Proceedings of ICFTBA 2025 Symposium: Data-Driven Decision Making in Business and Economics
DOI: 10.54254/2754-1169/2025.BL31143

US Semiconductor Stock Forecast Based on ARIMA and ETS Models

Mingyuan Wang

College of Letters and Science, University of California, Davis, USA
mylwang@ucdavis.edu

Abstract. The US semiconductor industry is positioned as a key pillar in contemporary global manufacturing and technology. Predicting the semiconductor price index is critical in deriving investment decisions and evaluating policies. This study applies two time-series prediction models: ARIMA and Exponential Smoothing (ETS) in forecasting the US Semiconductor Industry price index using monthly data from 2015 to 2025. The author runs the time series data against the two models to evaluate which one offers a better prediction. The findings of the analysis demonstrate that the two models effectively capture the hypothesized growth in the semiconductor industry's price index; however, the ETS model demonstrates superior forecasting accuracy with a lower root-mean-square error (RMSE = 10.68) relative to the ARIMA model (RMSE = 20.73). The findings of the study showed that exponential smoothing offers a more stable short-term forecasting framework, while ARIMA remains valuable for analyzing cyclical and seasonal fluctuations. Overall, this paper provides a quantitative perspective on the trajectory of the U.S. semiconductor industry within an evolving technological and macroeconomic landscape.

Keywords: Forecasting, Semiconductor Industry, ARIMA, ETS

1. Introduction

Proper prediction of the semiconductor industry is significant to policymakers, investors, and manufacturing companies. Reliable forecasts assist in making sound decisions on investment levels, capacity expansion, and supply chain coordination, as well as informing innovative planning and policy making. Since the semiconductor industry is at the nexus of advanced manufacturing, technology, and national security, its outlook significantly influences macroeconomic stability, technological competitiveness, and strategic autonomy. Proper forecasting also contributes to the efficiency of capital allocation and risk management in environments where demand patterns are volatile and technological shifts are rapid [1].

The available literature on semiconductor market forecasting can be categorized into three streams. The former examines how the macroeconomic and policy-based variables, like interest rate, inflation, and fiscal interventions, affect the demand of semiconductors. Research has shown that volatile trends in the consumer electronics sector significantly contribute to the general sales trend [2,3]. The second stream applies architecture of machine learning and artificial intelligence, such as long short-term memory (LSTM) networks, convolutional neural networks (CNNs), hybrid

DOI: 10.54254/2754-1169/2025.BL31143

frameworks in order to enhance the precision of semiconductor demand and price prediction [4,5]. Stream three uses classical time series algorithms like Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing (ETS) and state space to forecast sales, production indexes and market values of semiconductors [6]. Some of the aspects that make these traditional models have been widely used, especially when making short, and medium-term predictions are the simplicity in interpretation, statistical consistency, and the fact that they do not need large volumes of data to be effective [7].

In this paper, the future prediction of the monthly U.S. Semiconductor Industry Index (2015-2025) is done using ARIMA and ETS models. The training dataset will cover the period of 2015-2022, and the testing one would cover 2023-2025. The two models are effective in establishing the growth trend and the changes that occur in the industry in a cyclical manner. Based on the Root Mean Square Error (RMSE) metric, the ETS model achieves higher predictive accuracy than the ARIMA model. By comparing these two classical approaches, the study provides empirical insights into their predictive capabilities. It offers a data-driven perspective on semiconductor industry trends amid rapid technological advancement and an evolving macroeconomic landscape.

2. Data

The current study employs the monthly price index for the U.S. Semiconductor Industry Index from August 2015 to August 2025. The dataset used has 121 observations. The data were obtained from the FRED [8]. The dataset used captures major industry phases in the modern era, including the 2019 slowdown, the 2020 pandemic shock, the 2021–2022 post-COVID recovery, and the 2023-2024 acceleration attributed to artificial intelligence and increased demand [1].

