Forecasting Philippine Stock Market Prices Using ARIMA-GARCH Models

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Abstract: A myriad of studies have shown to forecast stock prices using time series analysis efficiently from different countries and industries. For Philippine financial markets, most studies have only focused on the PSEi (Philippine Stock Exchange index) series data and not much study has explored on forecasting individual public companies. Short term investors or day traders, who buy and sell stocks within the day or week, would not be able to utilize PSEi forecasts as it is not tradeable. This paper aims to apply time series analysis to three public companies listed in the Philippine Stock Exchange Inc. These are Ayala Land Incorporated (ALI), Banco de Oro (BDO), and Jollibee Foods Corp. (JFC). The models Autoregressive Integrated Moving Averages (ARIMA), Autoregressive Conditional Heteroscedasticity (ARCH), and Generalized ARCH (GARCH) were explored in describing these financial series. Due to the highly volatile characteristic of stock markets, volatility models were confirmed to be the best fit for ALI, BDO, and JFC, particularly the ARCH(1)-T, ARCH(2)-T, and ARCH(1)-N respectively. The fitted models were able to capture the stock market volatility and produce small forecast errors for closing prices. To assess the practicality of the forecasts in day trading, the closing prices were forecasted and anticipated from March 25-29, 2019. The results show that the ARCH models were able to forecast the week's closing prices with a low mean average percentage error (MAPE) of 1.57% for ALI, 1.87% for BDO, and 0.77% for JFC. Thus, there is a potential of the models to be used by traders for risk management and decision making for their daily stock trading activities.

Key Words: Time Series Analysis, ARIMA, GARCH, Philippine Stock Market

1. INTRODUCTION

Trading in the stock market is a way for investors to earn a profit whether for short term or long-term investing. Short term investors, or day traders, buy and sell stock shares as within the day, week, or month. Due to the volatility of stock prices, day trading risks for huge financial losses or gains.

For this reason, trading strategies are formulated to lessen these risks. One strategy is to forecast the stock prices to make well informed decisions for selecting and buying stocks.

The use of time series analysis to forecast stock prices has been proven effective by numerous studies. Afeef, et. al. (2018) used ARIMA to anticipate the stock price of Oil & Gas Development Company Limited, one of the largest companies in Pakistan. Adebiyi, et. al. (2014) concluded that the ARIMA models were efficient for short term forecasting of Nokia and Zenith Bank stock prices coming from the New York and Nigeria Stock Exchange. Sopipan (2017) utilized the logarithmic returns of Thailand gold prices and applied ARIMA-GARCH modelling to forecast its volatility.

These techniques have also been applied to the Philippine stock market. Gayo et. al. (2015) collected PSEi data and explored the mixture of ARIMA models and conditional variance equations such as ARCH, GARCH, and Exponential GARCH. Etac and Ceballos (2018) used PSEi data and confirmed the fit of GARCH models. The study of Estember and Maraña (2016) analyzed stock prices of six listed companies in the Philippine Stock Exchange using Brownian Motion.

Most of the research has been done on PSEi to study the economic growth of the country but not for the purpose of day trading. Therefore, forecasting companies' stock prices is of interest to day traders as PSEi is not tradeable. However, not much study has been done on the individual companies of Philippine stock markets. This paper aims to investigate the application of ARIMA and GARCH models to forecast the stock prices of ALI, BDO, and JFC.

2. METHODOLOGY

2.1 Data

As a procedure of confirming the validity of the study, the methodology was replicated using three different stock data, namely ALI, BDO, and JFC. The basis of selection was arbitrary Blue Chip companies from different industry sectors. These are the dominant companies heavily traded each day. Their daily closing prices were collected from January 2, 2014 to March 22, 2019 and has a total of 1271 observations. Nontrading days such as weekends and holidays are not included in the observations. The data is divided as in-sample (N_{train}= 1071) and out-of-sample (N_{test}= 100). Figure 1 shows the time plot of ALI.

