Jurnal Aplikasi Manajemen, Ekonomi dan Bisnis
Vol. 9, No.1, October 2024
ISSN 2541-1438; E-ISSN 2550-0783
Published by STIM Lasharan Jaya

Prediction Stock Price of Shanghai Pudong Development Bank with ARIMA and ARCH/GARCH Models

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ARTICLE DETAILS

History
Received : *August*
Revised Format : *September*
Accepted : *October*

Keywords :
stock, arima, arch, garch

ABSTRACTS

This research was conducted to predict stock prices from July 2024 to December 2024. The stock chosen for prediction was Shanghai Pudong Development Bank. The ARIMA and ARCH/GARCH models were used to make these predictions. The findings of this study revealed the ARIMA (3,1,3) model and the ARCH/GARCH (1,1) model. The ARCH/GARCH model was selected due to the heteroskedasticity present in the ARIMA (3,1,3) model. Applying the ARCH/GARCH (1,1) method resolved the heteroskedasticity issue, leading to more accurate stock price predictions.

Introduction

Based on the findings of the literature review of The Shanghai Pudong Development Bank, an opportunity for original research emerges in utilising ARIMA analysis to forecast the stock price of Shanghai Pudong Development Bank. Notably, no prior studies have applied ARIMA analysis to the stock price of Shanghai Pudong Development Bank, thus indicating a gap in the existing literature that this study aims to address. The Shanghai Pudong Development Bank is a prominent entity in the economic sphere of China, particularly within the realm of green growth capacity assessment. In a study conducted by Zhao (2018), an evaluation index system was established for measuring green growth capacity, emphasising the critical roles of government support capabilities, corporate green capabilities, NGO supervision and guidance, public participation capabilities, and park output benefits. Among the four National New Districts examined, Pudong was identified as possessing the strongest green growth capacity, demonstrating the substantial influence of government support capabilities on overall green growth capacity.

In examining the historical evolution of banking establishments in Shanghai, Wang (2024) provides insight into the significance of the Shanghai Women's Commercial and Savings Bank, which was established by affluent women from 1924 to 1955. Despite facing constraints in terms of capital and operational reach, this institution served as a representation of the changing roles of Chinese women within the financial sector, promoting notions of financial autonomy and feminist principles. The active involvement of pioneering women in the Shanghai Women's Bank, supported by their elite social connections, played a pivotal role in shaping the institution's durability and public image, underscoring the intricate interplay of gender, finance, and history in Shanghai. Seiler et al. (2022) conducted a thorough examination of the effects of special economic zones (SEZs) on economic growth, focusing on the Pudong New Area Open Economic Zone in Shanghai as a case study. Their comprehensive analysis reveals that SEZs, exemplified by the one in Pudong, have played a pivotal role in enhancing GDP per capita growth and bolstering the overall economic landscape. These findings underscore the significance of policy instruments such as SEZs in fostering economic advancement and prosperity in regions similar to Shanghai.

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In summary, the literature reviewed sheds light on the diverse and complex role that the Shanghai Pudong Development Bank plays in shaping China's economic and financial landscape. From evaluating green growth capacity to exploring historical banking legacies, from analyzing the impact of Special Economic Zones on economic growth to examining the relationship between bank credit risk and asset pricing, and from studying the influence of digital transformation on bank systemic risk, these research papers offer valuable insights for both scholars and policymakers. The Shanghai Pudong Development Bank remains a pivotal player in driving economic growth, promoting innovation, and ensuring financial stability within China's ever-evolving financial industry. In today's interconnected global economy, there are growing concerns about the ramifications of financial institutions' interdependence on their operations. In a study conducted by Wang & Kang (2023), the relationship between financial interconnectedness and bank risk-taking in China from 2011 to 2020 was empirically examined. The findings of their research revealed that as financial interconnectedness increases, so does the propensity for banks to engage in riskier behavior. This underscores the importance of comprehending how financial networks impact banks' risk profiles and the broader implications for financial stability. Moreover, the study identified various factors, including digitization transformation, law enforcement, and regulation, that can help mitigate the potential risks associated with financial interconnectedness. This research underscores the need for a deeper understanding of the interconnected nature of financial institutions and the measures that can be taken to safeguard against potential risks in the financial system. s and bank risk-taking, providing valuable insights for policymakers and regulators.

Schwantes (2022) delved into the restoration of the Chinese Banking Hall situated within the exalted walls of the former HSBC Building in Shanghai, unveiling a meticulous study that delves into the intricacies of uncovering the original paint finishes adorning the hall. Through a careful examination of historical documentation and preservation challenges, the research sheds light on the cultural significance of the decorations while emphasizing the imperative nature of conserving such architectural treasures. This scholarly endeavor significantly contributes to the broader discourse on cultural heritage preservation and architectural history in Shanghai, underscoring the critical importance of safeguarding emblematic structures like the former HSBC Building for posterity.

