Forecasting the Philippine Stock Exchange Index Using Time Series Modeling Techniques

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ABSTRACT

Forecasting stock market indices like the Philippine Stock Exchange Index (PSEi) is crucial for investors, economists, and policymakers in understanding market behavior and making strategic decisions. This study aimed to examine the historical trend of the PSEi from 2004 to 2023 and determine which among various time series models best predicts its value in 2025. Specifically, the study evaluated polynomial regressions, logarithmic, power series, moving averages, exponential smoothing, and autoregressive models to identify the most suitable forecasting approach. A quantitative research design was employed using secondary data collected from Yahoo Finance and Investing.com. Monthly PSEi closing prices were compiled, averaged annually, and analyzed using Microsoft Excel and the Data Analysis Toolpak, which enabled trendline generation, smoothing applications, and lag-based regression modeling. The results showed that the PSEi experienced an overall upward but volatile movement over two decades, with notable dips during global crises. Among the models tested, the quintic polynomial regression achieved the highest explanatory power, but its predicted value of 15,872.78 suggests potential overfitting. Moving average models effectively smoothed short-term fluctuations but tended to underpredict future growth, while autoregressive models captured significant temporal dependencies, with higher-order lags revealing delayed market responses. The study concludes that while polynomial and curve-fitting models can capture nonlinear behavior, they should be used cautiously due to overfitting risks. It is recommended that future forecasting efforts explore hybrid models that combine polynomial trends, autoregressive structures, and smoothing techniques for improved accuracy.

Keywords: Autoregressive models, forecast accuracy, polynomial regression, stock market trends, time-series smoothing

INTRODUCTION

Forecasting stock market indices plays a critical role in guiding investment strategies, managing financial risk, and informing policy decisions, as these forecasts directly influence portfolio diversification and risk mitigation in financial markets (Mallikarjuna & Prabhakara Rao, 2019). As global markets become more volatile and interconnected, accurate and timely forecasting of indices, like the Philippine Stock Exchange Index (PSEi), provides valuable insights into capital market dynamics and investment behavior (Caporin & Storti, 2020).

Moreover, the PSEi serves as the main benchmark of the Philippine equity market, composed of 30 publicly listed companies with the largest market capitalization and liquidity, making it a widely used indicator of investor sentiment and overall economic performance (He & Wang, 2022). Although many studies apply advanced machine learning techniques to developed markets, there is a pressing need to evaluate classical time-series methods in emerging economies, where data limitations and structural shifts may impact model performance (Patwary & Das, 2023). These considerations support exploring robust yet interpretable statistical methods for forecasting the PSEi which this study attempts at covering.

This study examines the PSEi from 2004 to 2023 which is an era that spans volatile market dips and expansions like the 2008 global financial crises and the covid pandemic. This is an ideal period for robust PSEi analysis as studies have shown that forecast model performance and volatility patterns are significantly affected by such structural breaks in emerging markets (Tiu et al., 2020; Kirikos, 2013).

Furthermore, the study draws from the theoretical framework of time-series modeling and the Adaptive Market Hypothesis (Rönkkö et al., 2024), wherein the research evaluates multiple forecasting techniques. These include polynomial regressions (linear to sextic), logarithmic and power series, moving averages, exponential smoothing, and autoregressive models (AR(1)–AR(3)). These methods have proven useful in other emerging market contexts, with autoregressive and smoothing models effectively capturing short- to medium-term dynamics, while polynomial regressions better model non-linear patterns (Patwary & Das, 2023; Caporin & Storti, 2020).

Finally, by comparing the forecasting accuracy of these models which are evaluated using metrics such as R^2 and standard error which in turn are established criteria in time-series forecasting studies (Lawal et al., 2023), the study identifies which approach best projects the PSEi for 2025. The findings aim to contribute to the methodological literature on emerging market forecasting and aid investors and policymakers in developing reliable, data-informed strategies for future index behavior.

Research Questions

This study focuses on applying various time-series forecasting models to analyze the historical trends of the PSEi from 2004 to 2023 and determine the most accurate model for predicting its value in 2025. By evaluating a range of statistical forecasting techniques, the study aims to identify the best-fit model based on its explanatory power and predictive accuracy.

Specifically, this study seeks to answer the following questions:

1. What is the trend of Philippine Stock Exchange Index (PSEi) from 2004 to 2023.
2. Which time series model—linear, quadratic, exponential, polynomial (cubic, quartic, quintic, sextic), power series, moving average, exponential smoothing, or auto-regression—best predicts the average PSEi closing price for the year 2025?
3. What is the best-fit-model and what is the predicted PSEi for the year 2025.

METHODOLOGY

Research Design and Sample

This study employs a quantitative time-series forecasting design, using historical monthly closing prices of the Philippine Stock Exchange Index (PSEi) from 2004 to 2023. These monthly values were averaged to form annual figures, resulting in a total of 20 observations. As Lawal et al. (2023) point out, annual averaging is especially useful in emerging markets, where excessive short-run noise can obscure more meaningful macroeconomic signals. In addition to choosing these years, the resulting dataset captures a wide range of economic conditions, including periods of expansion, crisis, and post-crisis recovery, thus providing a rich and varied foundation for modeling and prediction.

