

Prediction of Quantitative Easing Policy Effect on the U.S. Stock Market Using ARIMA Model

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Abstract. The rapid spread of the coronavirus impacted the global financial market dramatically. A “rush for cash” - the eager demand for liquidity only - that suspended financial markets and endangered to make an already dreadful situation much worse was spurred by the sudden contraction and intense concern about the future consequence of the virus. To minimize the economic loss due to the COVID-19 pandemic, the Federal Reserve has a bunch of policy tools to maintain the credit flow in the market. These included substantial mortgage-backed and government-backed securities purchases as well as lending to households, businesses, participants in the financial market, and governments at different level. The Fed also initiated purchase of debt securities on a wide scope, which is an effective resort to combat economic crisis. In this paper, effect of the increased money supply on financial assets in stock market will be evaluated, revealing the impact of the aggressive expansionary monetary policy on the stock market performance through applying the autoregressive integrated moving average (ARIMA) models. The process of using ARIMA model to predict the stock market will be illustrated. Published stock data are obtained from S&P500 and M2 data from Board of the Federal Reserve System. Results obtained from the selected model revealed that the un-disciplined monetary policy had a tremendous positive impact on the stock market.

Keywords: Quantitative Easing, S&P500, ARIMA model.

1. Introduction

After the outbreak of the COVID-19 pandemic, the terror spread out in the market and drove up the demand for liquidity. This run on the liquidity forced the Fed to take measures to reinstall the function of the Treasury and mortgage-backed securities (MBS) markets, which are vital to provide credit flow in economic activities.

The Fed changed the goal of quantitative easing (QE) to help the economy on March 15, 2020. It stated that it would acquire Treasury securities worth at least \$500 billion and MBS that are worth \$200 billion. The stock market is always affected by the quantitative easing (QE) program run by the Federal Reserve. The policy of quantitative easing lowers interest rates. As a result, the investments with least risk like money market accounts, corporate bonds, certificates of deposit (CDs), and treasuries can expect lower returns from investors. For greater returns, investors are compelled to make investments that are somewhat riskier. Stocks make up a large portion of these investors' portfolios, driving up stock market prices [1].

To evaluate the effect of the QE on the stock market, the ARIMA model will be applied to make prediction about the stock market based on previous 10 years market data and compare the prediction with the actual stock market performance after the implementation of QE policy.

Since prediction will always be a fascinating field of study, experts devote themselves to develop better predictive algorithms. Stock price prediction has long been deemed as the most challenging activity in the financial markets because individuals and institutional investors involve in the market and make investment decisions which can collectively influence the price reflected in the market.

ARIMA models are based on statistical models. Predictions can generally be made from two perspectives, according to the literature: techniques based on statistics and artificial intelligence. When it comes to time series forecast of economic and financial aspects, ARIMA models outperform even the most widely used ANNs in the. In economic and financial study, this model has been extensively used [2,3,4,5]. ARIMA model can function to predict the stock price index in New York stock market,

palm oil price in Thailand and consumption of electricity in Netherland. This model is a versatile and useful tool to predict data sets which demonstrate continuous trend and can be used as training set in ARIMA model to predict the short-term future trend.

A step-by-step procedure for building ARIMA models for market performance prediction following 2020 QE policy is described in this paper. The ARIMA model takes the historical price of S&P 500, forecasting the trend after the QE policy published. The result of the prediction reveals that the QE policy has a tremendous effect on the stock market and drives up the general performance of the market. QE policy is like a stimulus after the destruction of COVID pandemic. The released money drove up the price of financial assets significantly.

This paper consists of three main sections: the second section is methodology; the third section is result and the fourth section is conclusion. In the methodology part, the mechanism of ARIMA model and how it is applied to the topic of this paper will be introduced. In the result part, the outcome of the optimal model will be presented, and the model's performance will be evaluated. In the conclusion part, the impact of the QE policy will be concluded based on the prediction result of the model chosen.

