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The ARIMA Model for the Indonesia Stock Price

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ABSTRACT

Prediction of stock price volatility is an important topic either in economics or in finance as it benefits both the investors and economists. In this paper, we conducted the prediction of Indonesia stock price by using Autoregressive Integrated Moving Average (ARIMA). The ARIMA model was chosen as the model to predict the volatility of Indonesia stock price due to its simplicity and wide acceptability. To this end, the daily Indonesia Composite Stock Price Index (CSPI) in the period January, 4th 2010 until December, 5th 2014 was employed. This study reports empirical evidences that ARIMA models are applicable for forecasting Indonesia stock price. Furthermore, the results obtained in the study revealed that ARIMA model has a strong potential for short-term prediction and can compete favourably with the existing techniques for stock price prediction. The best ARIMA model was selected using Akaike Information Criterion (AIC) criteria and it was found that ARIMA (0,0,1) is the best model for forecasting the Indonesia Composite Stock Price Index.

Keywords: Composite stock price index, ARIMA

JEL Classification: E37, E31, E3.

INTRODUCTION

Composite Stock Price Index (CSPI) is a stock index of all companies listed on the stock exchange and an indicator of stock price movements. Increasing capital market condition indicates an increase in CSPI and market capitalization score. It is a positive signal and important information for prospective investors in making investment decision in the stock market. The influx of investors in capital market plays an important role in the growth of both the capital market and companies. For companies, the need to fund the company's operations can be

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obtained by issuing securities in the capital market. In this case, the stock market serves as an intermediary to link the owners of capital (investors) with parties who want to gain additional funds through the sale of stocks. Companies issue securities in capital market basically to avoid the process of financial intermediation. In other words, the parties who own the excess funds (the investors) hand over the funds directly to those who need funds (company) (Ang, 1997).

In investing activities, investor requires two important information namely stock risks and returns. Revenue (return) obtained by investors can be in the forms of dividends (dividend yield) as well as revenue obtained from the difference between the selling price and the stock purchase price (capital gain). In addition to considering the return and risk factors, investors in investing in stock market will also gather as much information as possible, including information relating to the stock price and company performance. Stock price consideration serves as the basis consideration for investors as the stock price reflects the value of the company. The higher the stock price means the higher the value of the company, whereas a low stock price indicates the low value of the company.

The assessment of stock price is heavily influenced by the level of investor optimism toward the company (issuer). Stock buyer wants the increasing stock prices after the purchase of stocks but the seller of stocks wants the decrease in the stock price after the stock sold. The different purposes of the buyer and seller are behind the revaluation which results in fluctuations in stock prices. Fluctuation in stock price is indicated by volatility–a statistical measure of price fluctuation over a given period (Firmansyah, 2006).

Public often equates volatility with risk. The higher the volatility means the higher the uncertainty of returns that will be obtained. When the daily volatility is very high then the stock price will highly increase and decrease so as to provide space for trade or transaction in order to generate profit gained from the difference (margin) between the initial price and the final price at the time the transaction is carried out. However, the risk is also very high hence "high risk high return" is applied. In contrast, the lower stock price volatility indicates the very low movement of the stock price. At the low volatility, investors are usually not able to generate profit but they must hold the stocks in the long term in order to obtain capital gain. Thus, investors who prefer to conduct trading strategy are very fond of high volatility; however long-term investors absolutely prefer low volatility but increasing stock price (Chan and Fong, 2000).

Quite high fluctuation of CSPI movement results in investment in the capital market that is full of uncertainty, particularly uncertainty concerning profit and risk. In each trading transaction, investors or investor managers are confronted with the choice to buy or sell stocks, where every mistake in making investment decisions will lead to losses for the investors themselves. Further, relatively complex the nature of stock market make the prediction of the stock price in the future is considered as one of the difficult tasks to achieve (Pai and Lin, 2005; Wang *et al*, 2012; Wei, 2013). Therefore, accurate and reliable analysis is needed to be used as the basis for making investment decisions.

Forecasting technique is employed by investors to analyze CSPI movement. In stock investment, there are two kinds of analysis namely fundamental analysis which analyses the economic condition of the country and technical analysis which employs the previous CSPI movement. Furthermore, to strengthen the justification on the fluctuations in stock prices, the approach using econometric modelling particularly ARIMA (Autoregressive Integrated Moving Average) will be very beneficial for investors in making decision to invest in the capital market.

