Forecasting index and stock returns by considering the effect of Indonesia pre-presidential election 2019 using ARIMAX and VARX approaches

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Abstract. Election is a national event that can create significant impact on many sectors in a country. One of the affected sectors is finance. The upcoming Presidential election in Indonesia has two strong candidates who are rival since the late presidential election in 2014. The effect of this election is expected to have a big influence in the capital market, especially for Indonesian Index (IDX composite). Moreover, the stock owned by the candidate or the candidate relative is also expected to behave unusual. Therefore, this study aims to predict the return of those stock and index with the influence of Indonesia Pre-Presidential Election 2019. The stock of interest is the stock of PT. Saratoga Investama Sedaya Tbk (SRTG). The method used in study is defined into two categories. The index and stock are analyzed individually by univariate method—Autoregressive Integrated Moving Average with Exogenous variable. Multivariate method is also conducted to examine the relation among these stock and index. The used approach is Vector Autoregressive with Exogenous variable. The exogenous variable in this study is the dummy variable of Indonesia pre-Presidential Election. The results show that pre-election vibe does not significantly affect the return of the index and stock.

1. Introduction
Indonesia Composite Index (IDX Composite) is predicted to be affected by 2019 Presidential Election as said by the head of Institutional Research MNC securities on November 2017. This was based on the experience of the previous election in 2009 and 2014 in which the political factor tends to affect IDX composite [1].

Previous work regarding the influence of election was conducted by Reference [2] in 2017 entitled "The effect of presidential election in the USA on stock return flow—a study of a political event." This work examined some returns on securities of the financial institutions listed on the New York Stock Exchange and revealed that there was a statistically significant negative impact of the event on stock return. Additionally, in terms of forecasting with exogenous variables, Reference [3] did a study about the comparison of ARIMA and ARIMAX to see which approach is better to analyze and forecast macroeconomic time series. This study was applied to gross domestic product per capita (GDPpc) and stated the ARIMAX model brings so much better results than simple ARIMA model.

In univariate study, the relationship between variables is not taken into account. However, the returns of IDX composite and SRTG are thought to have a relationship as they share the same market.
Multivariate study was done by Reference [4] on the potential loss of competitiveness because of higher oil prices through the monetary channel in a group of six oil producing countries. This work applied Vector Autoregressive Moving Average with exogenous variable (VARMAX) and found that there was mixed evidence of loss of competitiveness as the impact of high oil prices in the exchange rates of Southeast Asian countries to the United States dollar.

To get better forecasting results, this study will construct models that accommodate univariate and multivariate methods. The univariate method that will be used is ARIMAX model whereas the multivariate method that will be applied is VARX. One should note that the exogenous variable of interest is the effect of Indonesia pre-presidential election 2019 starting from the announcement of the fixed pair of candidates. This study wants to examine that effect in order to provide information that will be beneficial to the shareholder related to particular stocks or indexes and the government who is in charge of it.

This paper is organized as follows. The first section presents the background of study. Then, the following section provides some literature reviews including the univariate ARIMAX and multivariate VARX models. The material and method of the models are presented in the third section. The fourth section is the section in which the results are elaborated with some discussions. Finally, the fifth section concludes this study.

2. Literature Review

2.1. Autoregressive Integrated Moving Average (ARIMA)
ARIMA model is a combination of Autoregressive (AR) and Moving Average (MA) models and differencing processes (d order for non-seasonal data, and D order for seasonal data) to time series data [5]. Based on seasonality, ARIMA model can be divided into seasonal and non seasonal ARIMA. There will be an additional term for seasonal ARIMA model, which is the order for seasonality.

In general, non-seasonal ARIMA model can be written as ARIMA \((p,d,q)\) mathematically as follow [5],

\[
\phi_p(B)(1-B)^d Y_t = \theta_0 + \theta_q(B)a_t
\]

where,
\((p,d,q)\) = AR order \((p)\), differencing order \((d)\), and MA order \((q)\)
\(\phi_p(B)\) = the coefficients of non-seasonal AR model with order \(p\)
\(\theta_q(B)\) = the coefficients of non-seasonal AR model with order \(q\)
\(a_t\) = residual at \(t\).