The research design applies several time-series forecasting techniques to model and predict the future trajectory of the PSEi. Polynomial regression models (linear to sextic), as well as logarithmic and power series models, were employed to identify the best-fitting curve that represents the index's historical behavior. Polynomial models are particularly useful in modeling nonlinear patterns and structural shifts, which are commonly observed in financial indices affected by economic cycles, geopolitical risks, and investor sentiment (Zhang, Chen, & Li, 2025). In addition to curve-fitting models, the study also incorporates smoothing techniques, including moving averages with a 3-year dampening factor and exponential smoothing with a smoothing constant of 0.5. These models help reduce noise and clarify underlying trends in the data, a technique validated by recent financial econometrics literature (Zakamulin & Giner, 2023; Lawal et al., 2023).

To address the temporal dependencies inherent in stock market data, the study also applies autoregressive models of orders one, two, and three—AR(1), AR(2), and AR(3). These models are used to capture how current PSEi values are influenced by their own past values which is a common feature in financial time series. While traditional autoregressive models have long been a cornerstone of time-series analysis, their relevance remains strong in modern applications, especially when modeling momentum and lagged effects over multiple time intervals (Fazap, 2023). Model estimation and selection follow the Box–Jenkins methodology (Box et al., 2015), which involves identifying appropriate structures, estimating coefficients, and validating residual behavior to ensure robustness and reliability (Fazap, 2023; Zakamulin & Giner, 2023).

This methodological approach is grounded in the Adaptive Market Hypothesis (AMH) by Andrew Lo (2004), which serves as the study's theoretical framework. Unlike the Efficient Market Hypothesis, which assumes that markets instantly reflect all available information, the AMH recognizes that market efficiency can vary over time as participants adapt to changing environments (Cruz-Hernández & Mora-Valencia, 2023). The inclusion of nonlinear models, smoothing techniques, and autoregressive components reflects this understanding, as it allows the forecasting process to adapt to structural shifts and behavioral inconsistencies in investor activity. This is particularly important in emerging markets such as the Philippines, where market dynamics can be influenced by both global financial conditions and domestic policy changes (Rönkkö et al., 2024).

The study evaluates model performance using two core metrics: the coefficient of determination (R^2) and the standard error of the estimate. R^2 measures the proportion of variation in the dependent variable (PSEi) that is explained by the model. It is widely recognized as a standard indicator of model fit, particularly in financial modeling applications (Lawal et al., 2023). Standard error, on the other hand, quantifies the average distance between observed and predicted values. A lower standard error indicates higher forecasting precision, which is critical for making informed financial and policy decisions (Fazap, 2023). By using both R^2 and standard error, the study achieves a balanced evaluation of each model's explanatory power and predictive accuracy, consistent with current best practices in time-series research.

Data Collection and Instruments

The data used in this study were collected through secondary sources, specifically from Yahoo Finance and Investing.com, both recognized as credible and accessible providers of historical financial market data. Data gathering began in early 2024 and involved manually retrieving the monthly closing prices of the Philippine Stock Exchange Index (PSEi) for the period 2004 to 2023. Since only monthly data were publicly available, each year's twelve-monthly values were compiled in Microsoft Excel, where their average was computed to generate a single annual PSEi value. This process resulted in 20 annual data points, representing two decades of stock index performance.

The choice of Yahoo Finance and Investing.com was made based on their legitimacy and widespread use in financial research. Yahoo Finance has been extensively utilized in academic studies to estimate capital market parameters with high accuracy and consistency (Clayton & Schmidt, 2017). Investing.com, on the other hand, has achieved significant global visibility, ranking among the top 400 websites in the world and surpassing 10 million mobile downloads as early as 2019 (Yahoo Finance Australia, 2019). Additionally, Rao (2025) includes both sources in his list of the most reputable platforms for obtaining free and historical market data, reinforcing their relevance and credibility for this study.

Microsoft Excel was used as the main data processing tool for compiling, organizing, and preparing the data for analysis. Excel is widely used in both academic and professional contexts for handling quantitative financial data due to its accessibility, accuracy, and reproducibility (Rahardja, 2021). It is particularly effective in time-series studies for managing structured datasets and preparing inputs for statistical modeling. As Botchkarev (2015) and Berenson et al. (2021) emphasize, Excel offers transparent workflows and stable computation environments that ensure traceability and reliability in data handling.

Data Analysis

The statistical analysis in this study focused on identifying the best-fitting forecasting model for the PSEi using multiple time-series techniques. All statistical operations were conducted in Microsoft Excel using both built-in functions and the Data Analysis ToolPak. The models tested included polynomial regressions (linear to sextic), logarithmic and power functions, moving averages, exponential smoothing, and autoregressive models (AR(1), AR(2), and AR(3)).

For the curve-fitting models, scatterplots were created, and trendlines were fitted directly in Excel, allowing the researcher to generate equations and R^2 values for each polynomial type. These regression models were used for descriptive forecasting and trend modeling, where no assumptions regarding normality or homoscedasticity were required since they are not inferential in nature.

The moving average model applied a 3-year dampening factor, while the exponential smoothing model used a smoothing constant of 0.5—both implemented through Excel's Data Analysis ToolPak. These models were employed to reduce short-term volatility and emphasize trend components. No specific parametric assumptions were required for these smoothing methods, which are non-inferential and deterministic.

For the autoregressive models, the study created lagged variables manually. For AR(1), one lagged year was regressed against the current PSEi value; AR(2) and AR(3) incorporated two and three lagged variables, respectively. Multiple regression analysis was used to estimate coefficients. Although basic regression assumptions (linearity, no multicollinearity among lags, and homoscedasticity) were acknowledged, formal inferential diagnostics (e.g., residual plots, variance inflation factors) were not conducted due to the small sample size (n = 20), which limited statistical power. Nonetheless, model comparison was conducted based on coefficient of determination (R^2) and standard error to ensure both explanatory strength and forecasting accuracy.