LITERATURE REVIEW

Portfolio Theory

Return of the securities is one of important thing to note by an investor. Every investor wants to get a high return with low risk. However, not every investor is willing to face the risk (risk averse), therefore the convenience method to determine the relationship between the balance of risks and the expected rate of return is needed by investor.

One of the method that concern to concerning portfolio investment strategy is introduced by Markowitz (1952) with his theory of portfolio. The strategy explains about how to generate maximum returns with minimal risk. The assumption that investors make investment decisions based on two parameters namely expected return and variance of returns. Thus, Markowitz portfolio theory also called two-parameter models. That is, in the decision-making process, assuming the two parameters provide information about the inputs used by investors. In particular, it is assumed that the investor may receive compensation in the form of an opportunity to get a higher expected return if it has a greater risk. It also means that if investors are facing two options portfolios with the same expected return, investors will choose a portfolio with lower risk. Investors here are known as risk-averse investors.

Capital Asset Pricing Model (CAPM) Theory

Sharpe (1964), Lintner (1965) and Mossin (1966) developed the theory of Markowitz, known as the Capital Asset Pricing Model (CAPM). In principle, CAPM is a model to estimate the value of the return of an asset by comparing the variable return is received and the risks covered. The purpose of this model is to determine the level of expected return from risky assets and to calculate the risk that cannot be diversified (non-systematic risk) in a portfolio and compare it with the predictions of the rate of return. However, the use of CAPM theory should be assume that the market is efficient. Further, under market efficiency, the risk-averse investor will follow Markowitz portfolio risk reduction methodology by combining the assets of the covariance or correlation.

According to Bodie *et al*. (2014), the CAPM model is an important part of the financial sector that is used to predict the balance of expected returns and risks of an asset at equilibrium. The level of expected income from a securities can be calculated:

$$\bar{R}_t = R_f + \beta_i\,[\bar{R}_m - R_f] \qquad (1.1)$$

where $\bar{R}_t$ is the level of expected income from securities *i* containing risk, R_f is the risk-free income level, $\bar{R}_m$ is the level of income expected from the portfolio market and β_i measure of risk that can not be diversified from the *i-th* securities. The formula (1.1) states that the expected profit rate of a stock is a risk-free profit rate plus a risk premium. The greater the risk of the stock, the higher the expected risk premium of these shares. Thus the higher the expected profit rate of the stock. Furthermore, in order to estimate the magnitude of the beta coefficient, can be used the market model (Bodie.*et al*., 2014):

$$R_i = \alpha_i + \beta_i R_m + \varepsilon_i \qquad (1.2)$$

where R_i is the income level of securities *i*, R_m represent income level of market indices, β_i is a slope (beta), ε_i an intercept and a residual random error.

Andri (2010) explains that the state of equilibrium rates of return required by investors to a stock will be affected by the risk of the stock. In this case the calculated risk is simply the risk of systematic or market risk as measured by beta (β). While the unsystematic risk is not relevant, because this risk can be eliminated by diversification. Although the CAPM cannot be proven empirically, CAPM model has been widely used since this model has good accuracy in determining the return of a stock.

Arbitrage Pricing Theory (APT) Model

CAPM model is not the only theory that tries to explain how the funds will be determined by the market price. Stephen Ross (Zubir, 2013) formulated a theory called the Arbitrage Pricing Theory (APT), which is an alternative to the CAPM model. APT model is based on the law of one price at which the same asset can not be sold at different prices for the benefit arbitrage. Therefore, in case the difference in purchase price and the selling price of the asset asset, then the market will immediately refund the price of the assets to the balance point.

APT model assumes that the return of the securities is a linear function of various macro-economic factors and the sensitivity of each factor is expressed by beta coefficients of each factors and not by the unique risks. Three assumptions underlying the theory of Model Arbitrage Pricing (APT) is the capital market in conditions of perfect competition, investors always prefer the return value is higher than the high risks that led to the uncertainty of return, and the results of the stochastic process means that the income of the asset can be considered as a factor k models. Based on the assumption that the earnings is determined by the model k factorial risk factors, then the actual revenue for securities i can be determine using the following formula:

$$(R_i, t) = \alpha_i + \beta_{i1} F_{1t} + \beta_{i2} F_{2t} + \ldots + \beta_{ik} F_{kt} + \varepsilon_{it} \qquad (1.3)$$

where (R_i, t) is the income level of security i in period, α_i is constant, β_{ik} the sensitivity of *i* securities income to factor *k*, F_{kt} factors that affect revenue in period *t* and ε_{it} random error.