If \(d = 0\), then \(\theta_0\) is a mean of the process whereas \(d \geq 1\) means that \(\theta_0\) is the coefficient of deterministic trend.

For multiplicative Seasonal ARIMA Model, it can be written as ARIMA \((P,D,Q)\). The Box-Jenkins multiplicative model for seasonal ARIMA is presented below [5],

\[
\Phi_p(B^S)\phi_p(B)(1-B)^d (1-B^S)^D Y_t = \theta_q(B)\Theta_Q(B^S)a_t
\]

where,
\((p,d,q)\) = AR order \((p)\), differencing order \((d)\), dan MA order \((q)\)
\((P,D,Q)^S\) = AR order \((P)\), differencing order \((D)\), dan MA order \((Q)\), seasonal order \((S)\) for seasonal data
\(\phi_p(B)\) = coefficient of non-seasonal AR with order \(p\), where \(\phi_p(B) = (1 - \phi_1B - \phi_2B^2 - ... - \phi_pB^p)\)
\(\theta_q(B)\) = coefficient of non-seasonal MA with order \(q\), where \(\theta_q(B) = (1 - \theta_1B - \theta_2B^2 - ... - \theta_qB^q)\)
\[ \Phi_p(B^S) = \text{coefficient of seasonal AR (S) with order } P, \text{ where } \Phi_0(B^S) = (1 - \Phi_1 B^S - \Phi_2 B^{2S} - \ldots - \Phi_P B^{PS}) \]

\[ \Theta_q(B^S) = \text{coefficient of seasonal MA (S) with order } Q, \text{ where } \Theta_0(B^S) = (1 - \Theta_1 B^S - \Theta_2 B^{2S} - \ldots - \Theta_Q B^{QS}) \]

\[ \alpha_t = \text{residual at } t. \]

2.2. Autoregressive Integrated Moving Average with Exogenous Variable (ARIMAX)

ARIMAX is an ARIMA model with the addition of particular variables [6]. In this study, the variable of interest is the dummy variables for Indonesia presidential election in 2018. The model in the seasonal ARIMA equation can be rewritten as follows [7],

\[ Y_t = \frac{\theta_q(B)\Theta_\phi(B^S)\alpha_t}{\Phi_p(B^S)\phi_\phi(B)(1 - B^S)(1 - B^S)^\delta} \]  

(5)

The first model is known as ARIMAX model with stochastic trend. In this model, there will be non-seasonal or seasonal differencing order. The model is written below,

\[ Y_t = \beta_1 S_{1,t} + \ldots + \beta_p S_{p,t} + \delta_0 V_t + \ldots + \delta_j V_{t-j} + \frac{\theta_q(B)\Theta_\phi(B^S)}{\phi_\phi(B)\Phi_p(B^S)(1 - B^S)(1 - B^S)^\delta} \delta_t \]  

(6)

Another model is ARIMAX model with deterministic trend in which it does not involve differencing order. It can be presented as

\[ Y_t = \gamma t + \beta_1 S_{1,t} + \ldots + \beta_p S_{p,t} + \delta_0 V_t + \ldots + \delta_j V_{t-j} + \frac{\theta_q(B)\Theta_\phi(B^S)}{\phi_\phi(B)\Phi_p(B^S)(1 - B^S)(1 - B^S)^\delta} \delta_t \]  

(7)

where \( S_{1,t} - S_{p,t} \) is the seasonal effects, \( V_t - V_{tj} \) is the dummy variable for calendar variation, and \( \gamma \) is the coefficient for trend.