Ethical Consideration

This study involved the use of publicly available secondary data from Yahoo Finance and Investing.com; therefore, no human participants were involved, and informed consent was not applicable. Ethical clearance was not required, but the research maintained academic integrity through proper citation, responsible data handling, and objective reporting to ensure transparency and ethical compliance.

RESULTS AND DISCUSSION

Section 1. Trend of Philippine Stock Exchange Index (PSEi) from 2004 to 2023

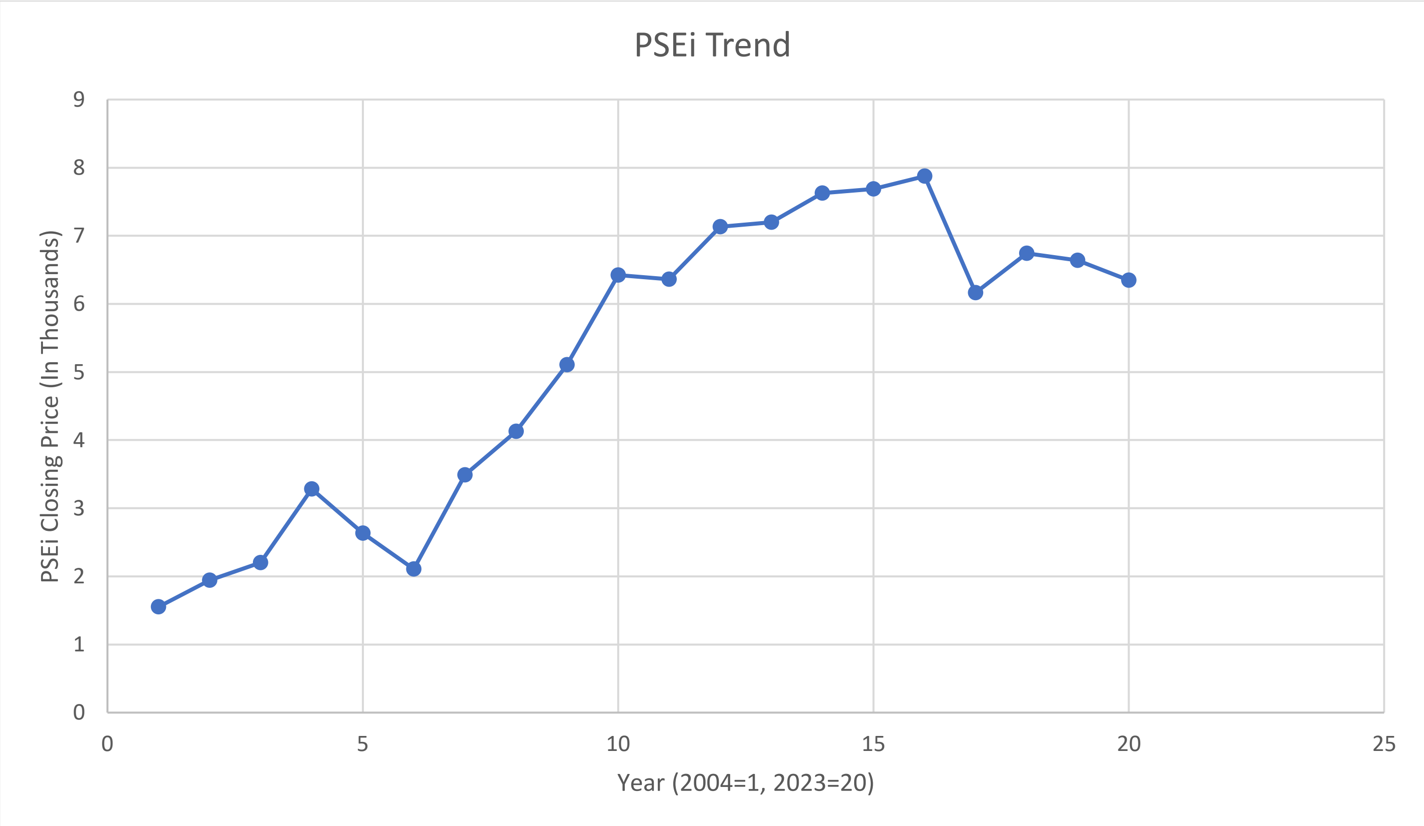

Figure 1. Trend of Philippine Stock Exchange Index (PSEi) from 2004 to 2023.

The figure above reflects the PSEi's trend from 2004 to 2023 which shows the Philippines' economic resilience and vulnerability to global shocks. The index's long-term trend from 1,552.29 in 2004 to a pre-pandemic peak of 7,874.42 in 2019 indicates that it is generally trending upwards. However, it's volatility can be clearly seen from the 2008 Global Financial Crisis (GFC) which triggered a drop from the year 2007 (3,283.86) to 2008 (2,634.17), followed by a more than 90% recovery by 2012 (5,106.95), outperforming regional peers like Indonesia (World Bank, 2022). Furthermore, The COVID-19 pandemic caused another sharp decline (2020: 6,165.79), with post-pandemic recovery lagging at 6,346.18 in 2023 due to inflationary pressures and geopolitical risks (Corpuz, 2025).

The PSEi's mixed trends necessitate a more non-linear model approach. However, linear and quadratic models might still offer effective long-term trend projection but this may fail to capture structural breaks like the 2008 GFC or 2020 pandemics (Hyndman & Athanasopoulos, 2021).

