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Modeling and Comparing S&P 500, FTSE and SSEC Stock Price with ARIMA Model

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Abstract

S&P 500, FTSE and SSEC are respectively leading indicator in The United States, The United Kingdom and People's republic of China's stock market. In addition, auto regressive integrated moving average (ARIMA) model is an important time series model which has been used for long time. This study aims to find out best parameters of each ARIMA model of each data and to build up an appropriate ARIMA model which best fit the daily stock closed price of S&P 500, FTSE and SSEC by using daily stock closed price in ten years, from 2015 to 2024. By using each best ARIMA model of each stock price, compare the accuracy of ARIMA Model on forecasting stock price in three different countries' stock market, finding whether ARIMA Model's validity varies as country changes. To analyze those data, this study will use EViews to develop best ARIMA model of each stock closed price data. This study will contain three main parts, ARIMA model selection, accuracy of forecasting test and comparison of accuracy of ARIMA model on different stock market. This study indicates that there actually are differences on ARIMA model's validity between United Kingdom, United States and China.

Keywords

Time Series; ARIMA; Stock Price Index; Forecasting.

1. Introduction

As finance develops extremely fast, researchers are seeking methods to forecast stock price. In order to better forecast the stock price, researchers have developed many time series models like Auto Regressive Model (AR) and Moving Average Model (MA). Bases on AR and MA models, researchers combine AR and MA models and developed ARMA Model. In 1976, Box and Jenkins, two statisticians, developed proper procedures for researchers to identify and estimate ARIMA (p,d,q) models, p corresponding AR(p), d corresponds to time of difference and q corresponds to MA(q). ARIMA is a classic time series model used to forecast time series data and presents significant utility in forecasting financial or economical time series data. Moreover, there are many researchers have proved that ARMA or ARIMA Model can greatly forecast the stock price of like S&P 500 or SSEC.

In general, an ARMA(p,q) process can be written as t

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} \ldots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (1)$$

Where Y_t is observed value and ε_t is the random error at t, $\emptyset_i$ and θ_i are the AR and MA coefficients respectively. An ARMA (p, q) model in the variable differenced d times is equivalent to an ARIMA (p, d, q).

However, we still do not know whether different countries' stock price index will affect the accuracy of forecasting since stock price is a sensitive index that can be impacted by small

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changes. Therefore, this study will focus on the identifying the differences of accuracy of ARIMA Model in three main stock price indexes.

This study has several major objectives, (1) develop the ARIMA (p,d,q) model that best fit the S&P 500, FTSE and SSEC, and (2) get the statistics which can present the validity of each model and use statistical method to identify whether ARIMA (p,d,q) model has different forecasting ability in different countries. (3) Indicate in which country ARIMA model has best performance. (4) Indicate what are those differences between these three countries' stock markets.

2. Literature Review

2.1. Specific Model

Auto Regressive Integrated Moving Average (ARIMA) Model has being widely used in different fields as a tool to predict, especially in finance and economics. For instance, Shanshan Cong et al. has indicated the utility of ARIMA Model in price of stock index futures in China's financial market [1]. And Nagendra Marisetty have indicated that ARIMA models' evolution and ability of analyzing different stock price like, FSTE 100, HANG SENG, NIKKEI 225, NIFTY 50 and S&P 500 [2]. In later years, more researchers have developed ARCH and GARCH model to improve accuracy of prediction on stock price. Xiao Chen and En Yang have done research on interaction between Chinese's stock market and American stock market by building up GARCH model [3]. Once people find out the great utility of ARIMA Model in predicting like stock price index, many researchers focused on the utility of ARIMA Model in worldwide main financial markets like The United States, The United Kingdom and China. Ayodele et al. highlighted the great ability, of predicting stock's price, of ARIMA Model in New York Stock Exchange, American stock market, and Nigeria Stock Exchange which is Nigerian stock market [4]. Yingshan Bai indicated that ARIMA model has a great performance on predicting stock price of SSEC in Chinese stock market [5].

