M), or none (N). By combining these three choices for each of the three components, a huge number of possible models is arrived at. For example, the ETS (A, N, N) model refers to simple exponential smoothing [3].

Through the state-space formulation of ETS models, they are easy to work with economic data showing trending and seasonal characteristics. This model is mainly used in economic and business forecasting as it is stable and able to capture seasonal patterns.

The model specification of the analysis does not pre-specify the ETS form (error, trend, seasonal). Instead, the ets() function from the forecast package in R (or equivalent) is used to select the best ETS model from a set of candidate ETS models based on the optimization of the indicated AIC or likelihood. The chosen ETS specification is fitted to the inflation series based on a data-driven approach.

DOI: 10.54254/2754-1169/2026.LD31616

2.4. Model evaluation

The fitted ARIMA model as well as the ETS models were compared using standard accuracy measures, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) [4]. More specifically, the last k observables (6 12 months, for example) are reserved for out-of-sample evaluation, while the preceding data is used for model estimation (train set). These measures are an illustration of the credibility and efficiency of the model.

3. Empirical analysis and forecasting results

3.1. Data characteristics and preliminary analysis

Before time series modeling, this study pre-process the data this study collects before working on time series analysis. The CPI is reported as a year-on-year index whereby the previous year is normalised to 100. For this article, the inflation rate is constructed as.

$$Inflaton_t = CPI_t - 100 \tag{2}$$

The index is converted into an inflation indicator that shows changes in consumer prices against the level attained in the same period last year, which is seen as an economic interpretation.

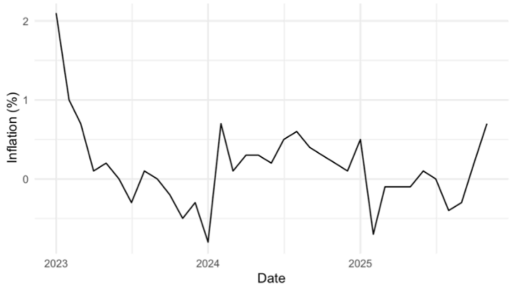

Figure 1. Monthly data of China's CPI (photo credit: origin)

The processed inflation rate time series is shown in Figure 1. The series shows minor fluctuations around the zero mark over time, which indicates that the inflation level is relatively stable during the period of the sample. Some short-term fluctuations have occurred, but no sustained upward or downward trend is observable, suggesting that inflation broadly remained contained during the time frame analysed.

Further descriptive statistical analysis reveals these findings. The inflation rate is expected to range between -0.80 and 2.10 with a mean value of zero. The overall pressure is inflationary but in a mild manner. Most of the observed movement in inflation mainly refers to a temporary change in the price. In other words, the price movement is not because of structural change. Instead, the price movement is due to the short-run dynamics influencing inflation.

3.2. Forecasting results

3.2.1. ARIMA model estimation and forecasting

Based on the pre-processed inflation series, the ARIMA model is applied to capture the short-run dynamics of inflation [5]. Since the series has relatively stable fluctuations in the values without any

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abnormalities, there's no need for differentiation, so the differencing order d = 0. The next step is to use the ACF and PACF graphs of the data to determine the p and q values. The following ACF and PACF plots are shown in Figure 2.

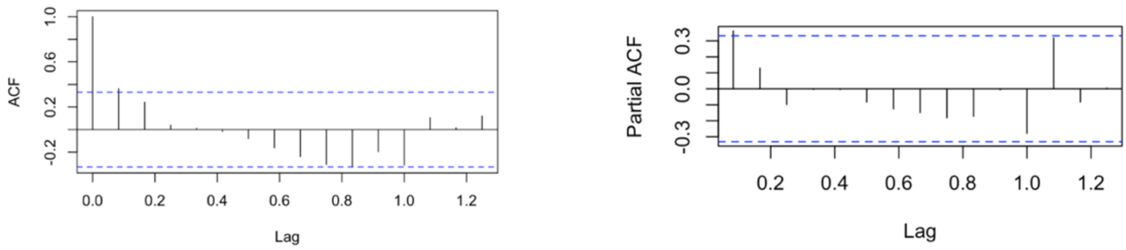

Figure 2. Sample ACF and PACF plots (photo credit: origin)

The autocorrelation function indicates diminishing correlation, while the partial autocorrelation function peaks sharply at the first lag and then declines. The inflation series appears to show a strong correlation in the short run, which is consistent with the AR(1) process.