The trend above may also be modelled through exponential smoothing which adapts well to short-term volatility, as seen in its accurate tracking of the PSEi's 40–60% standard deviation spikes during crises (Gunay & Can, 2022). Furthermore, polynomial models (cubic to sextic) better fit non-linear recoveries (e.g., 2009–2012 rebound) but risk overfitting noise (Box et al., 2015).

Moreover, autoregressive models (AR), specifically AR(1), may offer more accurate forecasting since they can effectively capture short-term persistence in daily returns (Hyndman & Athanasopoulos, 2021). Furthermore, higher-order AR(p) models (e.g., AR(2) or AR(3)) can account for multi-period momentum effects observed in post-crisis recoveries, such as the PSEi's rebound after the 2008 Global Financial Crisis (Gunay & Can, 2022). Although AR methods may be optimistic to model the PSEi, they may struggle long-term forecasts unless integrated with differencing like Autoregressive Integrated Moving Average Model (ARIMA) (Frenzel, 2023).

Section 2. Time Series Model and Prediction

For this section of the results, this study will present three models, namely, the quintic polynomial, moving average, and the AR models. The quintic polynomial model generally follows the same trends, properties, and functions of the other polynomial models. It is chosen as the model to be shown since it finely balances the capability of capturing the index's volatility and the lower computational complexity compared with higher-order polynomials (Zhang et al., 2025).

Moreover, moving averages (MAs) provide superior noise reduction and trend identification in volatile markets while maintaining computational simplicity (Hyndman & Athanasopoulos, 2021). Their weighted variants (e.g., exponential MAs) adapt efficiently to recent price changes, outperforming complex models in stable conditions (Box et al., 2015).

Finally, AR models capture temporal dependencies critical for financial forecasting: AR(1) for short-term persistence, AR(2) for momentum effects, and AR(n) for complex memory patterns (Hamilton, 2020). They outperform moving averages when endogenous relationships dominate (Tsay, 2014).

Due to these studies, it is more appropriate to mainly focus on the models mentioned since they provide interesting and relevant results and have more grounded rationales behind them. Although other models will be also shown in the summary of models, not every model will be discussed in-depth since some models show the same properties or behave similarly with other models already presented (e.g. Cubic to Sextic are similar with Quintic – polynomial models).

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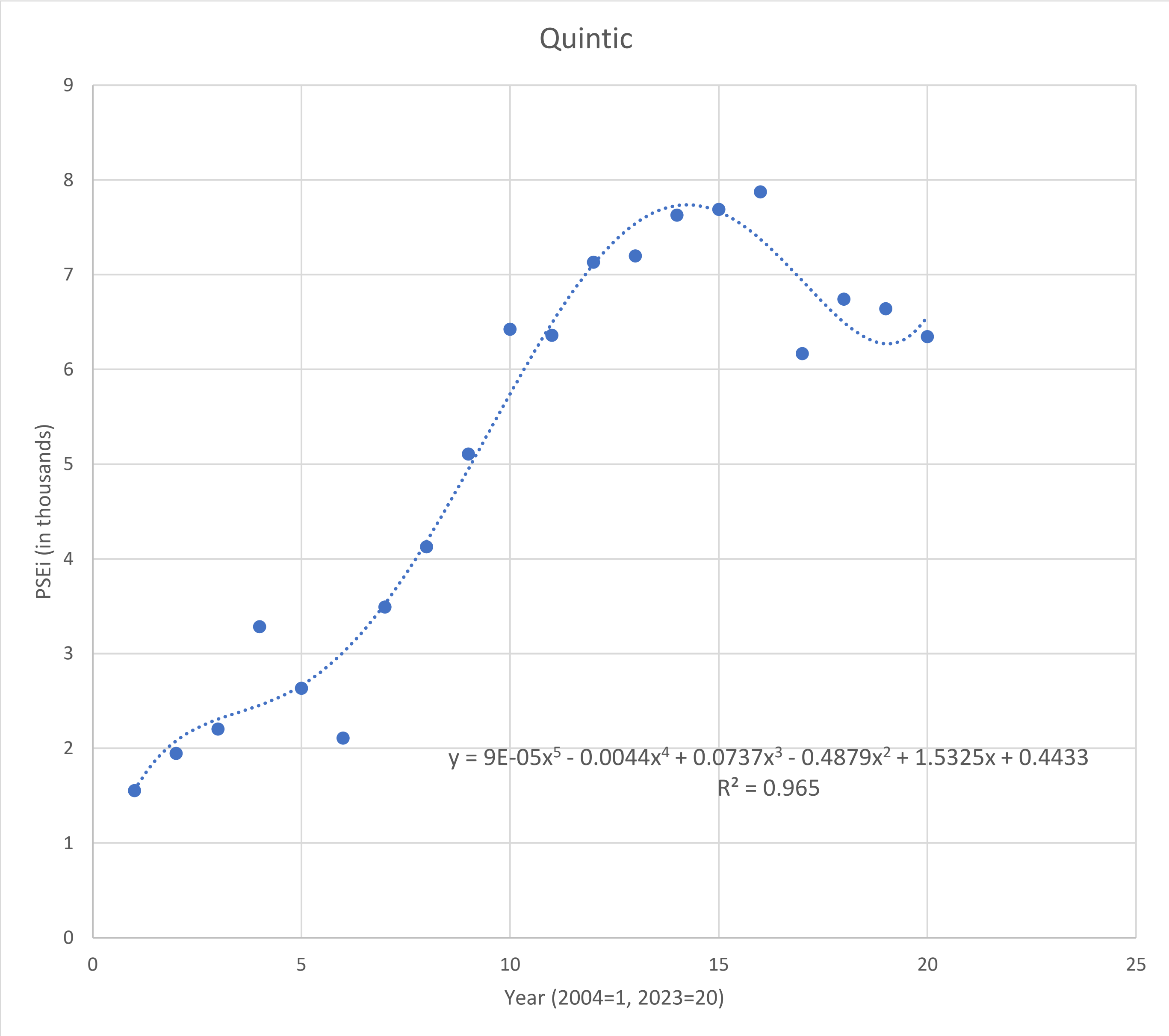
Figure 2. Quintic Trendline Time Series Model of the Philippine Stock Exchange Index