2.2. Hybrid Model

By combining other models like ARCH and GARCH models to ARIMA model, researchers found out that hybrid model has a better performance on prediction stock price. Farah Hayati Mustapa and Mohd Tahir Ismail used a hybrid model ARIMA-GARCH Model to predict S&P 500 stock prices, the result shows the hybrid model perform very well on predicting stock prices [6]. Moreover, Zheng Xiong and Wenggang Che have used ARIMA-GARCH-M model to predict short-term stock price in Chinese stock market [7]. Furthermore, researchers tried more hybrids in order to improve the accuracy of prediction on stock price, and they found that machine learning can help single ARIMA model to fix the problem, long-term variation, of single ARIMA model. Bicong Ci and Pinyi Zhang developed ARIMA-LSTM model to predict price index of Shanghai composite index, Dow Jones Industrial Average and London Gold Price and the hybrid model perform significantly well in three countries' stock price index [8].

3. Methodology

The tool used to develop ARIMA model in this paper is Eviews software version 12. The daily stock closed price data used in this paper is from 2th Jan, 2015 to 31th Dec, 2024. This paper only uses closed price to build up ARIMA model to predict the closed price in the nearly future.

In order to determine the best ARIMA model's parameters among several experiments performed, the following criteria are used in this study.

- Bayesian or Schwarz Information Criterion (BIC)
- Standard error of regression (S.E. of regression)
- Adjusted R2

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The BIC and S.E of regression should be relatively small and adjusted R2 should be relatively high.

In order to test the accuracy of each best ARIMA model of FSTE, S&P 500, and SSEC, this paper uses the following criteria.

- Symmetric Mean Absolute Percent Error (SMAPE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Error (MAE)

The formulas to calculate these criteria are following,

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n} (Actual_i - Forecast_i)^2} \quad (2)$$

$$SMAPE = \frac{100\%}{n} * \frac{\sum_{i=1}^{n} |Actual_i - Forecas_i|}{\frac{|Actual_i| + |Forecast_i|}{2}} \quad (3)$$

$$MAE = \frac{1}{n} * \sum_{i=1}^{n} |Actual_i - Forecast_i| \quad (4)$$

3.1. ARIMA (p,d,q) Model for FSTE

Table 1. Statistical results of different ARIMA parameters for FSTE

ARIMA(p,d,q)	Adjusted R^2	S.E of regression	BIC
(1,0,0)	**0.988548**	**65.74630**	**11.21946**
(2,0,0)	0.988543	65.75851	11.22255
(1,1,0)	-0.000731	65.82516	11.22005
(2,1,0)	-0.00107	65.83629	11.22331
(1,2,0)	0.249567	80.92321	11.63317
(2,2,0)	0.335042	76.17532	11.51506
(1,0,1)	0.988543	65.75850	11.22255
(2,0,1)	0.988554	65.72918	11.22439
(1,1,1)	0.002722	65.71150	11.22026
(2,1,1)	-0.000015	65.80161	11.22479
(1,2,1)	0.503078	65.85082	11.22669
(2,2,1)	0.502911	65.86192	11.22976
(1,0,2)	0.988539	65.77084	11.22565
(2,0,2)	0.988552	65.73296	11.22722
(1,1,2)	-0.000016	65.80164	11.22480
(2,1,2)	0.003251	65.69408	11.22519
(1,2,2)	0.503491	65.82347	11.22858
(2,2,2)	0.503509	65.82225	11.23128

The bold row the best ARIMA model among several experiments. ARIMA (1,0,0)

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Dependent Variable: FSTE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/15/25 Time: 05:52
Sample: 1/05/2015 8/13/2024
Included observations: 2507
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7169.034	256.4669	27.95306	0.0000
AR(1)	0.994586	0.001719	578.5653	0.0000
SIGMASQ	4317.403	57.85890	74.61953	0.0000