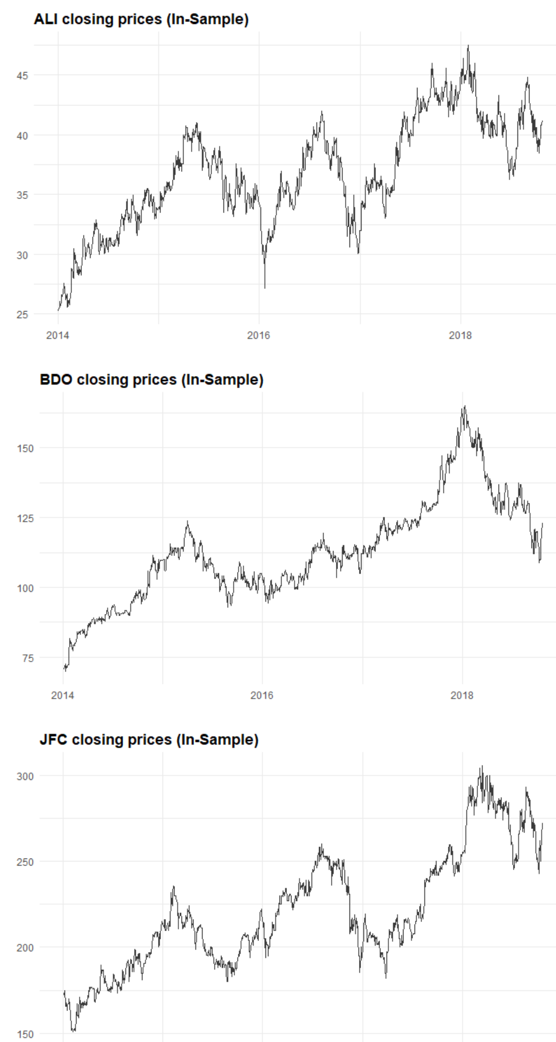

Fig. 1. Daily closing prices of ALI, BDO, and JFC for in-sample data

Let r_t be the log of returns of ALI defined as:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where P_t is the actual closing price at time t. This implies that the first observation in the in-sample data is omitted. The log return time plots are shown in Figure 2.

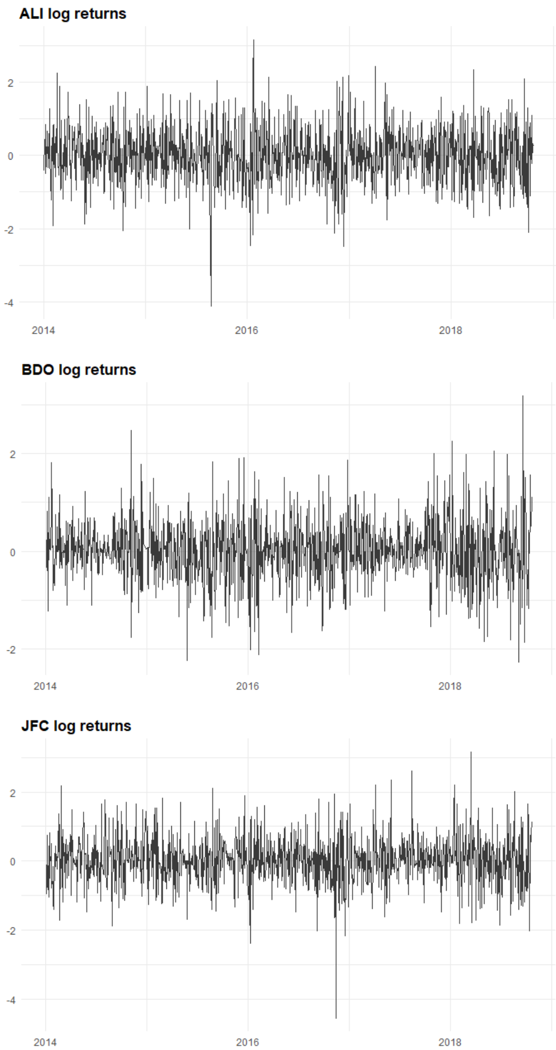

Fig. 2. Log return series of ALI, BDO, and JFC closing prices

The methodology discussed thoroughly in the succeeding sections focuses only on ALI. BDO and JFC would follow the same methodology and discussing these three at once will just be redundant. The results for the forecasting of BDO and JFC will be included in the discussion in Section III.

2.2 Model Identification

The methodology are as follows:

1. Use the Augmented Dickey Fuller (ADF) unit root test to test the stationarity of the series
2. The orders for ARIMA are identified from the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The orders are decreased when not all parameters are significant, and the model is refitted.
3. The residuals of the best fit ARIMA model is tested for the presence of heteroscedasticity using Lagrange Multiplier test. If present, GARCH models are then applied.