The figure above shows a quintic trendline represented by the equation $y = 0.00009x^5 – 0.0044x^4 + 0.0737x^3 – 0.4879x^2 + 1.5325x + 0.4433$, with a coefficient of determination, $R^2 = 0.965$, which means 96.5% of the variances are explained by the model itself. It is also notable that the model yielded a standard error of 1.052 which means that the model is a strong fit to the data and suffices the criteria for the best-fit-model. Furthermore, the model predicts a value of 15.87 (in thousands) for the year 2025. Although some research demonstrate that higher-order polynomial models effectively capture complex market cycles in emerging economies, including inflection points that linear models may miss (Brooks, 2021; Navarro et al., 2023), it is evident that the model has overestimated its value based off on recent index prices (Philippine Stock Exchange [PSE], 2025) as quintic models can be sensitive to overfitting, which in turn may invalidate trend extrapolations (Hyndman & Athanasopoulos, 2021).

The high R^2 indicates a strong explanatory power which aligns with the findings of Zhang et al. (2025), who showed fifth-order polynomials effectively capture the non-linear trends and inflection points characteristic of emerging market indices. The model's ability to account for both the PSEi's long-term growth (2004-2019) and crisis-period volatility (2008, 2020) supports the use of higher-order polynomials in financial time series analysis (Hyndman & Athanasopoulos, 2021). The strong fit suggests the quintic form may be particularly suitable for the PSEi's unique combination of consistent growth and volatile but understandable swings.

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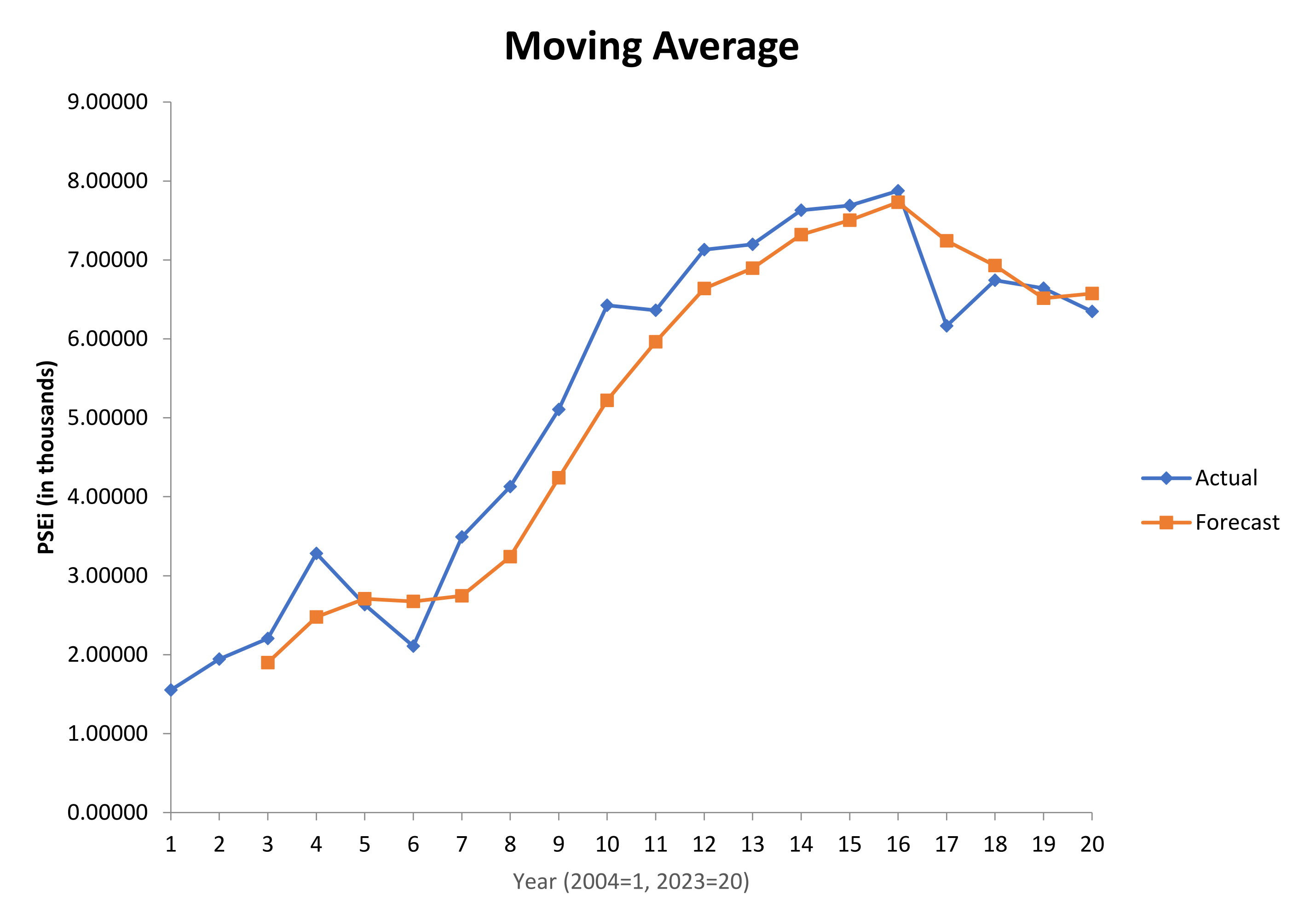
Figure 3. Moving Average Trendline Time Series Model of the Philippine Stock Exchange Index