The inflation series is described using the ARIMA (1,0,0) model based on this analysis. By comparing the Akaike Information Criterion (AIC) of feasible candidate models (e.g., ARIMA(0,0,1), ARIMA(1,0,1)), I validated this preliminary identification. The ARIMA(1,0,0) achieved the lowest AIC, supporting its usage as a parsimonious and statistically adequate specification. Results show the inflation level of the previous period has a partial influence on the inflation level of the current period. While the influence level can be said to be a long-term influence, it is not as significant as the more recent influences.

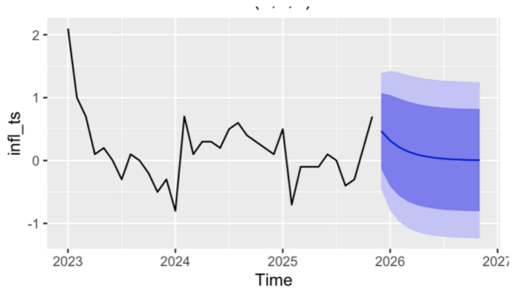

Figure 3. ARIMA (1,0,0) model (photo credit: origin)

Figure 3 shows the forecasting outcome of the ARIMA (1,0,0) model. Ultimately, the predicted path for inflation is generally stable, with moderate moves around the mean. The x-axis being a common trait of time series forecasts, the forecast intervals reflect increasing uncertainty.

3.2.2. ETS model estimation and forecasting

The inflation time series is modeled using the Exponential Smoothing (ETS) model in order to capture the trend and the short-term dynamics. As opposed to ARIMA, the ETS model captures patterns through the smoothing of level, trend, and seasonal components, rather than directly parameterising serial correlation [6]. Based on the AIC, the best ETS model was automatically selected, resulting in an ETS(A, N, N) specification. That is, the model had additive errors with no explicit trend or seasonal components for the series (Figure 4). Over the projection period, it is anticipated that inflation will continue to be quite stable, according to ETS forecasts. The levels displayed in the chart oscillate moderately around the long-run mean, and they do not exhibit strong

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inflationary or deflationary pressures in the future. The ETS forecasts are smoother than ARIMA model forecasts, indicating that the models focus on smoothing the trend rather than short-term variations.

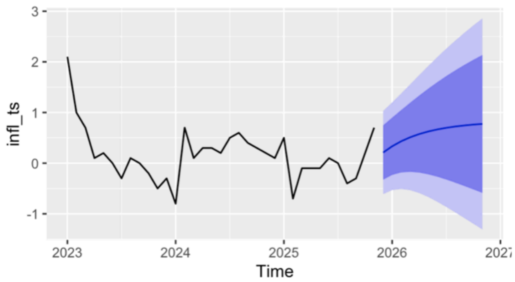

Figure 4. ETS model (photo credit: origin)

The length of the forecasting interval produced by the ETS model increases progressively with the length of the forecasting period [7]. This region mirrors an increment in uncertainty that is connected with long-run forecasts and follows principles of time series forecasting. In conclusion, the ETS model provides a good description of the long-run trend of inflation with stable and reasonable prediction results for future inflation

dynamics. Figure 4: The ETS Forecast. A visual comparison with Figure 3 (ARIMA forecasts) shows that the ETS forecast path is indeed smoother. It places more weight on more recent observations in a recursive manner, making it less responsive to individual random shocks.

3.2.3. Comparative model performance evaluation

The forecasting performance of the ARIMA model and ETS model has been compared through RMSE, MAE, and MASE, which is shown in Table 1. These metrics offer a quantitative gauge of how far off the size of forecast errors is, while also allowing us to compare model accuracy quantitatively.

Table 1. Out-of-sample forecast accuracy metrics

Model	RMSE	MAE	MASE
ARIMA	0.456	0.314	0.47
ETS	0.572	0.438	0.66

The results reveal that the performance of the ARIMA model is superior to that of the ETS model in all three criteria. In particular, the ARIMA model has an RMSE of 0.456 and an MAE of 0.314. Both of these values are lower than those of the ETS model, which has an RMSE of 0.572 and an MAE of 0.438.