Figure 1 shows a time series plot of the semiconductor industry index over the period under study. From Figure 1, a steady growth with cyclical volatilities, common in the industry's boom–bust dynamics, is observed. Price index is observed to have gradually risen between 2015 and 2019, dipped sharply in early 2020 amid global supply chain disruptions, and rebounded strongly from 2021 onward, a growth attributed to heightened demand for AI, data centers, and electric vehicles.

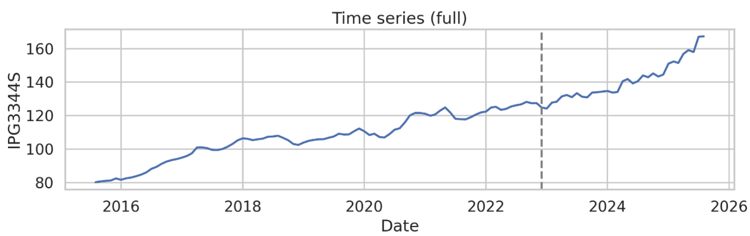

Figure 1. Time series

Table 1 shows descriptive statistics. From Table 1, the mean index value of 116.10 indicates stable long-term growth, while the standard deviation of 19.95 reflects moderate cyclical variation. The positive skewness (0.30) suggests slightly higher-growth months, whereas the negative kurtosis (–0.25) indicates a flatter-than-normal distribution. These characteristics-trend, seasonality, and moderate volatility-make the dataset suitable for ARIMA and ETS forecasting models.

DOI: 10.54254/2754-1169/2025.BL31143

Table 1. Descriptive statistics of the U.S. semiconductor industry index

mean	std	max	min	kurtosis	skewness	start	end
116.1033	19.9498	167.3866	80.2638	-0.24638	0.295572	8/1/2015	8/1/2025

3. Method

Time-series forecasting aims at determining the underlying patterns and trends in past data, in order to make correct predictions in the future. The two classical models used in this research are the Autoregressive Integrated Moving Average (ARIMA) model and the Error, Trend, and Seasonal (ETS) model in order to make a forecast of the monthly performance of the U.S. semiconductor industry. These models provide a comparative analysis of a parametric model (ARIMA) that absolutely specifies the correlation structure and a non-parametric model (ETS) that dynamically models the level, trend and seasonality.

3.1. ARIMA model

ARIMA considers the application of autoregressive (AR), integration (I), and moving average (MA) to describe the stationary time series [9]. The ARIMA can generally be written as follows:

$$\theta(B)\varepsilon_t = \varphi(B)(1 - B)^d y_t \tag{1}$$

Where y_t represents the observed series, ε_t represents a white-noise error term, $\varphi(B)$ and $\theta(B)$ represent polynomials of the backshift operator B, and d is the differencing order. For seasonal series, the extended form is ARIMA(p,d,q) × $(P,D,Q)_s$, where s is the seasonal period:

$$\varphi_p(B)\Phi_P(B^s)(1 - B)^d(1 - B^s)^D y_t = \theta\_q(B)\Theta\_Q(B^s)\varepsilon_t \tag{2}$$

3.2. ETS model

The ETS (Error–Trend–Seasonal) model is based on exponential smoothing principles [10]. Unlike ARIMA, ETS does not rely on differencing or fixed lag structures; it decomposes the series into level (l_t), trend (b_t), and seasonal (s_t) components updated recursively:

$$y_t = l_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t \tag{3}$$

$$l_t = l_{t-1} + b_{t-1} + \alpha\varepsilon_t \tag{4}$$

$$b_t = b_{t-1} + \beta\varepsilon_t \tag{5}$$

DOI: 10.54254/2754-1169/2025.BL31143

$$s_t = s_{t-m} + \gamma \varepsilon_t \quad (6)$$

Where m is the seasonal period (12 months). The selected model follows an additive trend without seasonal components, effectively capturing the steady upward direction of the semiconductor index without imposing unnecessary complexity. The ETS achieved a training RMSE of 1.38, reflecting excellent in-sample accuracy.

3.3. Model comparison framework

Both models were trained using data from August 2015 to December 2022 and evaluated on the test set (January 2023–August 2025). Forecast accuracy was assessed using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE):

$$RMSE = \sqrt{(1/n\ \Sigma(y_t - \hat{y}_t)^2)} \quad (7)$$

$$MAE = (1/n)\ \Sigma|y_t - \hat{y}_t| \quad (8)$$

Lower RMSE and MAE values indicate better predictive accuracy.