Stock Market And Volatility

The term of volatility mainly refers to the unstable conditions, tend to vary and difficult to predict. Daly (1999) stated that volatility becomes an important issue in the study of market behavior. According to Daly (1999), there are two major components in the volatility that are predictable and unpredictable volatility. The fact that, in the stock market, the development of stock price data are generally showed a trend, unpredictable and risky. If the stock price is too volatile, it will have an impact on investor confidence (Ballie and De Gennaro, 1990). However, volatility also give provide benefits to the investor if the investor can buy on the lower price and sell at the peak. Therefore, volatility analysis is indispensable when investors are faced with circumstances prices tend to be volatile and increasingly irregular pattern (Sumaryanto, 2009).

Integration of financial markets, especially the stock market as a result of the higher volatility data on stock market, have made the study of volatility as an important topics in the financial markets discipline. Ackert and Smith (1993) states that one of the causes of price volatility in the stock market due to a change in the discount rate or the new information about future cash flows received by the shareholders. Therefore, policy makers often use these data in the estimation of the price volatility as an important indicator to measure the depth and vulnerability of financial market in order to set up monetary policy (Nasar, 1992). Further, forecasting model approach regarding market volatility will provide efficient financial decisions (Maddala & Rao, 1996).

The development of forecasting models regarding price volatility either exchange rate volatility, commodity prices volatility or oil price volatility, has been done by previous researchers. Piot-Lepetit and M'Barek (2011) explains that there are two ways to measure volatility. The first is historical volatility that indicates the volatility of the assets in the past. Historical volatility is aimed to observe the movement of prices in the previous years. The second is implicit volatility which is the market's view of how to price volatility in the future. This implicit volatility aims to explain how market expectations of commodity prices in the coming years. In financial markets, particularly the stock market, the method to measure the stock price volatility often use two main models namely the stochastic volatility model (SV model) and autoregressive conditional heteroskedastic (ARCH) models (see Aggarwal, Inclan and Leal, 1999; Asteriou and Price, 2001; Poon and Granger, 2003; Hansen and Lunde, 2005; Taylor, 2008; Hammoudeh and Li, 2008).

METHOD OF ANALYSIS

This study aims at predicting the price of CSPI using *Autoregressive Integrated Moving Average* (ARIMA) model. ARIMA is an equation that is assumed to have (*weakly*) stationary which means that the value of the average (*mean*) and variance of the time series (*weakly stationary*) is constant while covariance is time-invariant. However, in fact, many economic time series data are not stationary or in other words an integrated time series. In addition, ARIMA, also called as Box-Jenkins method, is only used for forecasting the dependent variables in a short term. Gujarati and Porter (2009) state that if a time series data has been stationary (although stationary in the first difference), then it can be modelled in some forms.

The ARIMA model, commonly referred to Box-Jenkins method, is a method intensively developed by George Box and Gwilym Jenkins (1976) and is regarded as a new development in the economic forecasting method. ARIMA is a method which generates predictions by synthesizing the patterns of historical data (Arsyad, 1995).

The time series model used is based on the assumption that time series is stationary, meaning that the average variance (σ^2) of a time series data is constant. However, a lot of time series data in economics are not stationary, but integrated. If the time series data is integrated with order 1 which is called I(1), it is the first differencing. If the series goes through the differencing processes for d times, it can be stationary and then the series is classified as the level d homogeneous non-stationary.