In conclusion, the research papers examined offer valuable insights into a variety of aspects pertaining to the Shanghai Pudong Development Bank. These include financial interconnectedness, bank risk-taking, cultural heritage preservation, urban renovation, and flood risk analysis. By delving into these diverse topics, scholars can attain a well-rounded comprehension of the obstacles and possibilities confronting financial establishments, historical structures, urban populations, and coastal metropolises such as Shanghai. These discoveries stand to guide forthcoming academic investigations and policy-making endeavors aimed at fostering sustainable development and resilience within the evolving framework of Shanghai. Based on the findings of the literature review, an opportunity for original research emerges in utilizing ARIMA analysis to forecast the stock price of Shanghai Pudong Development Bank. Notably, no prior studies have applied ARIMA analysis to the stock price of Shanghai Pudong Development Bank, thus indicating a gap in the existing literature that this study aims to address.

Literature Review and Theoretical Background

The history of Shanghai Pudong Development Bank (SPD) is a topic of interest for researchers studying the development patterns of investment banks. Cheddadi et al. (2019) discuss the importance of different investment bank development patterns, highlighting the mixed pattern as a more businesslike approach that can help reduce risks and promote healthy competition within the financial system. This mixed pattern is particularly beneficial for a developing country like China, where an effective financial environment is crucial for sustainable growth. In a study by Klimevsová et al. (2009), the impact of bank credit on the growth of the Nigerian economy is examined. The researchers found that while there was an insignificant short-run effect of bank credit on economic growth, there was a significant long-run effect. This highlights the importance of sustained investment in key sectors such as agriculture, manufacturing, and mining to drive economic development over time. The findings suggest the need for policies aimed at reducing interest rates and streamlining loan processes to encourage commercial farming and industrial growth in Nigeria. Tang (2019) delves into the establishment and spread of human populations in Morocco over the past 10,000 years, analyzing the relationship between population trends and landscape changes. The study reveals that lowlands were more strongly impacted by human activities during the Neolithic period, while mountainous areas showed less anthropogenic influence until around 4000 cal. BP. This research sheds light on the complex interactions between human populations and the environment, emphasizing the importance of considering regional differences in topography and climate when studying historical development patterns. Adebisi (2023) explores the formation of bud banks in a clonal herb species, highlighting the importance of plant establishment and growth phases in determining future vegetative regeneration. The study challenges existing hypotheses about bud responses to stress and substrate heterogeneity, suggesting that factors influencing bud-bank formation are more nuanced than previously thought. This research contributes to our understanding of plant life cycles and the mechanisms underlying clonal growth strategies in different environmental conditions. Overall, the literature reviewed provides valuable insights into the history of Shanghai Pudong Development Bank and its role in the broader context of investment banking, economic growth, and environmental interactions. By considering the findings from these diverse studies, researchers can gain a more comprehensive understanding of the historical development patterns shaping the financial landscape and its impact on sustainable growth. The history of Shanghai Pudong Development Bank (SPDB) is a significant aspect of China's financial landscape. As Shanghai transformed from a traditional labour-intensive industry to a service economy, the reuse of industrial heritage along the Shanghai waterfront has played a crucial role in reshaping urban cultural identity and promoting economic development (Luo & Cao, 2023). The development of community gardens in Shanghai has also contributed to urban renovation and neighbourhood relationships, enhancing the quality of local life and promoting a harmonious society (Ge et al., 2022). Furthermore, the spatial pattern of three-dimensional green volume (TDGV) in Lingang New City, Shanghai, reflects the quality and quantity of urban green space, with natural factors such as distance from water and land formation time significantly influencing its distribution (Zheng et al., 2021). In the context of weed species and their impact on crop yield, the genetic basis of early flowering in ruderal weeds has been studied using Cardamine occulta as a model. The impairment of the vernalisation response regulator gene FLC and a dominant mutation in the blue-light receptor gene CRY2 have been identified as genetic drivers for the establishment of a short life cycle in ruderal weeds, enabling them to dominate local populations and spread in East China quickly (L. Z. Li et al., 2023). Overall, these research papers provide valuable insights into different aspects of urban development, community engagement, environmental planning, and genetic adaptation. By understanding the historical context and evolution of institutions like SPDB, the impact of community gardens on local life satisfaction, the spatial distribution of green spaces in urban areas, and the genetic mechanisms of weed adaptation, researchers can gain a comprehensive understanding of the multifaceted dynamics shaping Shanghai's development. This knowledge can inform future research and policy decisions aimed at promoting sustainable urban development, preserving cultural heritage, and enhancing environmental quality in Shanghai and beyond.