2. Methodology

2.1 ARIMA Model

In 1970, ARIMA model is developed by Box and Jenkins. It was named as Box-Jenkins methodology as well, which consists of steps including locating, estimating, and diagnosing the selected ARIMA models which takes time series as training data. The model is frequently used in economic prediction [6,7,8]. ARIMA models have demonstrated powerful prediction power over the short-term trend. This model demonstrated excellent short-term performance compared to other complex structure models [9]. In ARIMA model, a linear combination which contains the previous errors and values reflects the forecasted value of a variable. The equation of this prediction process exhibited as follows:

$$Y_t = \vartheta_0 + \vartheta_1 Y_{t-1} + \vartheta_2 Y_{t-2} + \cdots + \vartheta_p Y_{t-p} + \varepsilon_t - \delta_1 \varepsilon_{t-1} - \delta_2 \varepsilon_{t-2} - \cdots - \delta_q \varepsilon_{t-q} \quad (1)$$

where Y_t is the stock price of S&P 500c and ε_t is the unpredicted error at time t, δ_i and ϑ_j are the coefficients; p stands for the order of regression and q stands for the order of moving average. Complete procedures in generating ARIMA forecast model includes model identification, coefficients tuning and verifying selected parameters [10].

In the section below, the method adopted to develop ARIMA model is demonstrated. The mechanism behind the stock price prediction will be illustrated. The tool used for implementation is R. Training data utilized in this research are daily closing prices from S&P500 historical data. The original data includes six columns, namely date, closing price, open price, high price, low price, volume change. The closing price is the only data used in the model of this study.

2.2 Unit Root Test

Stationarity of the selected time series requires to be checked. The Augmented Dickey-Fuller (ADF) test is the test utilized for stationarity checking in this paper. It is used to determine whether the series contains a unit root, assisting the process to determine whether the series is stationary.

The null hypothesis of this test is that there are unit roots in the series and the alternate hypothesis is that there is no unit root in the given series. The series could be linear or difference stationary if the null hypothesis cannot be rejected.

2.3 Data

Historical data of S&P 500 index from website www.investing.com is used for this study. S&P 500 index is a weighted index of 500 most influential publicly traded companies in the U.S. For this reason,

it can reflect the general situation of the U.S. financial market. S&P 500 data will be used in this study covers the time span from 2nd January 2010 to 15th March 2020, containing a total number of 2872 observations. The historical stock price of S&P 500 before the 2020 QE and after the first trading day of 2010 will take the task to predict the trend of the stock market in near future. The predicted trend will be used to compare with the real performance of the stock market to evaluate the impact of the QE in covid time. The QE may not be the sole cause of the deviation of the market. In this paper, the main reason will be accounted to the quantitative easing of the Fed. All missing data are excluded.

3. Results

3.1 Descriptive Statistics

Figure 1 illustrates the raw pattern of the series. From the figure, the original stock index exhibits a random walk attribute. Significant drops of the market normally reflect major events in the market such as financial crisis, monetary policy expectation and pandemic spread globally. At each time point, the unpredictable shock will be imposed on the existed time series and the shock will accumulate because the random walk pattern is highly persistent. The past trend of the stock market cannot be used to predict the future movement, so any method to predict the future stock market in the long run is not practical.