R-squared	0.988557	Mean dependent var	7140.988
Adjusted R-squared	0.988548	S.D. dependent var	614.3588
S.E. of regression	65.74630	Akaike info criterion	11.21249
Sum squared resid	10823731	Schwarz criterion	11.21946
Log likelihood	-14051.85	Hannan-Quinn criter.	11.21502
F-statistic	108156.9	Durbin-Watson stat	2.008332
Prob(F-statistic)	0.000000		

Inverted AR Roots	.99

Figure 1. ARIMA (1,0,0) estimation output with closed price of FSTE

Date: 03/15/25 Time: 05:55
Sample (adjusted): 1/05/2015 8/13/2024
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.005	-0.005	0.0522	
		2	-0.005	-0.005	0.1050	0.746
		3	0.002	0.002	0.1173	0.943
		4	-0.019	-0.019	1.0298	0.794
		5	0.014	0.014	1.5221	0.823
		6	-0.036	-0.036	4.7845	0.443
		7	0.051	0.051	11.363	0.078
		8	-0.034	-0.035	14.280	0.046
		9	0.012	0.013	14.630	0.067
		10	-0.004	-0.006	14.663	0.101
		11	0.010	0.014	14.929	0.135
		12	0.007	0.003	15.055	0.180
		13	-0.082	-0.077	31.903	0.001
		14	0.041	0.035	36.059	0.001
		15	0.029	0.033	38.160	0.000
		16	-0.007	-0.009	38.276	0.001
		17	-0.036	-0.037	41.488	0.000
		18	-0.002	-0.000	41.504	0.001

Figure 2. Correlogram of residuals of the closed price of FSTE

Figure 2 is the residuals of the series of ARIMA (1,0,0). If the model is well-fitted, the residuals of this model should be white noise. According to the figure 2, we can see that no significant spikes of ACFs and PACFs in this graph, combine to probability which are always greater than 0.1 which means cannot reject the assumption that the residuals are white noise. Therefore, there is no need to consider any AR(p) and MA(q) further.

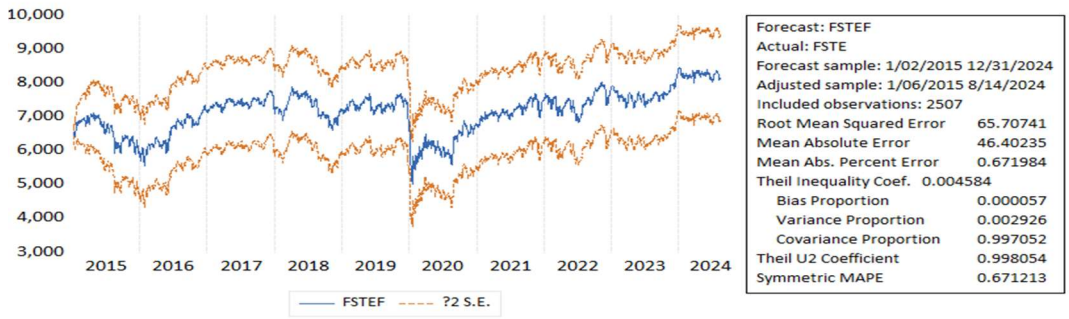


Figure 3. Forecast result of ARIMA (1,0,0) of FSTE

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From figure 3, we can get RMSE is 65.70741, MAE is 46.40235, and SMAPE is 0.671213.

3.2. ARIMA (p,d,q) Model for S&P 500

Table 2. Statistical results of different ARIMA parameters for S&P 500

ARIMA(p,d,q)	Adjusted R^2	S.E of regression	BIC
(1,0,0)	0.998810	37.39761	10.09226
(2,0,0)	0.998817	37.29907	10.08971
(1,1,0)	0.005155	37.25656	10.08168
(2,1,0)	0.006026	37.23958	10.08349
(1,2,0)	0.308051	45.60632	10.48627
(2,2,0)	0.380247	43.16156	10.37888
(1,0,1)	0.998815	37.30683	10.09013
(2,0,1)	0.998817	37.28527	10.09186
(1,1,1)	0.005830	37.24392	10.08372
(2,1,1)	0.006736	37.24568	10.08653
(1,2,1)	0.538134	37.26025	10.08777
(2,2,1)	0.538535	37.24408	10.08959
(1,0,2)	0.998817	37.28132	10.09147
(2,0,2)	0.998816	37.28837	10.09458
(1,1,2)	0.005814	37.24422	10.08645
(2,1,2)	**0.032092**	**36.74871**	**10.06246**
(1,2,2)	0.537464	37.28727	10.09190
(2,2,2)	0.542066	37.10133	10.08470