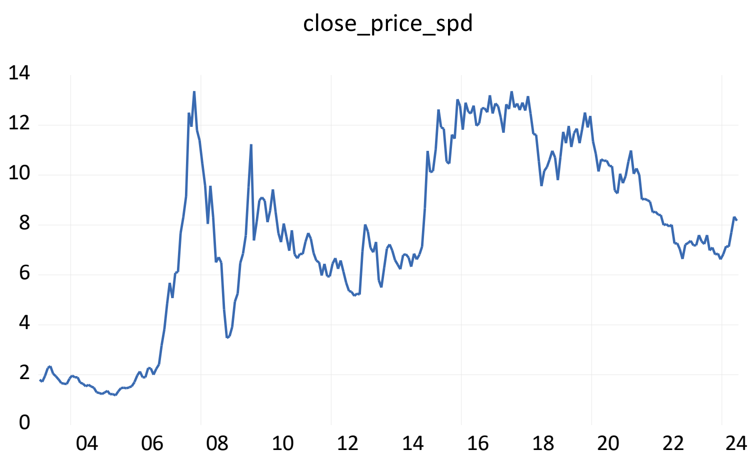
Theoretical Framework

Stock price forecasting is a critical aspect of financial decision-making, with implications for investors worldwide. Various methods have been explored to predict stock prices accurately, including statistical time series models like ARIMA and neural network-based approaches such as LSTM. Chowdhury & Islam (2021) conducted a study to forecast the daily share prices of companies listed on the Chittagong Stock Exchange using ARIMA models. The study involved selecting suitable ARIMA models based on autocorrelation tests, ACF, PACF, and other statistical metrics. The results indicated that the ARIMA model was effective in forecasting daily share prices. In a similar vein, (Bielskis & Belovas (2022) compared the performance of statistical time series (ARIMA, SARIMA) and neural network-based (LSTM) models in predicting stock prices of companies like Amazon, Apple, Google, Netflix, and Tesla. The evaluation was based on measures like MAE and MRE, highlighting the strengths and weaknesses of each approach. The study provided insights into improving forecasting methods for stock prices. Furthermore, Akhtar et al. (2022) focused on exchange rate prediction, utilising ARIMA and GARCH models to forecast USD/PKR currency exchange rates. In conclusion, the literature review highlights the diverse applications of ARIMA models in various fields, including transportation systems, epidemiology, seismology, and telecommunications. The studies reviewed support the hypothesis that ARIMA models can effectively predict trends and anomalies in time-series data, offering valuable insights for researchers and practitioners in their respective domains. Further research and advancements in ARIMA modelling techniques can enhance the accuracy and applicability of these models in addressing complex real-world problems.

Methodology

The stock price data of Shanghai Pudong Development Bank (SPD) was sourced from the Yahoo Finance website. It covers a period of 258 data points, from February 2003 to June 2024. The visualisation depicted below showcases the closing stock prices of Shanghai Pudong Development Bank in graphical form over the specified time period.

Fig 1 Close Stock Price Shanghai Pudong Development Bank (SPD)



Research models and variable definitions in ARIMA have been explored in various studies to enhance forecasting accuracy and provide valuable insights for researchers. (Ahorsu et al. (2021) focused on the factors influencing users in using electronic money, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) as a research model. Independent variables such as performance expectations, social influence, and perceived values were considered, with actual use as the dependent variable. The study emphasised the importance of trust in electronic money usage, highlighting the need for system security to attract users. Mai & Tolson (2019), emphasised the significance of sensitivity analysis (SA) in model construction, particularly in environmental and water resources simulation models. The study introduced the Model Variable Augmentation (MVA) approach to assess the quality of SA results without additional model runs or bootstrapping. MVA proved to be effective in enhancing the reliability of sensitivity estimates, especially when applied to global SA methods like the Sobol' and PAWN analyses. On the other hand, Alfansi and

Daulay (2021) discussed the impact of COVID-19 on global economies and the need for accurate forecasting models to understand future occurrences. The study utilised the autoregressive integrated moving average (ARIMA) model to forecast the monthly consumer price index (CPI) in Kosovo. The ARIMA (3, 1, 2) projections indicated a potential rise in monthly CPI values, suggesting the implementation of health, political, and economic policies to mitigate the effects of the pandemic. Furthermore, Bunjaku et al. (2023) highlighted the design and evaluation of a variable chipping clearance cassava chipper for processors, emphasising the importance of operational speeds and chipping clearances in determining chipping capacity and efficiency. The study demonstrated the machine's average throughput capacity and chipping efficiency at different chipping clearances, providing valuable insights for processors. In conclusion, the research papers reviewed shed light on the diverse applications of research models and variable definitions in ARIMA, ranging from electronic money usage to environmental modelling and pandemic forecasting. By incorporating these insights into their research, scholars can enhance the accuracy and reliability of their forecasting models, contributing to advancements in various fields. The research question of interest in this literature review is the "Research model and variable definition in ARIMA." By combining these models, the researchers aim to capture both linear and non-linear patterns in the volatility time series, providing better predictions for investors interested in trading risk associated with highly volatile stocks like Tesla. Kumar & Middey (2023), investigate extreme climate indices and their association with environmental-meteorological parameters using a random forest-ARIMA hybrid model. The study focuses on the Vidarbha region in India and highlights the increasing severity of drought over the years, emphasizing the importance of accurate forecasting models for climate-related events. Pokou et al. (2024), discuss the hybridization of ARIMA with learning models for forecasting stock market time series. By considering a non-Gaussian framework with a Student's distribution for the random disturbance process, the researchers demonstrate the power of hybrid models in capturing stylized facts observed in financial time series analysis. Overall, the literature review of these research papers highlights the versatility and effectiveness of hybrid ARIMA models in various domains. These models offer a promising approach to improving forecasting accuracy by combining different techniques to capture complex patterns in time series data. Researchers can benefit from the insights provided in these studies to enhance their understanding of research models and variable definitions in ARIMA for their own investigations.