The stationary random process cannot merely be explained by moving average model or autoregressive, because it contains both processes. Therefore, a combination of the two models, called ARIMA model explain the process more effectively. At this combined model, stationary series is the function of the value of the past, present and past mistake. The common formula of this model is as follows (Mulyono, 2000):

$$Y_t = b_0 + b_1 Y_{t-1} + ... + b_n Y_{t-n} - a_1 e_{t-1} - .... - a_n e_{t-n} + e_t$$

where:

Y_t = stationary value series

Y_{t-1}, Y_{t-2} = value of past series

e_{t-1}, e_{t-2} = independent variable – lag of the residual

e_t = residual

b_1, b_n, a_1, a_n = coefficient models

This process is stationery if $b_1 + b_2 + ... + b_n < 1$. The process is denoted by ARIMA (*p, d, q*), where: *q* shows the autoregressive (AR) order or degree, *d* is the level of differencing process, and *p* indicates the order or degree of moving average (MA).

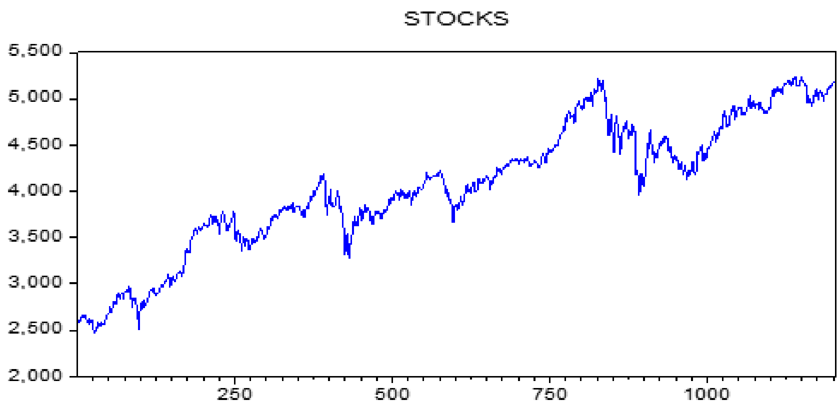
RESULTS AND ANALYSIS

ARIMA method was employed in predictive analysis of composite stock price in Indonesia. The data used was the daily CSPI data published by the Central Bureau of Statistics, Republic of Indonesia. The next step was analysing data using ARIMA method. The results of seven steps employed in ARIMA method comprise:

1. Identification of Data Patterns

The stock price data used are the daily CSPI in the period of January 4th, 2010 to December 5th, 2014. The number of observation data was 1,204 series. The stock index employed was stock index at closing (close price). Based on the identification of data patterns as shown by figure 1, the daily data pattern of CSPI had an upward trend pattern meaning that the stock prices during the observation period tended to continually increase. The increasing stock price indicates that the improvement in capital market is positively responded by the market players so that the level of stock capitalization rises.

Furthermore, based on the descriptive statistics calculation on the observed data, 1204 data of daily stock prices had an average stock index of 4061. The lowest index value was 2476 whereas the highest index value was 5246. The deviation of the index was 700. This showed that the data was not stationary because its average and variance tended to fluctuate.



Source: data processed, 2016.

Figure 1: Daily Data Pattern at CSPI

Table 1: Descriptive Statistics of CSPI Stock Prices

Variable	Obs	Mean	Std. Dev.	Min	Max
Stock	1204	4061	700	2476	5246

Source: data processed, 2016.

2. Stationary Test

Stationary test was conducted to identify that the observation data was stationary. The stationary test was carried out using Augmented Dikey Fuller Test (ADF Test). The results are presented in the following table:

Table 2: Results of ADF Test

	t-Statistic	Probability	Conclusion
Level	-1.515855	0.5254	Not Stationary
1st Difference	-22.60146	0.0000	Stationary

Source: data processed, 2016.

The test results shown in table 2 indicated that the level (the original data) obtained t value of -1.515855 with the probability of 0.5254, thus the data was not stationary. Therefore, the 1st difference transformation of the closing stock price data was carried out. The results of stationary test of 1st difference obtained t value of -22.60146 with probability of 0.000. It showed that the probability was lower than the level of significance (alpha (α) = 5%), then H0 was rejected so that the data was considered as stationary on the 1st difference transformation.