The bold row the best ARIMA model among several experiments. ARIMA (2,1,2).

Dependent Variable: D(SPX)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/15/25 Time: 18:25
Sample: 1/06/2015 8/26/2024
Included observations: 2515
Convergence achieved after 74 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.519545	0.729116	2.084092	0.0373
AR(1)	-1.765091	0.021071	-83.76892	0.0000
AR(2)	-0.882123	0.019984	-44.14038	0.0000
MA(1)	1.703709	0.025837	65.94176	0.0000
MA(2)	0.802629	0.024727	32.45925	0.0000
SIGMASQ	1347.246	21.48468	62.70728	0.0000

R-squared	0.034017	Mean dependent var	1.520250
Adjusted R-squared	0.032092	S.D. dependent var	37.35296
S.E. of regression	36.74871	Akaike info criterion	10.04855
Sum squared resid	3388324.	Schwarz criterion	10.06246
Log likelihood	-12630.06	Hannan-Quinn criter.	10.05360
F-statistic	17.67076	Durbin-Watson stat	1.972759
Prob(F-statistic)	0.000000		

Inverted AR Roots	-.88-.32i	-.88+.32i
Inverted MA Roots	-.85-.28i	-.85+.28i

Figure 4. ARIMA (2,1,2) estimation output with closed price of S&P 500

Figure 4 is the residuals of the series of ARIMA (2,1,2). According to the figure 4, there are no significant spikes of ACFs and PACFs. According to the ACFs and PACFs, can conclude that the residuals are white noise. But according to the Q-stat, there are still significant statistics show there are probability that residuals on some lags are not white noise. Therefore, there are further check should be done to verify that whether ARIMA (2,1,2) is the best ARIMA model of S&P 500, there are ARIMA (1,0,2), ARIMA (2,0,1), ARIMA (3,1,2) and even ARIMA (2,1,3). Residuals of those ARIMA model of different parameters which are relative best also still show that there are some significant Q-stat on some lags even though no significant spikes of ACFs and PACFs occur on these lags. Therefore, according to the table, we still choose ARIMA (2,1,2) as best model used to predict S&P 500 closed price.

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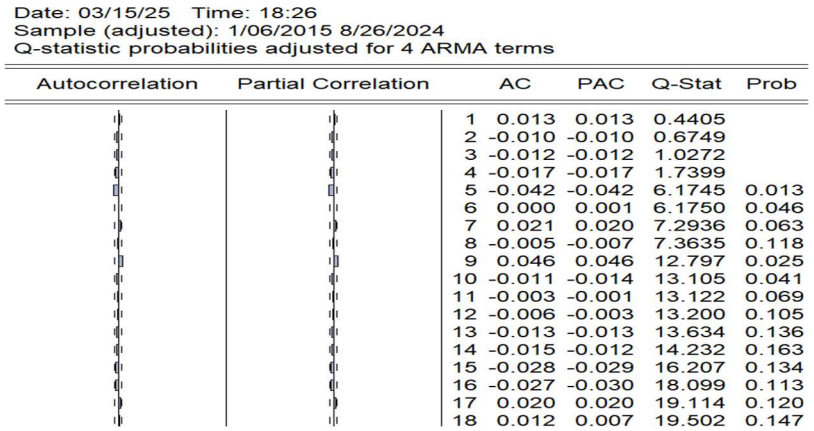


Figure 5. Correlogram of residuals of the closed price of S&P 500 with ARIMA (2,1,2)