2.3. Vector Autoregressive with Exogenous Variable (VARX)

Vector autoregressive (VAR) is a model that is used to describe the interdependence between several time series. This model is a generalization of the univariate AR model. All variables in VAR are arranged symmetrically by entering an equation that explains the development for each variable based on its own lag and the lag of all other variables in the model. The general model for VAR (p) is as follows [5],

\[ \hat{y}_t = \Phi_1 \hat{y}_{t-1} + \ldots + \Phi_p \hat{y}_{t-p} + \alpha_t, \]

\[ \hat{y}_t = \sum_{i=1}^{p} \Phi_i \hat{y}_{t-i} + \alpha_t, \]

\[ \Phi(B)\hat{y}_t = \alpha_t \]  

(8)

where,

\[ \hat{y}_t = \text{vector with size } m \times 1 \text{ of variables at time } t, \text{ note that } \hat{y}_t = y_t - \mu \]

\[ \Phi_p = \text{matrix with size } m \times m \text{ from parameter order } p \]

\[ \alpha_t = \text{vector with size } m \times 1 \text{ of residuals at time } t. \]
The equation (8) with additional seasonal order can be written as,
\[
([1 - \Phi_1 B - \cdots - \Phi_p B^p][1 - \Phi_{1s} B - \cdots - \Phi_{ps} B^{ps}]) (1 - B^s)(1 - B^d) \mathbf{y}_t = \mathbf{a},
\]
where,
- $\mathbf{y}_t$ = vector with size $m \times 1$ of variables at time $t$
- $\Phi_p$ = matrix with size $m \times m$ from parameter order $p$
- $\Phi_{ps}$ = matrix with size $m \times m$ from parameter order $p$ with seasonal order $s$
- $\mathbf{a}$ = vector with size $m \times 1$ of residuals at time $t$.

VARX is a Vector Autoregressive with considering the influence of exogenous variables. The VARX($p,s$) model is
\[
\mathbf{y}_t = \sum_{i=1}^{p} \Phi_i \mathbf{y}_{t-i} + \sum_{i=0}^{s} \Theta_i \mathbf{x}_{t-i} + \mathbf{a},
\]
where,
- $\Phi(B) = I_m - \Phi_1 B - \cdots - \Phi_p B^p$
- $\Theta(B) = I_m - \Theta_1 B - \cdots - \Theta_s B^s$
- $\mathbf{y}_t = (y_{t1} - \mu, \ldots, y_{tm} - \mu)^T$
- $\mathbf{a} = (a_{11}, \ldots, a_{m1})^T$
- $\mathbf{x}_t = (x_{t1}, \ldots, x_{tm})^T$
- $\Phi_i$ is a matrix with size $k \times k$ whereas $\Theta_i$ is a matrix with size $k \times r$.

3. Material and Method

3.1. Data Sources and Research Variables

The data used in this study is secondary data obtained from yahoo finance. The data includes the data of the IDX composite and SRTG stock prices. The data is daily data from 18th September 2015 – 19th September 2018. Firstly, the return of the data will be computed in the form of log return in which $R_t = \ln(S_t/S_{t-1})$, $S_t$ denotes the stock or index price. In this study, the data are divided into training data and testing the data. Three-year data are collected from yahoo finance. The data from 18th September 2015 to 19th September 2018 are defined as training data, while one-month data after the training data are set for testing data.

The index return is denoted by JKSE whilst SRTG is the SRTG stock return. The variable of interest in this study is the dummy variable to examine the effect of Indonesia Presidential election in 2018. The details are given below,
\[
Dt = \begin{cases} 
1, & \text{9th August 2018 onwards;} \\
0, & \text{otherwise.}
\end{cases}
\]

The 9th of August 2018 is chosen as the starting effect of the election because each party announced their fixed pair of candidate on that day. This is expected to have unusual impact on index and related stock returns.

3.2. Steps of Analysis

The steps of analysis in this study are as follows. Firstly, the descriptive statistics analysis is conducted in order to see the characteristic of the returns. This step is followed by the univariate and multivariate modelling using ARIMAX and VARX. ARIMAX modelling involves the following steps: (1) Identifying data patterns through the results of a time series plot, (2) Determining the type of trend,
namely deterministic trend, (3) Eliminating the effects of calendar variations of response with deterministic trend fitting equation so that we will get an error, (4) ARIMA modeling of the error if the error does not meet the assumption of white noise that involves identifying the model order by looking at ACF and PACF plots to obtain a significant lag, parameter estimation of ARIMA model with Conditional Least Square estimation, examining the assumption of residuals. If not met, then go back to identification step. If the assumptions are met then we merge ARIMA model with the model equations in step (3). Then, we calculate the goodness criteria of the model obtained by using RMSE. Final model will be used to forecast the data.