3. ARIMA Model Identification

For identifying the type of ARIMA model, correlogram test at the 1st difference level was carried out by determining the bartlet limit based on the following formula:

Bartlet Limit = $\frac{1}{\sqrt{n}}$

The results of ACF and PACF ARIMA model show that the value of ACF lag over the Bartlet line ($\pm \frac{1}{\sqrt{n}} = \pm 0.02882$) was the 1st lag, then it could be identified that the formed MA(q) model was MA (1). On the other hand, PACF value over the Bartlet line ($\pm \frac{1}{\sqrt{n}} = \pm 0.02882$) was the 1st lag, so that the formed AR (p) model was AR (1). The temporary results were further tested to determine the appropriate models to be used as the predictor of CSPI stock price. The models consisted of:

1. ARIMA (1,1,0)
2. ARIMA (1,1,1)
3. ARIMA (0,1,1)

4. Parameter Estimation

Parameter estimation was conducted for the three formed ARIMA models by employing two tests i.e. testing assumption model and selecting the best model.

Testing Assumption Model

Testing assumption model utilized two criteria namely normality assumption and white noise assumption.

- Normality Assumption

To verify whether the data distribution was normal or not, normality test was carried out. The results of the detection of normality assumption showed that all models generated symmetrical histogram. Therefore, it can be concluded that the residuals of all models had normal distribution.

Table 3: Results of Normality Test Assumptions

Model	Value of Jarque-Bera Test	Probablility	Information
ARIMA (1,1,0)	1131.863	0.0000	Normal Distribution
ARIMA (1,1,1)	1132.064	0.0000	Normal Distribution
ARIMA (0,1,1)	1138.515	0.0000	Normal Distribution

Source: Data processed, 2016.

- White Noise Assumption

White noise assumptions aim to identify the presence of correlation among the residuals generated by ARIMA models. White noise assumption tests were carried out using Ljung-Box (Q) test based on the following hypothesis.

H0 : The residuals has white noise (there is no correlation among the residual series)
H1 : The residuals do not have white noise (there is correlation among the residual series)

The results of white noise assumption test are presented below:

Table 4: Results of White Noise Assumption Test

Model	Information
ARIMA (1,1,0)	Has white noise and is appropriate
ARIMA (1,1,1)	Has white noise and is appropriate
ARIMA (0,1,1)	Has white noise and is appropriate

Source: Data processed, 2016.

Based on the results of normality assumption test, the values of Jarque Bera test of the three model were > level of significance (alpha (α) = 5%) so that the distributions are classified as normal. The results of white noise assumption test, on the other hand, showed that all ARIMA models have probability (Ljung-Box (Q)) > level of significance (alpha (α) = 5%), thus all of ARIMA models have white noise and are appropriate.

Selecting the Best Model

Criteria used to determine the best model was comparing the value of Akaike Information Criterion (AIC) obtained from the test results of each model. The results of AIC of each ARIMA model are summed as follows:

Table 5: Model Selection Test Results

Model	AIC Value
ARIMA (1,1,0)	10.54258
ARIMA (1,1,1)	10.54424
ARIMA (0,1,1)	10.54212

Source: Data processed, 2016.

The above table shows that ARIMA (0,1,1) model has the lowest AIC value among other ARIMA models. Therefore, ARIMA (0,1,1) model is recognized as the best model.

5. Testing the Significance of ARIMA (0, 1, 1) Model

The results of testing the significance of closing stock price data of ARIMA (0,1,1) model are presented below.

Table 6: Results of Significance Test of ARIMA Model (0, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic	Probablility
MA (1)	0.051527	0.028806	1.788792	0.0739

Source: Data processed, 2016.

Based on table 6, MA (1) variable generated t value of 1.788792 with a probability of 0.0739. These results indicated that the probability value < level of significance (alpha (α) = 5%), so that H0 is accepted. However, if the level of significance (alpha (α) = 10% was used, then the H0 is rejected which indicates that errors in the previous period affect the Closing Stock Price in the current period.