For ARIMA and GARCH model selection, the model with the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) is selected as the best fit.

In figure 2, r_t can be visually observed to have a constant mean but may have nonconstant variance. The rejection of the ADF unit root test, with P-value < 0.01, implies the stationarity of r_t.

2.3 ARIMA Parameter Estimation

The integers p, d, and q are the orders for autoregressive, differencing, and moving average. ARIMA(p,d,q) models are used to describe homogeneous nonstationary time series with nonconstant mean.

Since r_t is stationary, then differencing may be excluded (d=0). For identifying the AR and MA orders, a visual inspection of the ACF and PACF plot of r_t both show significant spikes up to lag 4. This suggests the orders p=q=4. However, by the principle of parsimony, only orders up to 2 were considered. Upon fitting, only one of the parameters in the ARIMA(2,0,2) model was significant. By decreasing the orders, ARIMA(2,0,1) and ARIMA(1,0,2) all had significant parameters at $\alpha = 0.01$. The latter was chosen as the best fit for the data due to the selection criteria. The model has the following coefficients: 0.0067 for intercept, 0.6041 for ar1 (P-value = 0.00), -0.6409 for ma1 (P-value = 0.00), and -0.0745 for ma2 (P-value=0.05).

2.4 Test for Heteroskedasticity

A series exhibits the presence of heteroscedasticity if a_t, the residuals from its ARIMA model, displays no serial correlation, and if a_t^2 is serially dependent. The Ljung-Box test is used to check for this behavior. With P-value=0.98, the Ljung-Box test for a_t is not rejected. This shows serial uncorrelatedness of the residuals. The rejection of the test for a_t^2 with P-value=0.00 implies its serial dependence. These suggests the presence of conditional heteroskedasticity in the series.

2.5 GARCH Parameter Estimation

The integers m and s are for the order of ARCH and GARCH parameters respectively in a GARCH(m,s) model. With the presence of heteroscedasticity in r_t, GARCH and ARCH models with the Normal and Student T distributions were fitted. The results show that both $\tilde{a}_t = \frac{a_t}{\sigma_t}$, the standardized residual, and $\tilde{a}_t^2$ of the GARCH models are serially uncorrelated and does not exhibit ARCH effect. The ARCH models were able to satisfy the serial independence and dependence at lag 15 of the $\tilde{a}_t$ and $\tilde{a}_t^2$ respectively; it also shows significance in ARCH effects. This concludes that ARCH satisfies the model assumptions.

Table 1. ARCH Model Estimates for ALI

		ARCH-N	ARCH-T
intercept	estimate	0.016	0.014
	p-value	0.470	0.526
omega	estimate	0.519	0.532
	p-value	0.000***	0.000***
alpha1	estimate	0.108	0.094
	p-value	0.004**	0.026*
shape	estimate		10
	p-value		0.000***
AIC		2.282	2.278
BIC		2.3	2.296

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Since all of the parameters from both ARCH-N and ARCH-T models are significant, the criteria for selecting the best model is by the lowest AIC and BIC. By these criteria, ARCH(1)-T was selected as the best model. The estimated parameters are shown in Table 1.

Table 2 shows the summary for diagnostic checking of the ARCH-T model. The Jarque-Bera and Shapiro-Wilk test is rejected; this shows that $\tilde{a}_t$ is not normally distributed. The rejection of the Ljung-Box Test implies that $\tilde{a}_t$ and $\tilde{a}_t^2$ are still autocorrelated. The model, however, fails to be the optimal model for this series as its residuals is not a white noise process.

Table 2. Standardized Residuals Tests

			Statistic	p-value
Jarque-Bera Test	$\tilde{a}_t$	χ^2	35.164	0.000
Shapiro-Wilk Test	$\tilde{a}_t$	W	0.994	0.000
Ljung-Box Test	$\tilde{a}_t$	Q(10)	25.225	0.005
Ljung-Box Test	$\tilde{a}_t$	Q(15)	25.615	0.042
Ljung-Box Test	$\tilde{a}_t$	Q(20)	33.415	0.03
Ljung-Box Test	$\tilde{a}_t^2$	Q(10)	27.063	0.003
Ljung-Box Test	$\tilde{a}_t^2$	Q(15)	38.143	0.001
Ljung-Box Test	$\tilde{a}_t^2$	Q(20)	43.735	0.002
LM Arch Test	$\tilde{a}_t$	TR^2	26.073	0.01

2.6 Forecasting

The forecasted closing price $\hat{P}_{t+1}$ is formulated as:

$$\hat{P}_{t+1} = e^{\hat{r}_{t+1}} \cdot P_{t-1}$$

Upon calculating the MAPE as an assessment of forecast accuracy, the measurement concludes that the forecasts are off by 1.8% of the actual value.