Result And Discussion

By analysing the data depicted in Figure 1 and utilising the software e-Views 12, one can extract the descriptive information pertaining to Shanghai Pudong Development Bank. This includes:

Table 1: Descriptive statistic from data stock price SPD

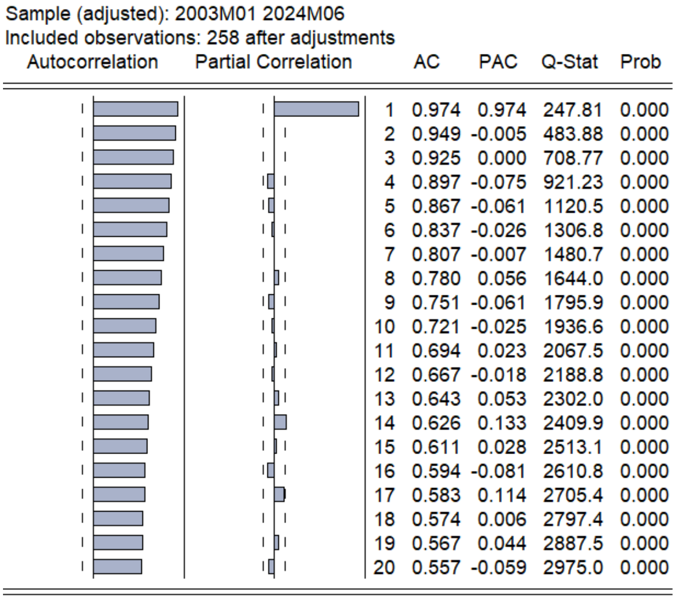
Variables	Mean	Std. Dev	Min	Max
Stock Price SPD	3,548	0.1736	1,172	13,366

The data presented in Table 1 show that the mean value is 7.599, with a median value of 7.419. Furthermore, the highest value for SPD stock is 13.366, while the minimum stock price is 1.172 from February 2003 to June 2024.

Model Autoregressive (AR)

The initial step in the analysis process involved constructing an Autoregressive (AR) model, which included testing the stationarity of the data. The findings are as follows:

Fig 2 Autocorrelation & Partial Correlation Test for Data Before Difference



Sample (adjusted): 2003M01 2024M06
Included observations: 258 after adjustments

	AC	PAC	Q-Stat	Prob
1	0.974	0.974	247.81	0.000
2	0.949	-0.005	483.88	0.000
3	0.925	0.000	708.77	0.000
4	0.897	-0.075	921.23	0.000
5	0.867	-0.061	1120.5	0.000
6	0.837	-0.026	1306.8	0.000
7	0.807	-0.007	1480.7	0.000
8	0.780	0.056	1644.0	0.000
9	0.751	-0.061	1795.9	0.000
10	0.721	-0.025	1936.6	0.000
11	0.694	0.023	2067.5	0.000
12	0.667	-0.018	2188.8	0.000
13	0.643	0.053	2302.0	0.000
14	0.626	0.133	2409.9	0.000
15	0.611	0.028	2513.1	0.000
16	0.594	-0.081	2610.8	0.000
17	0.583	0.114	2705.4	0.000
18	0.574	0.006	2797.4	0.000
19	0.567	0.044	2887.5	0.000
20	0.557	-0.059	2975.0	0.000

Based on the data analysis from Figure 2, it is evident that the data is non-stationary because, based on the data analysis presented in Figure 2, it is apparent that the data exhibits non-stationarity, as evidenced by several key indicators. Specifically, the autocorrelation plot at the first lag falls outside Bartlett's line. It demonstrates an exponential or gradual decrease, with the potential to surpass Bartlett's line if continued, despite the shift of the bar chart to the left. Bartlett's line is delineated by dashed lines on both sides of the center line in both the autocorrelation and partial autocorrelation plots. The autocorrelation coefficient value can be observed as the AC value is significantly high at 0.974 (ranging from -1 to +1) and decreases gradually. The probability values from lag 1 to lag 20 are approaching zero, indicating values smaller than a = 5%. The next step involves conducting a Unit Root Test using the Augmented Dickey-Fuller test statistic. The results of the Unit Root Test are as follows:

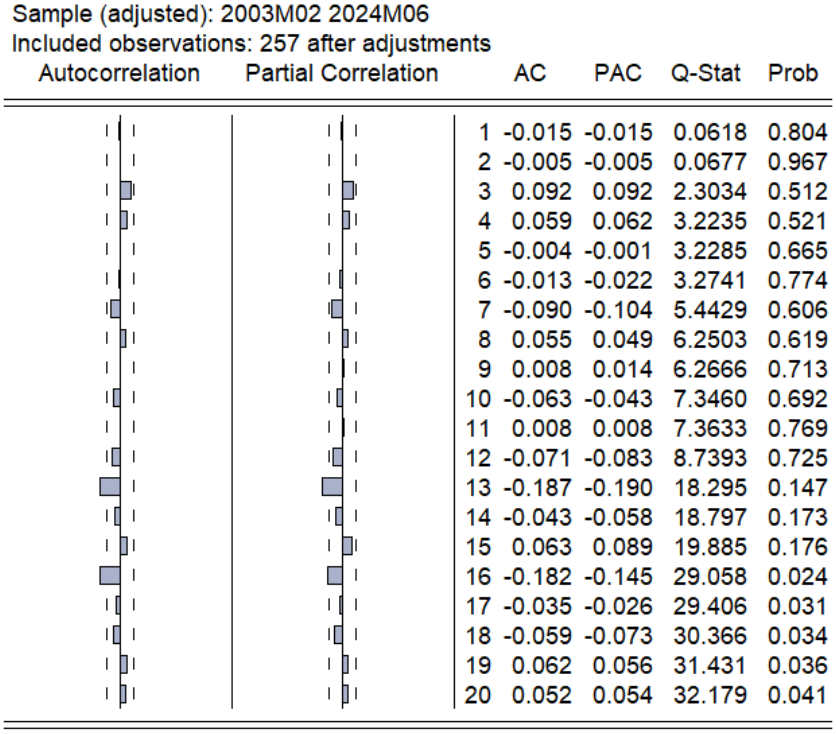
Table 2 : Unit Root Test Before First Difference

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.999811	0.5983
Test crtical values :	1% level	-3.994167	
	5% level	-3.427407	
	10% level	-3.137018	

*MacKinnon (1996) one-sided p-values

Based on the data in Table 2, the probability value of 0,2713 is greater than the value of a = 5%. Therefore, it can be concluded that the SPD stock closing prices data are still non-stationary. Based on the explanation above, it is known that if the data of SPD stock closing prices is non-stationary, the next step is to perform the differencing process on the SPD stock closing prices data. After the differencing process is carried out on the data, the results of the Unit Root Test are as follows:

Fig 3 The second phase of stationary testing


Sample (adjusted): 2003M02 2024M06
Included observations: 257 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.015	-0.015	0.0618	0.804
		2	-0.005	-0.005	0.0677	0.967
		3	0.092	0.092	2.3034	0.512
		4	0.059	0.062	3.2235	0.521
		5	-0.004	-0.001	3.2285	0.665
		6	-0.013	-0.022	3.2741	0.774
		7	-0.090	-0.104	5.4429	0.606
		8	0.055	0.049	6.2503	0.619
		9	0.008	0.014	6.2666	0.713
		10	-0.063	-0.043	7.3460	0.692
		11	0.008	0.008	7.3633	0.769
		12	-0.071	-0.083	8.7393	0.725
		13	-0.187	-0.190	18.295	0.147
		14	-0.043	-0.058	18.797	0.173
		15	0.063	0.089	19.885	0.176
		16	-0.182	-0.145	29.058	0.024
		17	-0.035	-0.026	29.406	0.031
		18	-0.059	-0.073	30.366	0.034
		19	0.062	0.056	31.431	0.036
		20	0.052	0.054	32.179	0.041

Based on the above data, it can be inferred that the probability value is greater than the value of a = 5%, thus indicating that the data for the first difference in SPD stock closing prices is stationary. Subsequently, the analysis proceeded with a Unit Root Test on the differential close price data of SPD.