6. Forecasting

The results of the significance test of the three ARIMA models showed that the best model for forecasting was ARIMA (0,1,1) model. The detailed descriptions of ARIMA (0,1,1) model are presented below.

$$\Delta Y_t = E_t - \theta_1 E_{t-1}$$

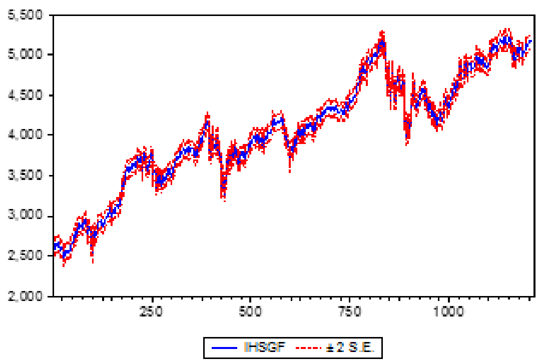
$$Y_t - Y_{t-1} = E_t - \theta_1 E_{t-1}$$

$$Y_t = Y_{t-1} + E_t - \theta_1 E_{t-1}$$

Thus

$$Y_t = Y_{t-1} + 0.051527 E_{t-1}$$

In ARIMA Model (0,1,1), coefficient θ1 was 0.051527 meaning that an increase of IDR 1,- errors in Closing Stock Price one day earlier will increase the current Closing Stock Price for IDR 0.051527,-. Furthermore, the identification results of ARIMA (0,1,1) model were used for forecasting the Closing Stock Price data in the next 10 days and produced visually forecasting shown in the following figure.

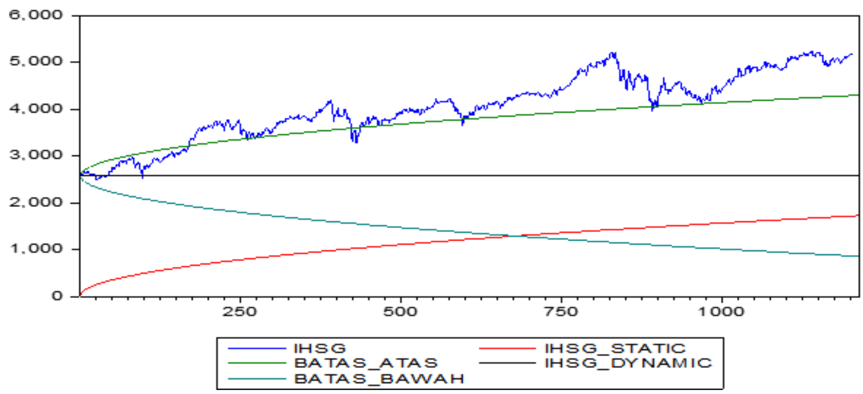


Forecast: IHSGF	
Actual: IHSG	
Forecast sample: 1 1214	
Adjusted sample: 2 1214	
Included observations: 1203	
Root Mean Squared Error	47.05369
Mean Absolute Error	33.46008
Mean Abs. Percent Error	0.843198
Theil Inequality Coefficient	0.005710
Bias Proportion	0.001927
Variance Proportion	0.000168
Covariance Proportion	0.997905

Source: Data processed, 2016.

Figure 2: Results of Stock Price Forecasting for the Next 10 Days

Figure 2 and 3 show that the results of stock price forecasting indicate an increase. The values of stock price forecasting demonstrate the quite low variance score of the increasing upper limit and lower limit. It shows that ARIMA (0,1,1) model is able to generate good results in forecasting the daily movement of stock price.



*) JCI refer to Jakarta Composite Index, also represent of Composite Stock Price Index (CSPI)
Source: Data processed, 2016.

Figure 3: Results of Stock Price Forecasting

7. Evaluation on Forecasting Results

Based on the analysis of ARIMA (0,1,1) and the value of forecasting daily stock price, the guideline of Mean Absolute Percent Error (MAPE) values can be utilized to determine the accuracy of the results of analysis. The small MAPE value shows that errors that occur in forecasting results tend to be small, so the forecasting results generated by ARIMA model are stated as accurate.

Table 7: MAPE Value of ARIMA (0,1,1) Model

Forecasting Model	MAPE
ARIMA (0,1,1)	0.8431

Source: data processed, 2016.

Forecasting results of ARIMA (0,1,1) resulted in MAPE value of 0.8431 or 84,31%. It indicated that the error rate of Closing Stock Price data forecasting results was 84,31%. Thus, it can be said that the use of ARIMA (0,1,1) to predict daily stock price movement in Indonesia has a high degree of accuracy.