Both differences in the MASE value indicate that ARIMA has a better prediction than ETS. However, an additional check on the accuracy of the training data is essential since further development is needed for the forecasting model. Specifically, ARIMA and ETS both return MASE of less than 1 (ARIMA: 0.47; ETS: 0.66), meaning both beat a simple naïve forecast benchmark (where MASE = 1). Moreover, the lower MASE of the Multiple Linear Regression model is another evidence of its nil superiority over the benchmark as well as the ETS model.

The ARIMA model provides superior short-term forecasts of inflation to the ETS model as illustrated above. The smoother forecast path obtained from the ETS model yields a larger error

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measure, indicating that the predictive accuracy in the evaluation period was low. In the case of this specific dataset and forecast horizon, the results uniformly favour the ARIMA(1,0,0) model. ARIMA modeling of the time series may be recommended for short-term forecasting of inflation in low volatility regimes like China recently experienced.

4. Discussion

4.1. Core findings and their theoretical significance

Within the forecasting framework of this study, ARIMA and ETS models were applied to observe the monthly inflation of China from December 2022 to November 2025. The ARIMA model outperformed the ETS specification in all three evaluation metrics, RMSE, MAE, and MASE [8]. This finding has important implications that go beyond just numbers. Moreover, it appears that short-horizon inflation movements in China within this period are better explained by models that maintain short-horizon dependence and do not smooth in the long run.

Such a finding doesn't seem surprising at first. It would appear that a simple ARIMA (1,0,0) does not yield any better forecasts than an extensive exponential smoothing class. In order to answer this question, this study needs to go beyond just comparing accuracy and instead look at the relationship between the mechanisms of the models and the inflation process itself.

4.2. Unpacking the superiority of ARIMA: a synthesis of empirical evidence and model mechanics

4.2.1. Alignment with data characteristics: short-term persistence and the AR(1) structure

The inflation series is extremely short-term persistent, but no clear long-run trend can be said to exist [9]. Data-wise, this study observes the presence of first-order autocorrelation from the ACF and PACF, which suggests that inflation is primarily influenced by its immediate predecessor. In these circumstances, it is ARIMA (1,0,0), the model that best fits the series empirically.

In terms of methods, ARIMA models incorporate lag dependence through autoregressive features. The AR(1) term allows inflation shocks to be transmitted forward quickly in this study. This responsiveness is especially valuable when inflation variability is mainly produced by transitory factors, such as short-lived supply-demand imbalances or temporary policy changes, rather than persistent structural changes.

In terms of economic processes, this behavior is consistent with inflation determined by price rigidity and inertia of expectations. The effect of policy signals or cost shocks on price is usually one or two months. After that, the effect dissipates. In the first place, the consideration of higher-order AR terms is neglected during the preliminary diagnostics since their addition has a negligible performance increment. This reinforces the idea that inflation persistence in the sample period operates at a very short horizon.

4.2.2. The smoothing dilemma of ETS: attenuation of informative short-term fluctuations

Conversely, the ETS structure underscores the smoothing process and extraction of level or trend components. Whereas, if tightly-controlled inflation occurs continuously, then modeling the mean response as a weighted average of past values can be advantageous in practice. The automatically chosen model ETS(A, N, N) is very parsimonious but gives more weight to historical averaging, which can dampen the high-frequency inflation signal.

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There is a tension not to overlook. Smoothing deal noise but it has a cost. If inflation is stable over time, then excessive smoothing may eliminate economic significance from short-term variation. During the model comparisons, it was noticed that the ETS forecasts adjusted more slowly following sudden but temporary inflation spikes. This resulted in systematic forecast lags against ARIMA.

This does not mean that ETS models are necessarily worse. The model may not adequately align with the characteristics of the current data. In a regime of low volatility and short-memory inflation, it appears that the strengths of ETS (extraction and stability) emerge as a disadvantage for short-term accuracy.

4.2.3. Quantitative validation: MASE results and forecasting efficiency

MASE values of both models being less than unity confirm that inflation in China exhibited exploitable temporal structure during the sample period, exceeding a naïve benchmark. Nonetheless, the extent of progress varies significantly. The ARIMA model achieves notable improvements in RMSE compared to the ETS model, signifying its relative efficiency in tracking short-term inflation dynamics [10]. The distinction is an important one, because while outperforming a naïve forecast is a minimal requirement, outperforming it by a substantial margin is consistent with genuine information gain. In contrast, a mechanical fitting of a previous model can easily achieve the former, but struggles to attain the latter.