4. Results and analysis

4.1. Model fitting results

This segment shows the valuation findings of the ARIMA and ETS models for the U.S. Semiconductor Industry Index. The selected specification for the semiconductor industry index, based on AIC and BIC, was ARIMA(2,2,3)(0,1,1)$_{12}$, accounting for both non-seasonal and seasonal differencing (See Table 2).

Table 2. ARIMA(2,2,3)(0,1,1)(12) parameter estimates

Parameter	Estimate
AR(1)	-0.7225
AR(2)	-0.4190
MA(1)	0.3515
MA(2)	-0.4479
MA(3)	-0.9037
Seasonal MA(12)	-1.0000
σ^2	1.6577

Negative coefficients indicate a mean-reverting process with strong seasonal adjustment. The near -1.0 value of the seasonal MA term confirms the presence of annual periodicity typical of semiconductor production cycles. The fitted model achieved AIC = 228.44, BIC = 242.98, and LLF = -107.22, indicating a satisfactory fit. The two models both reflect the growth trend of the

DOI: 10.54254/2754-1169/2025.BL31143

semiconductor industry over the long-term period from 2015 to 2025. The key model fitting statistics: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the log-likelihood (LLF) are summarized in Table 3. A low value of AIC and BIC implies that the model fits the data better, whereas a high LLF value demonstrates a high probability of the observed data occurring at the model parameters.

Table 3. Model fitting summary

Model	Specification	AIC	BIC	Log-Likelihood
ARIMA	ARIMA(2,2,3)(0,1,1)(12)	228.44	242.98	-107.22
ETS	Additive trend, no season	64.92	—	—

The ARIMA model recorded an AIC of 228.44 and a BIC of 242.98, whereas the ETS model attained a lower AIC of 64.92, as shown in Table 3. This suggests that the ARIMA framework had a better overall fit compared to the ETS framework. The in-sample behavior of the ETS model is also found to be more stable, as indicated by the relatively small training RMSE (1.38), which is used in comparison with the ARIMA model. These findings imply that the ETS model better emulates the trend-oriented behavior of the semiconductor industry index.

4.2. Forecast accuracy comparison

Forecast accuracy was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) based on the 32-month out-of-sample test period (January 2023-August 2025). Table 4 presents the comparative results for the ARIMA and ETS models.

Table 4. Forecast accuracy comparison

Model	RMSE	MAE
ARIMA	20.73	17.38
ETS	10.68	8.15

As shown in Table 4, the ETS model achieved a significantly lower RMSE (10.68) and MAE (8.15) than the ARIMA model (RMSE 20.73; MAE 17.38). This indicates that the ETS model provides more accurate short-term forecasts of semiconductor industry performance. Figure 2 illustrates the actual and predicted values for both models, showing the ETS forecast tracking the observed data more closely.

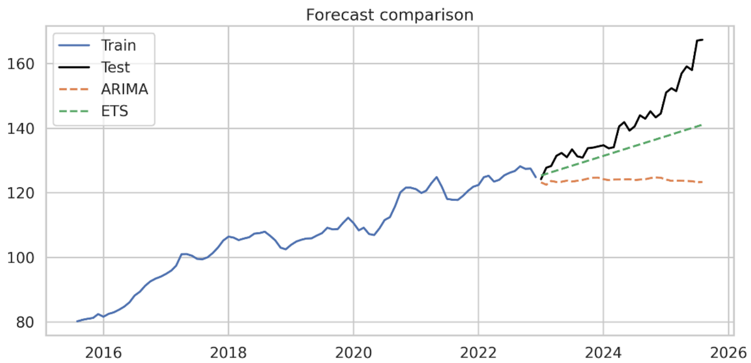

Figure 2. Comparison of actual vs forecasted values for ARIMA and ETS models

DOI: 10.54254/2754-1169/2025.BL31143

4.3. Discussion

The findings revealed that the ETS model yields better predictive performance in the U.S. semiconductor industry than the ARIMA model. The semiconductor index is characterized by a high long-term upward trend with brief periods of stagnation, and in these cases, exponential smoothing models would work better. The dynamism of the ETS model at the level and trend movements, without differentiation, enables the model to respond swiftly to market movements caused by technological and policy shocks.