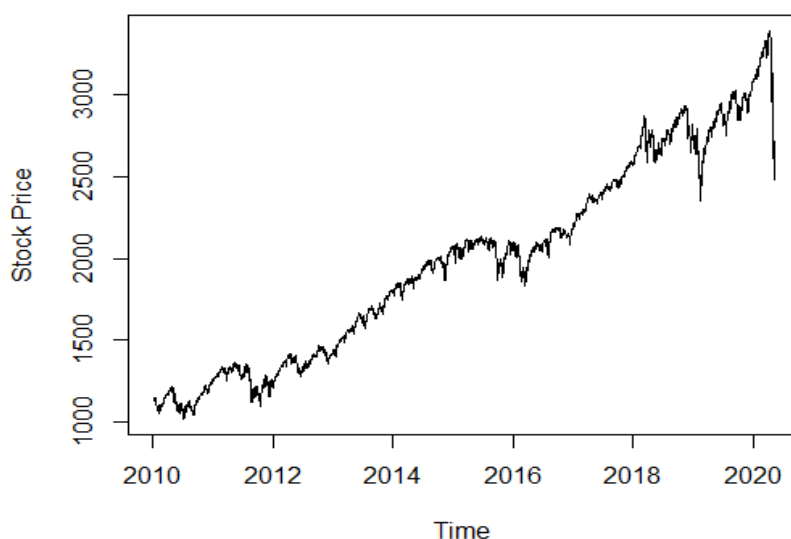


Fig.1 Original data of S&P500 stock index before 2020 QE policy

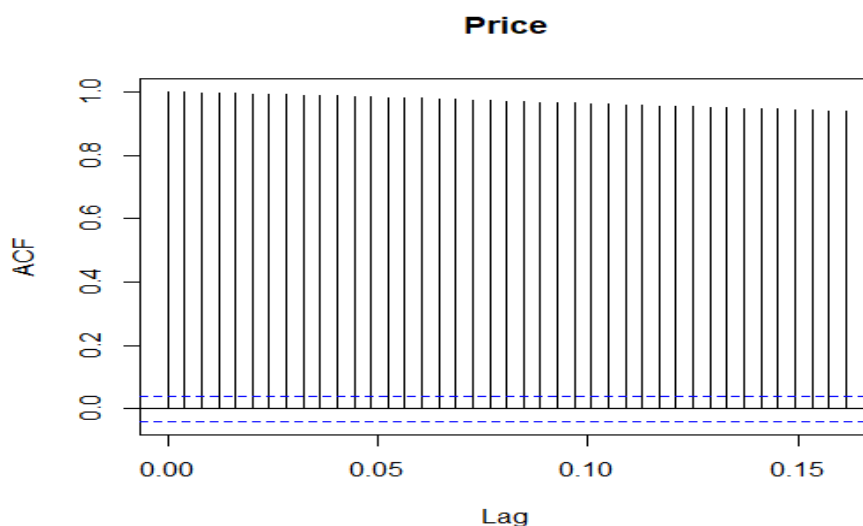


Fig.2 The correlogram of unprocessed S&P500 stock index

Figure 2 is the ACF graph original data set of S&P500. This graph can present an intuitive view of the stationarity of the time series used for the tremendous number of lags shown. Through vertical lines with similar height level, the ACF dies out at an extremely slow pace, which intuitively implies that the time series is not stationary. The lagged autocorrelation has significant correlation from this graph.

The autocorrelation of a random walk can be derived as follows:

$$\rho_k(t) = \frac{\text{Cov}(x_t, x_{t+k})}{\sqrt{\text{Var}(x_t)\text{Var}(x_{t+k})}} = \frac{t\sigma^2}{\sqrt{t\sigma^2(t+k)\sigma^2}} = \frac{1}{\sqrt{1+k/t}} \quad (2)$$

This equation demonstrates that in a long time series, with lags in short term, the autocorrelation is almost unity. The extremely high autocorrelation does not die out at a rapid pace as the lag increases. Thus, the correlogram of S&P 500 possesses the attributes of the random walk which is not stationary.

When the time series does not demonstrate stationary attributes, proper transformation should be applied. Most frequently used procedures are to take the log of the original data or to difference the original time series. The seasonality and trend need to be removed from the series. After the second difference of the log of the series, the S&P500 index eliminates significant trend and seasonality and manifests stationary pattern as shown in Figure 3. There is no obvious seasonality and trend shown in Figure 3.

Figure 4 presents the ACF residual of the series. There is no peak shown in the ACF plot. The limited number of lags implies that there is no obvious autocorrelation in the given time series. The ACF dies out rapidly in this graph, which is an attribute of the white noise for residuals of this chosen ARIMA model.