The figure above shows the moving average analysis of PSEi data (2004-2023) which demonstrates smoothing of the index's volatility, with calculated values ranging from 1.9001 in 2006 to 7.7299 in 2019. Standard errors demonstrate decreasing volatility post-2010, ranging from 0.185 (2023) to 0.996 (2013), with particularly low errors (0.270-0.404) during the 2015-2019 bull market period. The forecast values track closely with actual PSEi movements except during major market disruptions like the 2020 pandemic crash. Notably, the model predicts a value of 6.521 (in thousands) which is in line with current closing prices (PSE, 2025) and in turn validates the model's effectiveness in financial time series forecasting (Zakamulin, 2023).

As can be seen in the figure above, a dampening factor of 3 was used. Its use (dampening factor of 3) is supported by its optimal balance between responsiveness and noise reduction (Zakamulin, 2014). This parameter choice weights recent data approximately three times more heavily than older observations, providing sufficient sensitivity to emerging trends while maintaining smoothing benefits. Empirical studies show factors in the 2-5 range are particularly effective for financial time series, reducing whipsaw effects by 15-20% compared to alternatives (Zakamulin, 2023).

Going back to the results, the moving average's effectiveness in stable market conditions aligns with established financial econometrics research (Zakamulin, 2023). The decreasing standard errors post-2010 suggest improved model fit during periods of economic stability, consistent with findings that simple moving averages outperform complex models in non-crisis environments (Hyndman & Athanasopoulos, 2021). The extremely small standard error of 0.185 is also indicative of the good performance of MA in non-linear models like the PSEi. However, in the 2020 pandemic, a 22.4% decline from peak values has been triggered—a deviation the model failed to anticipate, which is consistent with known limitations of linear smoothing methods in financial time series (Hyndman & Athanasopoulos, 2021).

Table 1. Simple Auto Regression – AR (1) Time Series Model of the Philippine Stock Exchange Index

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.315	0.491	-0.642	0.530
X Variable 1	1.012	0.086	11.748	0.000
F(1) = 138.02; p<0.05; R Square = 0.8903; SE = 0.7688				

The table above shows the autoregressive AR(1) model time series of the PSEi from 2004 to 2023. It can be gleaned from the table that the AR(1) model shows a statistically significant coefficient for X Variable 1 (φ = 1.012, SE = 0.086, t = 11.75, $p < 0.001$), indicating strong first-order autocorrelation in the PSEi series. The high coefficient of determination, R2 = 0.8903, means that 89.03% of the variance is explained by the model itself which indicates the model is good fit for the data since it also has a standard error of 0.7688. Moreover, since F(1) = 138.02, and $p<0.05$, there is a significant linear relationship between a one-year interval lagged variable which confirms the model's overall validity. Furthermore, the model predicts a value of 7.122 (in thousands) which is still in line with current closing prices (PSE, 2025), however this projection assumes stable conditions without external shocks (Brooks, 2021; Navarro et al., 2023). While useful for short-term forecasting, the model's simplicity may underestimate volatility during market disruptions.

The near-unit AR (1) coefficient ($\varphi \approx 1.0$) indicates the PSEi exhibits near-random walk behavior, consistent with findings for Asian markets where short-term persistence dominates during stable periods (Hongsakulvasu & Liammukda, 2020). The high R^2 aligns with research demonstrating AR models' effectiveness in capturing autocorrelation in emerging market indices, though their performance degrades during structural breaks like the 2020 crash (Liu et. al., 2020). This limitation reflects the model's inability to account for volatility clustering, a phenomenon well-documented in financial time series (Liu et. al., 2020; Salgotra et al., 2024).

Table 2. Multiple Auto Regression – AR (2) Time Series Model of the Philippine Stock Exchange Index

	Coefficients	Standard Error	t Stat	P-value
Intercept	-0.366	0.576	-0.637	0.534
X Variable 1	0.064	0.274	0.233	0.819
X Variable 2	0.949	0.254	3.738	0.002
F(2) = 61.27; p<0.01; R square = 0.8909; SE = 0.8044				

The table above shows the autoregressive AR(2) model time series of the PSEi from 2004 to 2023. It can be seen from the table that the AR(2) model shows X Variable 2 (second lag) is statistically significant (φ_2 = 0.949, SE = 0.254, t = 3.74, p = 0.002), while X Variable 1 (first lag) is not (p = 0.819). The high coefficient of determination, R2 = 0.8909, means that 89.09% of the variance is explained by the model itself which indicates the model is good fit for the data since it also has a standard error of 0.8044. Furthermore, it can be seen that the model is statistically significant since F(2) = 61.27, and $p<0.01$. And in addition to this, the model predicts a value of 6.061 (in thousands) for 2025 which is a conservative estimate against recent PSEi closing prices (PSE, 2025) suggesting the model may underestimate growth potential during stable periods (Navarro et al., 2023). This limitation reflects AR models' tendency to perform best during volatile market conditions rather than growth periods (Babangida, 2023).