Table 3 : Unit Root Test for data first difference in close price SPD

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.19371	0.0000
Test crtical values :	1% level	-3.994310	
	5% level	-3.427476	
	10% level	-3.137059	

*MacKinnon (1996) one-sided p-values

Based on Figure 4, it is observed that the data difference level 1 for the closing price of SPD stock is stationary. This is evident from the Augmented Dickey-Fuller (ADF) test statistic, where the calculated probability value of 0.0000 is less than the significance level of 5%. After conducting the stationarity test, the next step was to build an AR(1) model using the e-Views 12 application. The processed data yielded the following results:

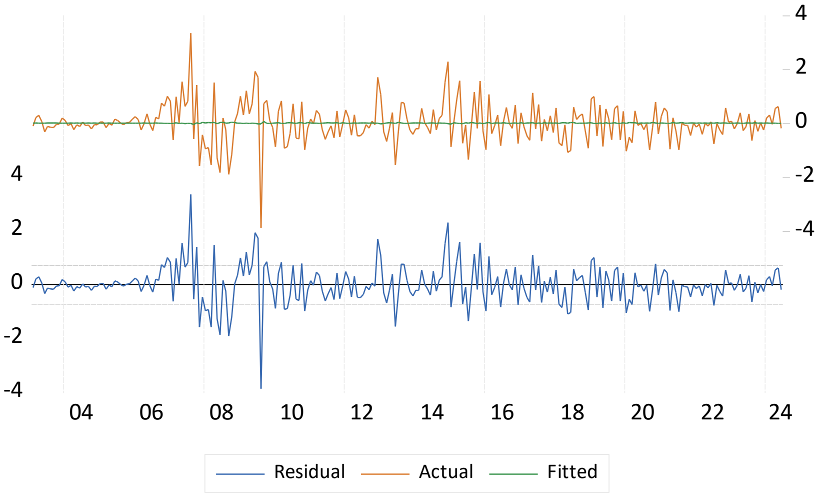
Table 4 : The results of the AR(1) analysis of the SPD stock price

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	0.025317	0.053184	0.476032	0.6345
AR(1)	-0.015065	0.051941	-0.290048	0.7720
AR(2)	-0.003344	0.048242	-0.069317	0.9448
AR(3)	0.091777	0.046933	1.955474	0.0516
Prob(F-statistic)	0.691252			
Akaike info criterion	2.199006			

Based on Table 4, it can be observed that the forecasting model that meets the requirements is the AR(3) model, as its probability value is equal to a = 5%.

Based on the analysis results in Table 4, it is known that the probability value of AR(1) is 0,7289, which is greater than the value of a = 5%. Therefore, it can be stated that the AR(1) model can be used as a predictive model for SPD stock prices. When observing the residual graph, it is as follows:

Fig 4 The residual model AR(1) graph for SPD stock prices



After analysing the AR(1) model, the next step involves performing a white noise test to determine whether the residuals are random. The results of the autocorrelation function for the AR(1) residuals are as follows :

Fig 5 White Noise Test for model AR(3) data stock price SPD

Sample (adjusted): 2003M02 2024M06
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.021	-0.021	0.1198	
		2	-0.002	-0.003	0.1211	0.728
		3	0.003	0.003	0.1234	0.940

In Figure 5, the probability value is greater than α = 0,05%. Therefore, it can be inferred that the level-1 difference data for SPD stock closing prices is free from white noise.

Model Moving Average (MA)

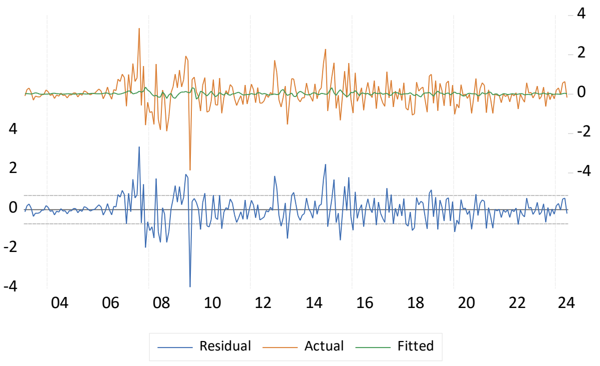
In the analysis process of the moving average (MA) model, it is similar to finding an AR(3) model. Since the stationarity test and unit root test have already been conducted in the analysis of the AR (3) model, the steps to create an MA model can be expedited. After processing the data in Figure 1 using the e-Views 12 application, the results for the MA model are as follows:

Table 5 : Model MA for Data Close Price Stock SPD

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	0.025365	0.052536	0.482810	0.6296
MA(1)	-0.030002	0.053828	-0.557365	0.5778
MA(2)	0.000273	0.049253	0.005553	0.9956
MA(3)	0.101069	0.047304	2.136606	0.0336
Prob(F-statistic)	0.645145			
Akaike info criterion	2.198024			

The MA(3) model is suitable for conducting forecasting processes, as its resulting probability of 0,0336 is less than a = 5%. For the residual graph of the moving average (MA), the following is presented. :

Fig 6 Residual graph of the moving average (MA)



Once it was determined that the MA(3) model was the best, the next step was to test for white noise, with the following results:

Fig 7 White Noise Test for model MA(3) data stock price SPD

Sample (adjusted): 2003M02 2024M06
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.023	-0.023	0.1332	
		2	-0.001	-0.001	0.1335	0.715
		3	-0.001	-0.001	0.1336	0.935

Upon completion of all the analysis processes, including AR, Indifference, and MA, the best ARIMA model for this study is determined to be ARIMA(3,1,3).