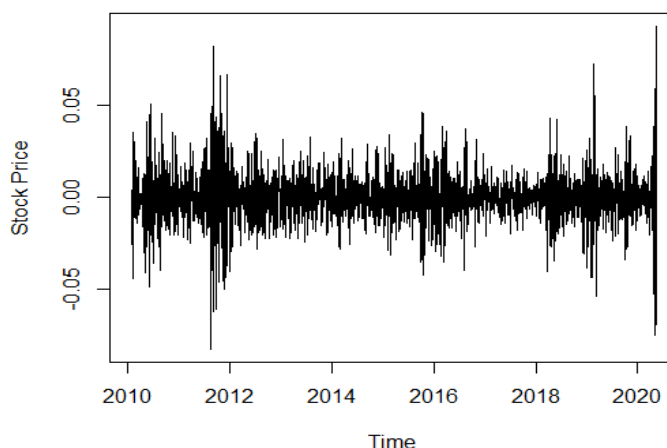


Fig.3 Processed S&P500 stock index after first order differencing

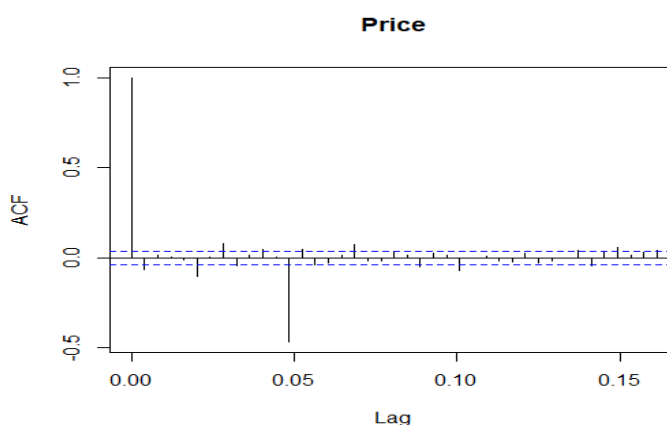


Fig.4 The ACF plot of S&P 500 stock index after differencing

3.2 ARIMA Model

The ACF/PACF graphs of various models are typically displayed to identify a probable candidate model, which then looking for a more precise model using AICc. The auto.armima command is applied in this study that it automatically chooses the optimal sequence for an ARIMA model. After determining the order of differencing through differencing tests, the ARIMA function fits models. The best order for seasonal differencing was chosen using the Canova-Hansen test if the seasonal option is turned on, ARIMA also tries to find the best hyper-parameters. The optimal hyper-parameters are also attempted to be found by ARIMA when the seasonal option is detected.

After implementing the auto. ARIMA function on the time series of S&P500 index before the March QE policy, the model selected is ARIMA(0,1,2). Coefficients of the ARIMA model (0,1,2) is shown in Table 1. MA (1) is the first order of the moving average model and MA (2) is the second order of the moving average model. The first order moving average has a statistically significant effect.

Table 1. Coefficients of ARIMA (0, 1, 2) Model

	Coefficients
MA (1)	-0.103*** (0.0197)
MA (2)	0.0296 (0.0206)

Table 2. Akaike and Bayesian information criterion of ARIMA (0,1,2)

AIC	AICc	BIC
24632.53	24632.54	24650.06

Table 3. Accuracy metrics of ARIMA (0,1,2)

MSE	MAE	RMSE	MAPE
1	20.39309	30.49769	5.046373

From Table 2 and Table 3, the prediction power of the model is poor. Table 2 and table 3 are two metrics used to evaluate the prediction quality of the selected model. The smaller the AIC and BIC, the better the model is. Metrics in Table 3 measure the deviation of the forecasted value and the real historical values. Thus, a smaller deviation in the measured error represents a better prediction result. The predicted value deviates a lot from the actual historical data followed by the QE policy.