4.3. From model performance to economic insights

4.3.1. Practical recommendations for short-term inflation surveillance

From a policy point of view, the findings illustrate the utility of the ARIMA-type models in short-term inflation monitoring. Macroeconomists and central banks usually need fast signals of surging inflationary tension, not so much accurate long-run forecasts. In this aspect, the responsiveness of ARIMA forecasts lends itself well to use for near-term monitoring and quick policy evaluation.

Firms engaged in cost management or short-term pricing decisions may benefit from forecasts that down-weight events from inflation history. When decisions take place in months rather than years, then capturing short-run persistence becomes more relevant than smoothing the long-run trend.

4.3.2. Characterizing China's inflation dynamics: evidence of short-memory persistence

The ARIMA model can show strong performance forecasting ability on stock price returns. According to the model structure, China's inflation process within the sampling period possesses strong short-term continuity but weak long-term momentum. The above-stated behaviour is consistent with an environment in which price changes respond rapidly to recent developments but do not cumulate into prolonged inflationary processes.

This result helps advance ongoing discussions about the inflation persistence in a low inflation area. Some theoretical models focus on structural determinants and long-run inflation anchoring. However, the results here suggest that in the Chinese context at least, inflation dynamics may be better characterized as short memory processes driven by transitory shocks.

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4.4. Limitations and avenues for future research

In spite of this knowledge, there are several limitations. Because of a relatively short sample period, it is not possible to assess long-run structural changes in the behaviour of inflation. In addition, the univariate framework this study adopts here precludes the consideration of exogenous factors (such as commodity prices, exchange rates, or policy indicators), which may become more significant at longer horizons.

Subsequent studies may extend this work by employing multivariate or structural time series models and investigating whether the short-term persistence this study finds is constant in all inflation regimes. Using a variety of forecasting methodologies may also improve robustness, especially when inflation dynamics change rather than remain constant.

5. Conclusion

5.1. Summary of findings and interpretation

This research applies a univariate time-series framework to examine China's inflation using monthly CPI data from December 2022 to November 2025. By means of estimating and comparing the ARIMA and ETS models, the analysis assesses the forecasting mechanisms in a relatively stable inflation environment. Furthermore, this study interprets the performance gap between Tuned-BART and S-BART through the data-generating process it embeds.

During the sample period, inflation does not appear to have been volatile in the long run, but observed changes are mostly of the short-run variety. The presence of short-term volatility in the absence of a strong direction, especially a clear trend, provides an environment in which ARIMA's explicit modelling of lag-dependence is a key advantage over ETS's smoothing orientation. This model is not necessarily complex in structure, but it allows for the short-run dependence inherent in the inflation process. ARIMA shows better results than others in all accuracy measures, RMSE, MAE, and MASE.

Conversely, the ETS model puts more emphasis on level-based representation, which leads to smoother forecast trajectories. At a short delay, ETS is less accurate, but it provides a more stable estimate of underlying inflation behavior. The distinction highlighted implies that the two models have different analytical purposes, which do not imply any hierarchy of superiority, when the objective shifts away from the short term towards medium- or long-term directional insight, smoothing-based models may still be useful.

5.2. Methodological and practical implications

Findings lead us to a broader methodological conclusion about model selection in forecasting. This model should depend on the data and the forecasting objectives. If environments are subject to relatively short-lived shocks with low volatility, becoming responsive to recent observations becomes a matter of necessity. On the other hand, stability may be preferred to precision in the short term. Thus, the combination of multiple forecast perspectives can enhance interpretability and lower reliance on a single model structure in applied settings.

5.3. Limitations and future research directions

A number of limitations of this study are noted. A brief sample period may hinder the identification of structural breaks in inflation dynamics. Further, the exclusive focus on univariate models rules

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out the impact of external drivers like monetary policy interventions, shifts in energy prices, and global conditions. Extended data sets, multivariate specifications, or regime-dependent modeling strategies enhance inflation forecasting and provide deeper economic interpretation, and future research may incorporate such specifications into this framework.

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