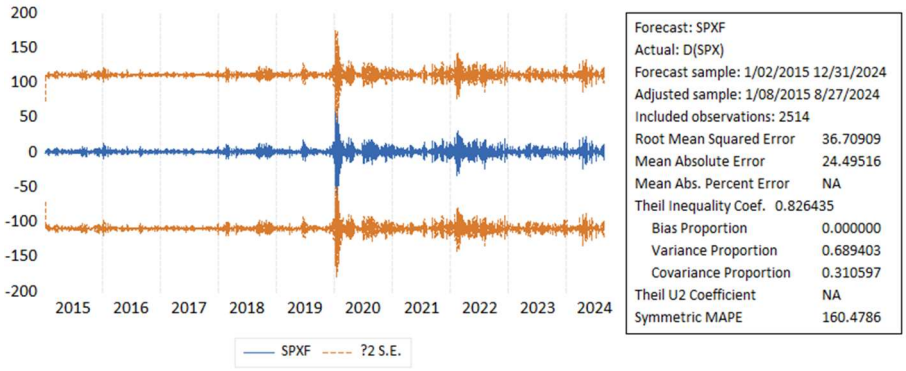


Figure 6. Forecast result of ARIMA (2,1,2) of S&P 500

From figure 6, we can get RMSE is 36.70909, MAE is 24.49516, and SMAPE is 160.4786.

3.3. ARIMA (p,d,q) model for SSEC.

Table 3. Statistical results of different ARIMA parameters for SSEC

ARIMA(p,d,q)	Adjusted R^2	S.E of regression	BIC
(1,0,0)	**0.988101**	**63.69541**	**11.15629**
(2,0,0)	0.988097	63.70665	11.15936
(1,1,0)	-0.000720	63.71341	11.15481
(2,1,0)	-0.000683	63.71221	11.15749
(1,2,0)	0.243534	78.69482	11.57729
(2,2,0)	0.333423	73.87143	11.45361
(1,0,1)	0.988097	63.70659	11.15936
(2,0,1)	0.988094	63.71648	11.16239
(1,1,1)	-0.000977	63.72158	11.15779
(2,1,1)	-0.001081	63.72489	11.16060
(1,2,1)	0.504164	63.71189	11.16061
(2,2,1)	0.504201	63.70951	11.16326
(1,0,2)	0.988097	63.70829	11.16214
(2,0,2)	0.988092	63.72082	11.16524
(1,1,2)	-0.001092	63.72522	11.16061
(2,1,2)	0.005338	63.52027	11.15694
(1,2,2)	0.504100	63.71600	11.16345
(2,2,2)	0.504004	63.72218	11.16638

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The bold row is the best ARIMA model among several experiments. ARIMA (1,0,0)

Dependent Variable: SSEC
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/15/25 Time: 20:37
Sample: 1/05/2015 4/29/2024
Included observations: 2431
Convergence achieved after 35 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3209.898	115.3344	27.83123	0.0000
AR(1)	0.991302	0.001505	658.6519	0.0000
SIGMASQ	1942.720	24.12037	80.54272	0.0000

R-squared	0.983296	Mean dependent var	3196.654
Adjusted R-squared	0.983282	S.D. dependent var	341.0972
S.E. of regression	44.10352	Akaike info criterion	10.41386
Sum squared resid	4722753.	Schwarz criterion	10.42101
Log likelihood	-12655.04	Hannan-Quinn criter.	10.41646
F-statistic	71461.16	Durbin-Watson stat	1.867057
Prob(F-statistic)	0.000000		

Inverted AR Roots	.99

Figure 7. ARIMA (1,0,0) estimation output with closed price of SSEC

Figure 7 is the residuals of the series of ARIMA (1,0,0). According to the figure 7, there are some significant spikes of ACFs and PACFs. According to the ACFs and PACFs, we cannot conclude that the residuals are white noise. Moreover, according to the Q-stat, we also find out that the assumption, residuals are white noise, cannot be rejected. Therefore, there should be more ARIMA model with different parameters to try.