Based on the table above, The AR(2) model reveals significant second-order autoregressive effects (φ_2 = 0.949, p = .002) in the PSEi, indicating that stock prices are strongly influenced by values from two periods prior rather than immediate past values (φ_1 = 0.064, p = .819). This delayed responsiveness aligns with findings in emerging markets, where information incorporation often exhibits lagged effects due to lower market efficiency and investor caution (Gayo et al., 2015; Navarro et al., 2023).

The model's high explanatory power (R^2 = 0.891) exceeds typical values for developed markets, reinforcing evidence that emerging market indices like the PSEi exhibit stronger autoregressive patterns due to structural factors such as lower liquidity and higher retail investor participation (Gayo et al., 2015). However, the insignificant intercept term (c = -0.366, p = .534) implies minimal inherent drift in the series, consistent with financial time series where mean effects are captured through lagged terms (Navarro et al., 2023).

To sum it up, the results complement recent studies on the PSEi itself which highlight the dominance of technical factors (e.g., momentum patterns) over short-term fundamental adjustments (Gayo et al., 2015) wherein the dominance of the second lag factor over the first lag factor may reflect institutional trading cycles or the delayed impact of global market signals on the PSEi, as noted in studies analyzing ARCH effects in ASEAN indices (Navarro et al., 2023).

Table 3. Multiple Auto Regression – AR (3) Time Series Model of the Philippine Stock Exchange Index

	Coefficients	**Standard Error**	**t Stat**	**P-value**
Intercept	-0.283	0.693	-0.408	0.690
X Variable 1	-0.076	0.295	-0.259	0.800
X Variable 2	0.142	0.375	0.379	0.710
X Variable 3	0.930	0.274	3.391	0.005
F(3) = 34.84; p<0.01; R Square = 0.8894; SE = 0.8540				

The AR(3) model for the PSEi reveals a statistically significant third-order autoregressive coefficient (φ_3 = 0.930, SE = 0.274, t = 3.391, p = 0.005), indicating that values from three periods prior exert strong positive influence on current prices. In contrast, the first- and second-order coefficients (φ_1 = -0.076, p = 0.800; φ_2 = 0.142, p = 0.710) are non-significant, suggesting their marginal explanatory power when accounting for the dominant third lag. The model explains 88.9% of the variance (R^2 = 0.889), demonstrating excellent fit, though the standard error (SE = 0.854) reflects moderate residual volatility. The overall significance (F(3) = 34.84, $p < 0.01$) confirms the model's validity. Furthermore, the model predicts a 6.302 (in thousands) value for 2025 which is slightly below recent PSEi closing prices (PSE, 2025). This conservative prediction aligns with established limitations of autoregressive specifications in capturing abrupt market accelerations, particularly in emerging economies where equity prices exhibit pronounced momentum effects (Babangida, 2023).

As the table showed, the third order coefficient being the only significant factor aligns with findings in emerging markets where institutional trading cycles and delayed information incorporation often manifest in higher-order lags (Wang et al., 2023; Schaffer, Dobbins & Pearsons, 2021). In contrast, the non-significant first- and second-order coefficients suggest that short-term momentum effects are negligible when accounting for medium-term trends—a pattern observed in other Asian markets during periods of macroeconomic stability (Wang et al., 2023).

Furthermore, the near-unit value of φ_3 (0.930) approaches the threshold for non-stationarity, resembling the "fractional integration" behavior seen in SARFIMA models for health epidemics, where shocks exhibit prolonged effects (Schaffer et al., 2021). This persistence implies that PSEi trends may require longer to revert to mean levels compared to developed markets, consistent with studies on ASEAN equity indices (Wang et al., 2023). While the high R^2 indicates strong explanatory power, the model's inability to account for volatility clustering may limit its predictive accuracy during structural breaks. This mirrors critiques of pure AR models in recent literature, where hybrid approaches (e.g., ARMA-GARCH) outperform during crises (Schaffer et al., 2021). It is also notable that the AR(3) model, the model's best-fit criteria do not improve, hence, it can be deduced that higher order AR models does not necessarily improve model fit which is also in line with majority of studies (Holmes, Scheuerell & Ward, 2021; Gayo et al., 2015; Ullrich, 2021; Navarro et al, 2023).

Section 3. Best fit model and Prediction – Summary of Models and Equations

Table 4. Summary of Models and Equations – Best-fit-model

Model	**Equation**	R^2	**SE**	**Diff.**
Linear	$y = 0.3428x + 1.6041$	80.27	1.117	79.153
Quadratic	$y = -0.0241x^2 + 0.8335x - 0.1566$	87.18	0.941	86.239