3.3 Forecasting

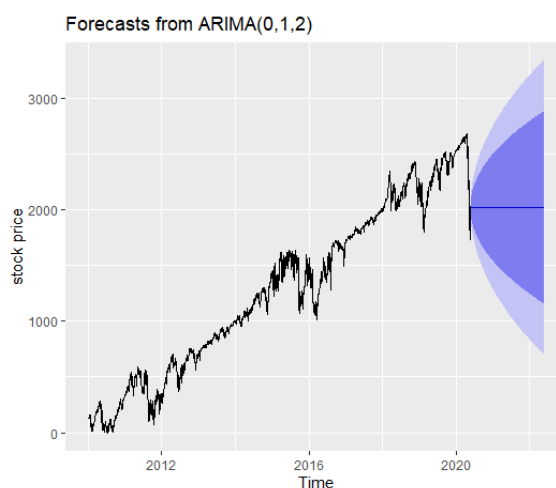


Fig.5 Forecasts of S&P500 index after the QE policy

Presented in Figure 5, the forecasted result of the selected ARIMA model is around the 2000 points of the index. Since the price of the stock market is a random walk series, the prediction can be applied to the most recent data, which generates a straight-line prediction around the final data, while as shown in the blue shaded area, the predicted range of the S&P 500 index could reach as high as more than 3000 point as long as around 800 index point.

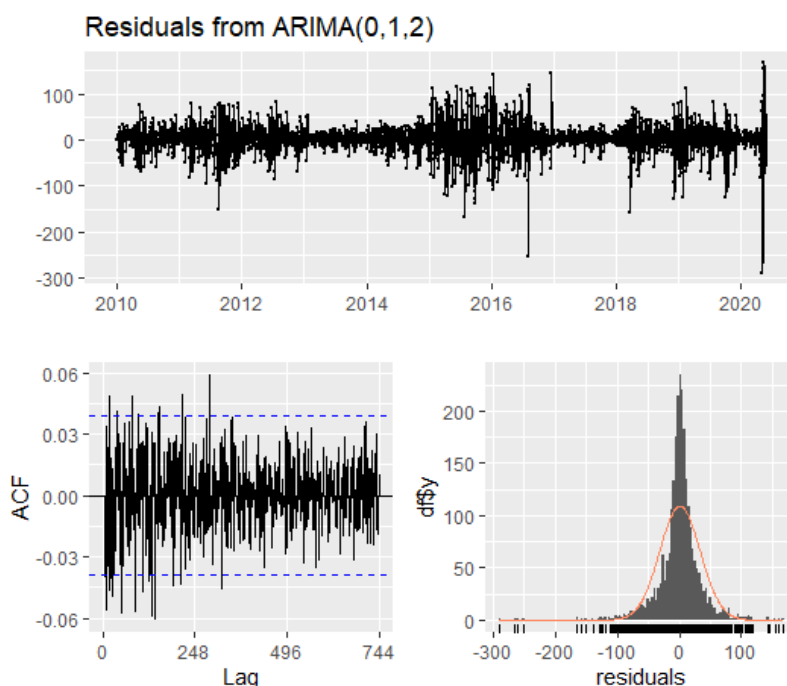


Fig.6 Residual check of selected ARIMA model (0,1,2)

Figure 6 is the residual check of the ARIMA model (0,1,2). The residual of the autoARIMA model fits the attributes of the white noise. Almost all autocorrelations in the ARIMA (0,1,2) model's residuals are within the threshold limits, as shown by the ACF plot, indicating that the residuals are acting like white noise. The mean of residual error is around zero and exhibits a pattern of uniform variance. From the density graph, the normal distribution exhibits a mean of zero. Because the p-value is greater than 0.05, it is not statistically significant at 5% level. For reasons above, a conclusion that residuals are white noise can be made.

Table 4. Ljung-Box test, Residuals from ARIMA (0,1,2)

Q*	df	p-value	Model df	Total lags used
510.97	494	0.289	2	496

Table 4 is the result of the Ljung-Box test. The null hypothesis of this test is that data points are independent. The alternative hypothesis is that data points are not independent. Since p value is 0.289 which is higher than 0.05, then the null hypothesis cannot be rejected. The conclusion that residuals are independent can be made.