Model ARIMA

The ARIMA model has been determined from the analysis of AR and MA components, resulting in the ARIMA(3,1,3) model. The analysis of the ARIMA model was further conducted using the software program E-Views 12, yielding the following results:

Table 6 : Model ARIMA(3,1,3)

Variable	Coefficient	Std.Error	t-Statistic	Prob.
C	0.025019	0.047666	0.524887	0.6001
AR(3)	-0.814207	0.082375	-9.884160	0.0000
MA(3)	0.933145	0.062004	15.04970	0.0000
SIGMASQ	0.490539	0.025847	18.97824	0.0000
Prob(F-statistic)	0.011946			
Akaike info criterion	2.160037			

Based on Figure 9, it is known that AR(3) and MA(3) models have probabilities smaller than a = 5%. Therefore, it can be concluded that the ARIMA(3,1,3) model can be used for predicting the closing stock prices of SPD from July 2024 to December 2024. The next step is to examine the residual plot, with the following results:

Fig 8 Displays the residual graph of the ARIMA(3,1,3) model

Subsequently, the procedure was continued by conducting a white noise test, with the following results:

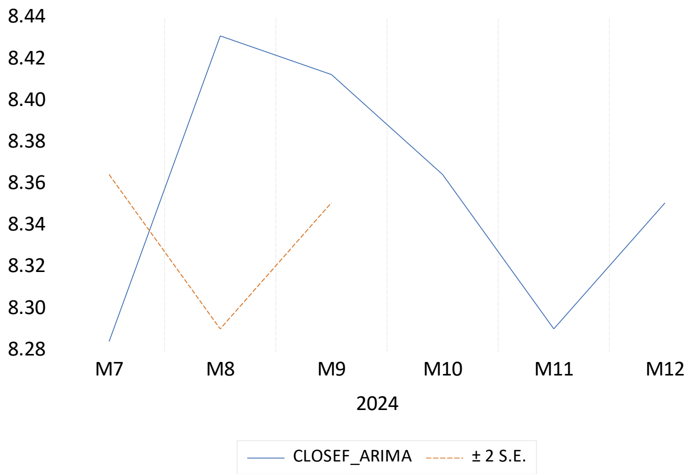
Fig 9 An examination of White Noise in the ARIMA(3,1,3) model

Sample (adjusted): 2003M02 2024M06
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.018	-0.018	0.0833	
		2	-0.002	-0.002	0.0840	
		3	0.013	0.013	0.1290	0.719

In Figure 9, it is shown that the probability value is greater than the value of a = 5%. Therefore, it can be stated that the ARIMA(3,1,3) model no longer has white noise. For the prediction of SPD stock closing prices from July 2024 to December 2024, the following can be observed:

Fig 10 Forecasting the Closing Price of SPD Stock using the ARIMA(3,1,3) Model



In Figure 12, the forecasted closing prices of SPD stock from July 2024 to December 2024 can be observed. The data for the predicted stock closing prices of SPD can be found in the following table:

Table 7 : The predicted closing prices of SPD stock with model ARIMA(3,1,3)

No.	Month	Prediction of SPD's Stock Price
1.	July 2024	8,29
2.	August 2024	8,43
3.	September 2024	8,41
4.	October 2024	8,37
5.	November 2024	8,29
6.	December 2024	8,35

Furthermore, the stock price graph of SPD, along with the stock price predictions, are as follows:

Fig 11 The closing price of SPD shares, along with a forecast of future stock prices

Heteroskedasticity Test

After conducting various analyses such as AR, MA, and ARIMA, the question arises whether the ARIMA model with parameters (3,1,3) is free from heteroskedasticity. To address this, a heteroskedasticity test analysis was performed on the ARIMA(3,1,3) model using the EViews 12 application, with the following results:

Table 8 : The outcome of the Heteroskedasticity Test on the ARIMA(3,1,3) model

F-Statistic	Obs R^2	Prob. F	Prob. Chi-Square
5.869620	16.71339	0.0007	0.0008

Based on the data in Figure 14, it can be observed that the probability value of F is 0.0007, which is smaller than the significance level of a = 5%. Therefore, we can conclude that the ARIMA(3,1,3) model still exhibits heteroskedasticity. Consequently, it is necessary to further transform the ARIMA(3,1,3) model into an ARCH/GARCH model