Date: 03/15/25 Time: 20:37
Sample (adjusted): 1/05/2015 4/29/2024
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.066	0.066	10.642	
		2	-0.041	-0.045	14.663	0.000
		3	0.015	0.021	15.193	0.001
		4	0.086	0.083	33.409	0.000
		5	0.006	-0.004	33.494	0.000
		6	-0.086	-0.080	51.538	0.000
		7	0.016	0.025	52.157	0.000
		8	0.076	0.061	66.095	0.000
		9	0.028	0.023	68.045	0.000
		10	-0.061	-0.048	77.179	0.000
		11	-0.034	-0.030	80.029	0.000
		12	0.030	0.013	82.171	0.000
		13	0.041	0.038	86.275	0.000
		14	-0.105	-0.092	113.08	0.000
		15	0.016	0.038	113.70	0.000
		16	0.038	0.012	117.31	0.000
		17	0.014	0.003	117.77	0.000
		18	-0.026	-0.003	119.47	0.000

Figure 8. Correlogram of residuals of the closed price of SSEC with ARIMA (1,0,0)

To promote the ARIMA model, we differenced closed price once and increase q and p several times. Finally find out that parameters covered by the table above are all not best ARIMA models. Therefore, increase some of the parameters to 3.

Figure 8 is the output of ARIMA (3,1,2), from the output we can see, adjusted R2 is 0.035047, S.E. of regression is 43.40410 and BIC is 10.38203. Compare to those ARIMA models on the table above, ARIMA (3,1,2) model's criteria have a significant better performance like smaller S.E. regression and BIC.

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Dependent Variable: D(SSEC)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/15/25 Time: 20:35
Sample: 1/06/2015 4/29/2024
Included observations: 2430
Convergence achieved after 104 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000435	1.003518	0.000434	0.9997
AR(1)	0.235151	0.015618	15.05610	0.0000
AR(2)	-0.966218	0.007406	-130.4555	0.0000
AR(3)	0.102499	0.011542	8.880314	0.0000
MA(1)	-0.170176	0.012181	-13.97086	0.0000
MA(2)	0.914483	0.011344	80.61498	0.0000
SIGMASQ	1878.489	25.41651	73.90822	0.0000

R-squared	0.037431	Mean dependent var	0.000510
Adjusted R-squared	0.035047	S.D. dependent var	44.18530
S.E. of regression	43.40410	Akaike info criterion	10.38203
Sum squared resid	4564729.	Schwarz criterion	10.39872
Log likelihood	-12607.17	Hannan-Quinn criter.	10.38810
F-statistic	15.70369	Durbin-Watson stat	2.003855
Prob(F-statistic)	0.000000		

Figure 9. ARIMA (3,1,2) estimation output with closed price of SSEC

Figure 9 is the residuals diagnostics for ARIMA(3,1,2), whichi shows there are no significant spikes of ACFs and PACFs. Moreover, the Q-stat also shows that there are correlations on some lags like lag 6, lag 14 or lag 15. Compared to previous ARIMA model, this one performs significantly better. So we do not need to try more further AR(p) or MA(q) again.

Date: 03/15/25 Time: 20:36
Sample (adjusted): 1/06/2015 4/29/2024
Q-statistic probabilities adjusted for 5 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.002	-0.002	0.0125	
		2	0.023	0.023	1.3126	
		3	-0.019	-0.019	2.2051	
		4	0.006	0.006	2.2983	
		5	0.018	0.019	3.1043	
		6	-0.019	-0.019	3.9436	0.047
		7	0.009	0.009	4.1550	0.125
		8	-0.005	-0.003	4.2089	0.240
		9	0.021	0.019	5.2666	0.261
		10	0.007	0.008	5.3950	0.370
		11	-0.023	-0.024	6.6849	0.351
		12	-0.046	-0.046	11.785	0.108
		13	0.023	0.025	13.110	0.108
		14	-0.056	-0.056	20.733	0.014
		15	0.051	0.049	27.040	0.003
		16	-0.023	-0.018	28.307	0.003
		17	-0.027	-0.031	30.055	0.003
		18	0.017	0.019	30.777	0.004