DISCUSSION

The movement of stock prices in the Indonesian capital market that relatively volatile is able predicted using ARIMA model. Based on ARIMA analysis, it is known that the ARIMA (0,1,1) was the best model to predict stock prices volatility in Indonesia. These results are consistent with previous studies that also uses ARIMA model to predict stock prices in Indonesia (Sadeq, 2008; Gestandi, *et al*, 2011; Anityaloka, *et al*., 2013). Sadeq (2008) conducted a research on the analysis of the stock price index prediction with ARIMA method produces ARIMA (1,1,1) with a percentage of average absolute error of 4.14% as the best model. While Anityaloka, *et al* (2013) conducted a study on forecasting Jakarta Islamic Index (JII) using ARIMA give results that the appropriate model obtained is ARIMA (1,0,0).

If we compared with other forecasting techniques, such ARCH/GARCH methods, we can conclude that the accuracy of ARIMA to predict stock price volatility shows that ARIMA is more accurate than ARCH/GARCH (Grestandi, *et al*, 2011). In his study, Grestandi found that GARCH (1,1) and ARIMA (0,2,1) is an appropriate model to predict stock prices in Indonesia, but after comparing the accuracy of prediction, the conclusion shows that ARIMA (0,2,1) more better to predict JII movement.

CONCLUSION

This study aims to determine the accuracy of ARIMA (Autoregressive Integrated Moving Average) method to predict the stock price and the amount of stock prices in the future. Based on the results of some experiments in this study, it is found that ARIMA (0,1,1) is the right ARIMA model for predicting the CSPI as indicated by the low value of MAPE. Although ARIMA (0,1,1) model is the best model to predict stock prices, the external and internal factors are correspondingly quite strong to influence the movement of the stock prices. The expectations of investors or prospective investors can influence and determine the stock price changes.

Stock prices which continue to show upward trend may have good and bad impact for the domestic economy. For example, good impact caused by the rising daily stock price is increasing funding obtained by companies listed on the stock exchange. Companies are increasingly flexible in expanding its business so as to contribute to the reduction of unemployment. In addition, the rising stock prices reflect that companies listed on the stock exchange are good companies and assessed as good by investors so that it becomes a bone of contention for any investors to buy stocks sold. Moreover, improving economic fundamentals also contribute to the increase in stock prices.

On the other hand, the negative side that may arise as a result of the rising stock price is the obstruction of access for potential investors with barely enough capital to invest in the stock market due to the increasing costs that must be provided to have the stocks of the listed companies. In addition, appreciation and depreciation factors of the currency have become the determinants of stock price changes. Appreciation of the domestic currency results in the higher purchase price of stocks for overseas investors.

Based on the findings, research on ARIMA modelling which is precise and accurate in predicting stock prices is very important to be carried out. However, every study conducted by researchers has its own uniqueness. Thus, the findings are quite diverse. This study used daily data stock index over a quite long period, more than 1000 days. Difference in the number of samples used can also be an important factor in determining the ARIMA modelling. In addition, the type of stock index can be a possible second important factor in determining the accuracy of ARIMA models to be studied.

This research still needs to be developed by considering that there are still some weaknesses as the data sample used is still limited and has not been developed into a sample over a longer period of time. If the sample is developed, it may change the shape of the right ARIMA model.

Therefore, the next research can further explore data sample over a longer period of time. In addition, the future research can be developed by employing the larger data sample and other indices. It is motivated by two basic reasons, namely: (i) by employing higher number of sample, ARIMA model can predict stock prices more accurately, (ii) by using other indices, the accuracy of some ARIMA models for predicting the same stock price can be compared.

REFERENCES

Andri (2010). Perbandingan Keakuratan CAPM dan APT dalam Memprediksi Tingkat Pendapatan Saham LQ45 (Periode 2006–2009). Skripsi UIN Syarif Hidayatullah. Jakarta: Tidak Diterbitkan

Ackert, LF & Smith, BF. (1993). "Stock price volatility, ordinary dividends, and other cash flows to shareholders." *The Journal of Finance*, Vol. 48 No. 4, pp. 1147–1160.

Aggarwal, R., Inclan, C., & Leal, R. (1999). "Volatility in emerging stock markets." *Journal of Financial and Quantitative Analysis,* Vol. 34 No. 1, pp. 33-55.

Ang, R.(1997). Buku Pintar Pasar Modal Indonesia. Jakarta: PT. Mediasoft Indonesia.

Arsyad, L. (1995). Peramalan Bisnis. Jakarta: PT. Gralia Indonesia.