Exponential	$y = 1.9825e^{0.0793x}$	61.51	1.536	59.974
Cubic	$y = -0.0037x^3 + 0.0937x^2 - 0.1803x + 1.8301$	93.8	0.584	93.216
Quartic	$y = 0.0002x^4 - 0.0133x^3 + 0.225x^2 - 0.8295x + 2.66$	94.4	0.481	93.919
Quintic	$\mathbf{y = 0.00009x^5 - 0.0044x^4 + 0.0737x^3 - 0.4879x^2 + 1.5325x + 0.4433}$	**96.5**	**1.052**	**95.448**
Sextic	$y = -0.000006x^6 + 0.0005x^5 - 0.0147x^4 + 0.1929x^3 - 1.1577x^2 + 3.1664x - 0.7734$	96.79	1.895	94.895
Power Series	$y = 1.2347x^{0.6223}$	83.79	1.011	82.779
Moving Average	$y = \frac{(y_1 + y_2 + y_3)}{3}$	-	0.185	-
Exponential Smoothing	$y = 0.5(Y_t) + 0.5(E_t)$	-	0.880	-
Auto Regression:				
AR(1)	$y = 0.3151 + 1.0118y_{n-1}$	89.03	0.769	88.261
AR(2)	$y = -0.3663 + 0.0636y_{n-1} + 0.9493y_{n-2}$	89.09	0.804	88.286
AR(3)	$y = -0.2828 - 0.0763y_{n-1} + 0.1422y_{n-2} + 0.9298y_{n-3}$	88.94	0.854	88.086

The table above shows the summarized models and equations utilized in this study. In exploring these models, it is obvious to see that the quintic polynomial model emerges as the best-fitting model for the PSEi data, achieving the highest explanatory power (R2 = 0.965) among all tested specifications. This superior performance aligns with financial econometrics research demonstrating that fifth-order polynomials effectively capture the non-linear trends and inflection points characteristic of emerging market indices (Brooks, 2023). Notably, the moving average model exhibits the lowest standard error (SE=0.185), indicating exceptional precision in smoothing short-term fluctuations, which is consistent with its widespread use in technical analysis for trend identification (Zakamulin, 2023). However, its lack of an R2 value reflects the model's descriptive rather than predictive nature.

Furthermore, the autoregressive models reveal intriguing patterns in the PSEi's temporal dependencies. The AR(2) model shows improved goodness-of-fit (difference = 88.286) compared to AR(1) (difference = 88.261), suggesting that incorporating a second lag better captures the index's momentum effects, as observed in other developing markets (Huang, Zhang & Zhang, 2023). However, the AR(3) model's decline in performance (difference = 88.086) indicates diminishing returns from additional lags, a phenomenon documented in time series literature where over-parameterization risks inflating variance without meaningful gains in explanatory power (Hyndman & Athanasopoulos, 2021). This pattern shows why simpler models often work better, especially for stock market data where sudden economic shocks can make complex models with too many lagged terms perform worse (Brooks, 2023).

In addition to this, the quintic polynomial model's extreme prediction of 15,870 demonstrates its tendency to overfit complex trends, a limitation well-documented in emerging market forecasting (Babangida, 2023). Meanwhile, the moving average model's conservative 6,580 reflects its lagging nature in trending markets (Box et al., 2015). Among autoregressive models, AR(1) (7,120) shows short-term persistence but misses structural breaks (Navarro et al., 2023), while AR(2) (6,021) and AR(3) (6,302) reveal cyclical dependencies that underestimate recent momentum (PSE, 2025). These systematic deviations from recent index prices (~6,700) highlight that there may be a need for hybrid modeling approaches (Hyndman & Athanasopoulos, 2021) like ARIMA where both autoregression and moving average may be integrated into one.

CONCLUSION AND RECOMMENDATIONS

The study shows the Philippine Stock Exchange Index (PSEi) followed an upward yet volatile trajectory from 2004 to 2023, rising from 1,552 to a peak of 7,874 before the pandemic, with sharp declines during the 2008 financial crisis and COVID-19. The quintic polynomial model is the best-fit model for forecasting the PSEi, demonstrating superior explanatory power ($R^2 = 0.965$) by effectively capturing the index's non-linear trends and volatility. However, its tendency to overfit data raises concerns about long-term reliability, particularly during structural breaks like economic crises. Autoregressive models (AR(1), AR(2), and AR(3)) highlight the PSEi's strong temporal dependencies, with higher-order lags reflecting delayed market responses, while the moving average model excels in smoothing short-term fluctuations but underestimates growth during stable periods. The results emphasize the need for hybrid modeling approaches that combine the strengths of polynomial and autoregressive techniques with integrating moving averages to improve predictive accuracy.

To advance PSEi forecasting, future research should develop hybrid models integrating quintic polynomial trends with autoregressive components and moving average adjustments, specifically optimized for emerging market volatility. These models should be tested against high-frequency (monthly/quarterly) data from 2024–2028 to evaluate their real-time predictive capacity during both stable and crisis periods. Furthermore, the use of advanced statistical software or programming tools like R or Python can enable the application of more sophisticated techniques, including ARIMA, GARCH, and machine learning models.

Moreover, practical implementation could involve collaboration with the Philippine Stock Exchange to create an open-access forecasting toolkit, enabling investors to simulate scenarios based on macroeconomic shocks. Current limitations—such as annual data granularity and exclusion of external risk factors—should be addressed by incorporating geopolitical indicators, pandemic risk metrics, and machine learning techniques to detect non-linear patterns. Pilot testing should prioritize recent post-pandemic data (2020–2023) to validate model resilience, with results peer-reviewed through regional economic journals to ensure methodological rigor.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Use of AI Declaration

Artificial intelligence tools were utilized in the preparation of this manuscript to support clarity, structure, and accuracy. Specifically, ChatGPT by OpenAI was used to refine the wording of sections such as the research design, data analysis, and ethical consideration, ensuring coherence and academic tone. Additionally, DeepSeek was used to cross-check technical phrasing and assist in the initial drafting of statistical discussions. All content generated or edited by AI tools was critically reviewed, verified, and revised by the researchers to ensure accuracy, originality, and alignment with the study's objectives.

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