Figure 10. Correlogram of residuals of the closed price of SSEC with ARIMA (3,1,2)

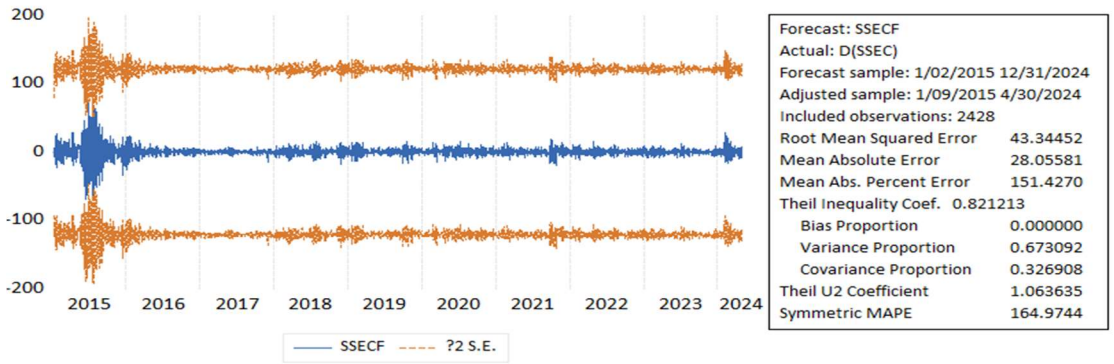


Figure 11. Forecast result of ARIMA (3,1,2) of SSEC

From figure 11, we can get RMSE is 43.34452, MAE is 28.05581 and SMAPE is 164.9744

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4. Performance Comparison

Table 4. RMSE, MAE and SMAPE of each best ARIMA model of FSTE, S&P 500 and SSEC

	RMSE	MAE	SMAPE
FSTE	65.70741	46.40235	**0.671213**
S&P 500	**36.70909**	**24.49516**	160.4786
SSEC	43.34452	28.05581	164.9744

From table 4 we can find out that RMSE and MAE of ARIMA model on S&P 500 closed price are smallest, but SMAPE of ARIMA model on FSTE is smallest and SMAPE of ARIMA model on S&P 500 and SSEC is significant great. This indicate that ARIMA model perform a better prediction on closed price in S&P 500, comparing to other two stock price index. And ARIMA model perform a worst prediction on closed price in SSEC. The reasons for SMAPE of S&P 500 and SSEC are too much great perhaps are great variation on these two stock markets or the actual stock closed price are small in some periods. Combine the RMSE and MAE, we still can conclude that ARIMA model still perform well on prediction of closed price in American and Chinese stock market even SMAPE is huge.

5. Conclusion

This study uses single ARIMA model to predict three stock price indexes of three different countries, The United States, The United Kingdom and China. This study develops the best ARIMA model, depending on Adjusted R2, S.E. regression and BIC, of each stock price index and use each best ARIMA model to forecast the stock price index. Finally get three criteria, RMSE, MAE and SMAPE, used as criteria to estimate the accuracy of each best ARIMA model. The results show that (i) ARIMA model can have well prediction utility in American, English and Chinese stock markets. (ii) ARIMA model's utility of prediction has difference when data come from different countries, and ARIMA model perform best in American stock market, and worst in Chinese stock market. (iii) ARIMA model has different problems in different countries' stock markets since ARIMA model forecasting has great SMAPE in American and Chinese stock market but small RMSE and MAE, but ARIMA model has small SMAPE in English stock market but greater RMSE and MAE.

This study uses ARIMA model to develop whether there are differences on utility of ARIMA model in different countries and indicate that there are indeed differences between three countries. In addition, this study points out that there are different problems of ARIMA model when researchers are using in different countries. But this study does not develop a way to fix these problems, in the future, can keep doing researches on how to fix these problems in order to develop a better time series model.

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