Asteriou, D., & Price, S. (2001). "Political instability and economic growth: UK time series evidence." *Scottish Journal of Political Economy*, Vol. 48 No. 4, pp. 383-399.

Baillie, R. T., & DeGennaro, R. P. (1990). "Stock returns and volatility." *Journal of financial and Quantitative Analysis*, Vol. 25 No. 2, pp. 203-214.

Bodie, Z., *et al*. (2014). *Manajemen Portofolio dan Investasi* (9th Ed.) Buku 1. Jakarta: Salemba Empat.

Box, G., and Jenkins, G. (1976). Time Series Analysis: Forecasting and Control. San Fransisco: Holden Day.

Chan, K., & Fong, W. M. (2000). "Trade size, order imbalance, and the volatility–volume relation." *Journal of Financial Economics,* Vol. 57 No. 2, pp. 247-273.

Daly (2000). *Financial volatility and real economic activity.* Ashgate Publishing Ltd, England.

Firmansyah. (2006). Analisis Volatilitas Harga Kopi Internasional. Jakarta: PT. Usahawan.

Gujarati, DN and Porter, DC. (2009). *Basic Econometrics* (5th Ed.) New York: McGraw-Hill.

Hammoudeh, S., & Li, H. (2008). "Sudden changes in volatility in emerging markets: the case of Gulf Arab stock markets." *International Review of Financial Analysis,* Vol. 17 No. 1, pp. 47-63.

Hansen, P. R., & Lunde, A. (2005). "A forecast comparison of volatility models: does anything beat a GARCH (1, 1)?." *Journal of applied econometrics,* Vol. 20 No. 7, pp. 873-889.

Lintner, J. (1965). "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets." *The review of economics and statistics,* pp. 13-37.

Maddala, GS & Rao, CR. (1996). *Handbook of statistics v. 14: Statistical methods in finance.* Elsevier Science BV, Netherlands.

Markowitz, H. (1952). "Portfolio selection." *The journal of finance*, Vol. 7 No. 1, pp. 77-91.

Mossin, J. (1966). "Equilibrium in a capital asset market." *Econometrica: Journal of the econometric society*, pp. 768-783.

Mulyono, S. (2000). "Peramalan Harga Saham dan Nilai Tukar: Teknik Box-Jenkins." *Ekonomi dan Keuangan Indonesia*, Vol. 48 No. 2, pp. 125-141.

Nasar, S. (1992). For Fed, a new set of tea leaves. *New York Times, 5*.

Pai, P. F., & Lin, C. S. (2005). "A hybrid ARIMA and support vector machines model in stock price forecasting." *Omega,* Vol. 33 No. 6, pp. 497-505.

Piot-Lepetit, I., & M'Barek, R. (2011). "Methods to analyse agricultural commodity price volatility." In *Methods to Analyse Agricultural Commodity Price Volatility* (pp. 1-11). Springer New York.

Poon, S. H., & Granger, C. W. (2003). "Forecasting volatility in financial markets: A review." *Journal of economic literature,* Vol. 41 No. 2, pp. 478-539.

Sharpe, W. F. (1964). "Capital asset prices: A theory of market equilibrium under conditions of risk." *The journal of finance,* Vol. 19 No. 3, pp. 425-442.

Sumaryanto, (2009). "Analisis Volatilitas Harga Eceran Beberapa Komoditas Pangan Utama dengan Model ARCH/GARCH." *Jurnal Agro Ekonomi*, Vol. 27 No. 2, pp. 135-163.

Taylor, SJ. (2008). *Modelling financial time series,* (2nd Ed.). World Scientific Publishing Co. Pte. Ltd., Singapore.

Wang, J. J., Wang, J. Z., Zhang, Z. G., & Guo, S. P. (2012). "Stock index forecasting based on a hybrid model." *Omega,* Vol. 40 No. 6, pp. 758-766.

Wei, L. Y. (2013). "A hybrid model based on ANFIS and adaptive expectation genetic algorithm to forecast TAIEX." *Economic Modelling,* Vol. 33, pp. 893-899.

Zubir, Z. (2013). *Manajemen Portofolio: Penerapannya dalam Investasi Saham*. Jakarta: Salemba Empat.