From Figure 7, The ARIMA model predicts the stock market performance at a level of 2000 points, and the actual stock market performance was higher than the predicted level generated from the data of the last 10 years. From the function of R, ARIMA (0,1,2) was selected as the most fitted model for S&P 500 stock index by using the auto.arma method. The graph depicts the forecasted values of the ARIMA model and the actual stock prices. The deviation from the model can provide a quantitative illustration of the positive impact of the QE policy on the stock market.

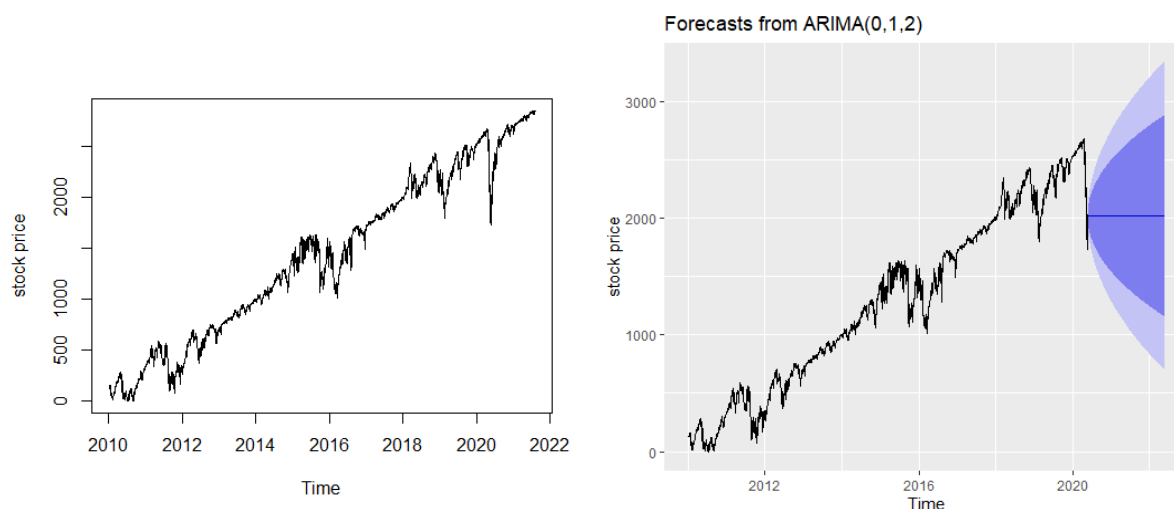


Fig.7 Comparison between actual market trend and predicted market trend

3.4 Discussion

The significant impact of the QE policy on the financial market is remarkable and nobody can ignore the rising trend of the S&P 500. This policy tool is like a stimulant to the stock market. The quantitative impact of this policy needs to be measured to evaluate the effect of the over-issued currency on the economy. The consequence of the QE policy will be reflected on the commodity and CPI index as well. Tracking the conducting mechanism of this over-issued money can reflect the economic activities of the society.

4. Conclusion

The model of the ARIMA has limited prediction power over random walk time series. The predicted target is the stock price which is intrinsically hard to be predicted. However, from the graph of the comparison between the prediction data and the real-world data, the conclusion that QE drove the stock market up dramatically can be made. The trend of the real-world data is along the upper boundary of the prediction model.

With the increased money supply flowing into the stock market, financial asset drives up the bubble. From the empirical evidence, QE policy often followed by a bull market. \$11 trillion has already flowed into the global economy since 2020 result from central banks of major economy. Though the aggressive QE policy helped to restore the economy in the short period of time, the following inflation is hard to control. The sudden blooming money supply and a sudden increase in the interest rate to combat the inflation

The inflation, which is still under investigation due to concerns about its impact on consumer spending and sentiment, will remain the obvious challenge to the stock market. The un-disciplined monetary policy will dampen the authority of the US dollar and foster the regional monetary cooperation. There is no free lunch in the world and the cost of the monetary policy abuse will be later examined by the time.

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