Mechanism ARCH/GARCH Model

The method Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Conditional Heteroskedasticity (GARCH) is a technique for forecasting time series data containing heteroskedasticity elements. For the source model to be derived from the ARIMA (3,1,3) model, followed by data processing utilising ARCH/GARCH analysis through the Eviews 12 application, the resulting ARCH/GARCH model will appear as follows:

Table 9 : Output model ARCH/GARCH, ARIMA and AIC

Model ARCH/GARCH	Model ARIMA	Akaike Info Criterion (AIC)
(1,1)	(3,1,3)	1.751422
(1,0)	(3,1,3)	2.021476

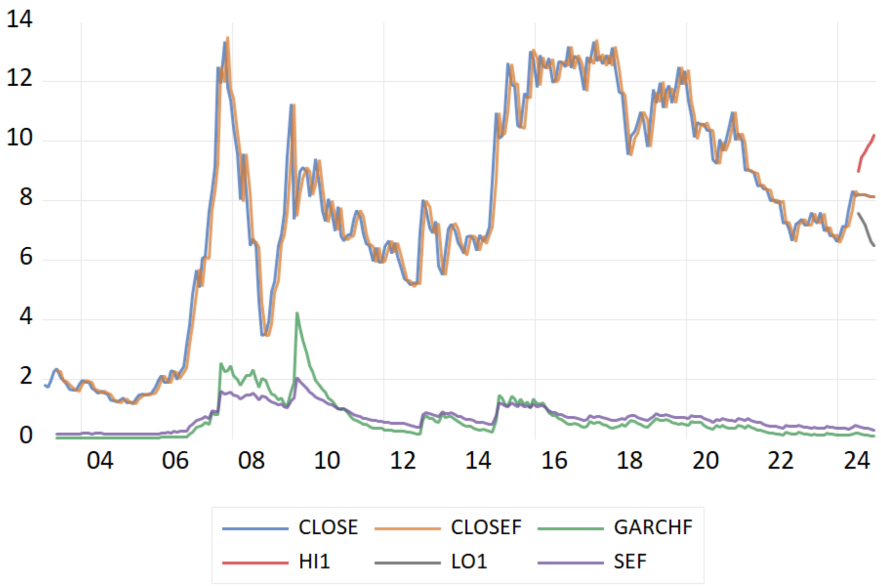
In the analysis of ARCH/GARCH, two models are used to find the best model, namely ARCH/GARCH(1,0) and ARCH/GARCH(1,1). The Akaike Information Criterion (AIC) values are considered to determine which model is the best. The model ARCH/GARCH(1,0) has an AIC value of 2.021476, while the model ARCH/GARCH(1,1) has an AIC value of 1.751422. Since the model ARCH/GARCH(1,1) has the lowest AIC value, it is considered the best model for forecasting. However, before predicting the stock prices of SPD, a Heteroskedasticity Test is conducted once again to ensure that the ARCH/GARCH(1,1) model is indeed appropriate. The results are as follows:

Fig 12 Heteroskedasticity Test for model ARCH/GARCH(1,1)

F-Statistic	Obs R^2	Prob. F	Prob. Chi-Square
6.673348	18.81893	0.0002	0.0003

Following the heteroskedasticity test, the subsequent step involves creating a graph predicting the closing price of SPD stock from July 2024 to December 2024. The graph is presented as follows:

Fig 18 Prediction of Stock Price for SPD using ARCH/GARCH(1,1) Model



The data table for the prediction of SPD stock prices from July 2024 to December 2024 with model ARCH/GARCH(1,1) is as follows:

Table 10 : The predicted closing prices of SPD stock with model ARCH/GARCH(1,1)

No.	Month	Prediction of SPD's Stock Price
1.	July 2024	8,18
2.	August 2024	8,21
3.	September 2024	8,18
4.	October 2024	8,17
5.	November 2024	8,14
6.	December 2024	8,14

Conclusion

The conclusion drawn from this research is that in order to obtain stock price predictions, one must go through several stages of analysis. The first step is to gather historical stock price data as well as external factors that may influence it. Following that, technical and fundamental analysis is conducted to identify price trends and potential factors affecting stock movements. By conducting various analyses, it is hoped that more accurate predictions regarding future stock prices can be obtained. Predicting stock prices requires ARIMA and linear regression analysis to evaluate historical data and create prediction models. Additionally, market sentiment analysis and global economic factors must also be considered in the prediction process. Through the use of comprehensive analysis methods, investors can make better investment decisions and minimise losses in volatile stock markets. In conclusion, stock price prediction is a crucial step in an effective investment strategy and must be done carefully and meticulously. In addition to ARIMA, the use of ARCH/GARCH analysis can be employed to address market volatility and account for heteroskedasticity effects in financial data. By utilising the right combination of analysis methods, investors can enhance the accuracy of stock price predictions and optimise their investment portfolios. Therefore, it is important for investors to continuously develop their knowledge and skills in market data analysis in order to make better investment decisions and generate optimal profits.

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