In contrast, the ARIMA model is more explicit in capturing cyclical patterns in the industry, and it helps identify periodic variations and explain temporal dependencies. The high seasonality of the MA(12) parameter of ARIMA indicates the presence of annual production and inventory cycles, which are clearly observed in semiconductor manufacturing.

Generally, ETS is more effective in relation to forecasting, but it could be beneficial to apply a hybrid structure of two models to enhance resilience by taking advantage of the benefits of each. This empirical data shows that traditional statistical models are still appropriate tools in industrial forecasting provided they are tailored to domain-specific dynamics.

5. Conclusion

This paper contrasts the performance of ETS and ARIMA models to forecast the monthly performance of the U.S. semiconductor industry index in the period between 2015 and 2025. As was determined in the analysis, the two models have been relatively successful in terms of how they relate to the general growth dynamics and intricate ups and downs of the industry. The ETS model was even more accurate between the two and delivered more consistent results, which is specifically convenient in cases where the data under scrutiny is mostly trend-followed but has a minor bit of variation, as well. The findings stress the importance of selecting the right time-series model, in regards to data behavior, as well as the goals of forecasting. Despite the fact that ARIMA is the superior choice to use when it comes to the analysis of the cycles and the seasonality, ETS model is more liberal and adjusts to different trends. A combination of the two models, where the hybrid model is formed, is likely to contribute to the predictive strength and offer feasible benefits to investors, not to mention policymakers. So far, in the current paper, it has been established that the traditional time-series methodology has been even more relevant in the industry forecasting, and it has also been accepted that the hybrid and machine-learning methods could render it even more precise. The future of work must be taken into consideration to combine this traditional design with the more sophisticated technological algorithms to refine them as it enters technological industries.

References

[1] Simons, C., & Kulik, B. (2024). 2023 semiconductor industry outlook. Deloitte Global. Retrieved October 4, 2024, from https: //www.deloitte.com/global/en/Industries/tmt/perspectives/semiconductor-industry-outlook.html

[2] WSTS semiconductor market forecast spring 2024. (2024). World Semiconductor Trade Statistics. Retrieved October 4, 2024, from https: //www.wsts.org/76/103/WSTS-Semiconductor-Market-Forecast-Spring-2024

[3] Li-We, L., & Koundé Moanu. (2024). Forecasting stock prices of Taiwan Semiconductor Manufacturing Company (TSMC) using recurrent neural networks: Evaluating predictive performance in a volatile market. International Journal Artificial Intelligent and Informatics, 2(2), 61–65.

[4] Hopp, D. (2021). Economic nowcasting with long short-term memory artificial neural networks (LSTM). SSRN Electronic Journal.

[5] Chatfield, C., & Xing, H. (2019). The analysis of time series: An introduction. CRC Press, Taylor & Francis Group.

DOI: 10.54254/2754-1169/2025.BL31143

[6] Derakhshan, A., & Beigy, H. (2019). Sentiment analysis on stock social media for stock price movement prediction. Engineering Applications of Artificial Intelligence, 85, 569–578.
[7] Hyndman, R., & Athanasopoulos, G. (2018). Forecasting: Principles and practice. OTexts.
[8] SimElectronic component (NAICS = 3344). (2024). Federal Reserve Bank of St. Louis. Retrieved October 4, 2024, from https: //fred.stlouisfed.org/series/IPG3344S
[9] Khashei, M., & Hajirahimi, Z. (2018). A comparative study of series ARIMA/MLP hybrid models for stock price forecasting. Communications in Statistics - Simulation and Computation, 48(9), 2625–2640.
[10] Zeng, Z., & Chen, Y. (2025). Identifying and forecasting recurrently emerging stock trend structures via rising visibility graphs. Forecasting, 7(2), 26.