The out-of-sample data with 100 observations was predicted with 100 1-step ahead forecasts of $\hat{P}_{t+1}$. Figure 3 shows the plot of the predicted and the actual ALI stock price values. Table 3 gives a preview of the actual and forecast values. The forecasts are off by 1.75% of the actual values as interpreted by the MAPE score.

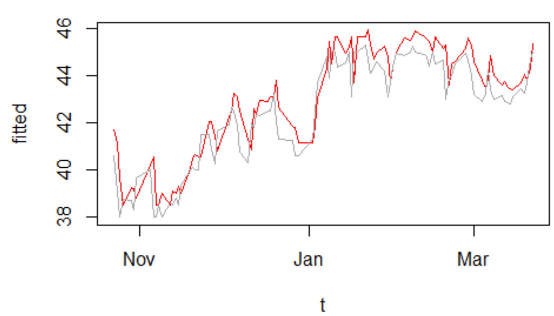

Fig. 3. Out-of-sample forecast(red) and actual ALI prices(gray) from Oct 23, 2018 to Mar 22, 2019.

Table 3. First 12 out-of-sample forecasts for ALI

Date	Actual	Forecast
2018-10-23	40.60	41.54
2018-10-24	39.10	40.99
2018-10-25	38	39.47
2018-10-26	38.75	38.36
2018-10-29	38.70	39.12
2018-10-30	38.30	39.09
2018-10-31	39.65	38.66
2018-11-05	40	40.03
2018-11-06	38	40.38
2018-11-07	38	38.36
2018-11-08	38.50	38.36
2018-11-09	38	38.86

3. RESULTS AND DISCUSSION

Using the same procedure of model identification and selection for the log return series of BDO and JFC, it is found that the best model that describes their process is the ARCH(2)-T and the ARCH(1)-N respectively; the estimates for these models are shown in Table 4.

Table 4. Model Estimates for BDO and JFC

		ARCH(2)-T for BDO	ARCH(1)-N for JFC
intercept	estimate	0.02	0.012
	p-value	0.217	0.544
omega	estimate	0.298	0.423
	p-value	0.000***	0.000***
alpha1	estimate	0.243	0.137
	p-value	0.000**	0.002**
alpha2	estimate	0.096	
	p-value	0.055.	
shape	estimate	4.985	
	p-value	0.000***	
AIC		1.848	2.106
BIC		1.87	2.119

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

Table 5. Forecast results for Mar 25-29, 2019

Date	ALI		BDO		JFC	
	actual	forecast	actual	forecast	actual	forecast
Mar 25	45	45.31	133.9	135.62	312.4	315.38
Mar 26	43.85	45.61	132.4	136.54	316	315.38
Mar 27	44.50	44.45	132	135.01	316.6	319.01
Mar 28	43.55	45.11	132	134.60	316	319.62
Mar 29	44	44.14	132.6	134.60	316	319.01

The models for ALI, BDO, and JFC were used to forecast their closing prices from March 25 - 29, 2019. The approach is to use the latest actual closing price to predict only the next closing price. In forecasting P_{t+1}, the actual price P_t has to be revealed. The forecast results are shown in Table 5. The MAPE is 1.57% for ALI, 1.87% for BDO, and 0.77% for JFC.

4. CONCLUSIONS

The model identification process was followed for ALI, BDO, and JFC stock price series. Their identified ARIMA models tests positive for heteroskedasticity and GARCH models were fitted. From the specified selection criteria, ARCH(1)-T was found to be the best model for ALI, but fails in the diagnostic checking of residuals. Therefore, this model is not the optimal fit which can then be further analyzed in future studies.

The results show that the ARCH models were able to forecast values that are close to the actual prices. However, the models fail to capture the movement of the stock prices of whether it will increase or decrease the following day. The ARCH model's strong points are in forecasting volatility and that may be used by investors to assess their risk management and decision making for stock trading.

5. ACKNOWLEDGMENTS

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