After that, we do multivariate modeling with VARX by following these steps: (1) examining the stationarity of the data. If the data is not stationary in variance, then we transform the data. Moreover, if the data is not stationary in the mean, we do differencing. (2) identifying the model order through MPACF and the minimum AIC value, (3) parameter estimation using least square estimation, (4) residual diagnostic checking. If the residual is autocorrelated, then return to step (2). (5) forecasting the data of the selected model, (6) Calculating the goodness of fit criteria using RMSE. Lastly, we do best model comparison between univariate and multivariate models that have been selected.

4. Result and Discussion
First of all, descriptive analysis was conducted to both return data in order to see the characteristic of the data. The results are shown in Table 1 where the description consists of the total count, mean, standard deviation, minimum and maximum, skewness, and kurtosis of the data.

| Variable  | Total Count | Mean    | StDev   | Minimum    | Maximum    | Skewness | Kurtosis |
|-----------|-------------|---------|---------|------------|------------|----------|----------|
| Rt_JKSE3  | 713         | 0.000412| 0.008810| -0.040884  | 0.031787   | -0.38    | 5.41     |
| Rt_SRTG3  | 713         | -0.00026| 0.02792 | -0.13799   | 0.18767    | 1.15     | 16.86    |

According to Table 1, these two returns have zero mean as they values are nearly zero. Moreover, the standard deviation of SRTG returns is higher than that of JKSE return. This means that the spread of SRTG returns are farther than that of JKSE returns to their mean values. In other words, SRTG returns are more volatile than JKSE returns. This is sensible as stocks are normally more fluctuated than the index. Furthermore, the distribution of JKSE returns are skewed to the left while for SRTG returns are skewed to the right. Skewed to the left means the left tail of the distribution is longer than the right. In other words, the data are mostly below the average. To have better description, the density plots of each return are presented in Figure 1. Kurtosis measures how tall and sharp the central peak of a distribution is. The kurtosis of both returns are far from the kurtosis of normal distribution, especially for SRTG returns. Figure 1 depicts the probability density function (pdf) of each return. SRTG return density is more peaked than that of JKSE return. This supports the value of kurtosis, which is higher than the index.
Figure 1. The density plots of (a) JKSE return and (b) SRTG return

Time series plots of both returns are given in Figures 2 and 3. One-year plots are also given in order to show the effect of the election on returns. For three-year JKSE return, one can see the existence of volatility clustering. The JKSE return was more volatile on the end of 2015 and 2016. Then, it started to have higher volatility again in 2018, especially in the time near the election vibe.
Figure 2. Time series plots of JKSE return for (a) 3 years and (b) a year

Similar to Figure 2, Figure 3 provides information on the daily return of SRTG during 3 years and one year period of time. Stock return is normally more volatile than index. As seen in Figure 3, there was an obvious volatility clustering on SRTG return. Before 2017 and in 2018, this stock return was very volatile. This supports the idea of examining the effect of the election.
Figure 3. Time series plots of SRTG return for (a) 3 years and (b) a year

Moreover, to see the relation between those index and stock returns, the correlation is computed and given in Table 2. The correlation coefficient is very low (0.083) which suggests that the relation between them is very weak. However, the correlation is significant that makes us want to see whether the return of the index depends on the stock and vice versa.

Table 2. The correlation between JKSE and SRTG returns

|                | JKSE  | SRTG  |
|----------------|-------|-------|
| Pearson correlation | 0.083 |       |
| P-value          | 0.026 |       |

Furthermore, the Augmented Dickey-Fuller (ADF) test was conducted to examine the stationarity of the return data. The results are given in Table 3 where both returns had very small p-value (less than 0.01). These prove that they were stationary series.

Table 3. The results of ADF test of JKSE and SRTG returns

|                | JKSE | SRTG |
|----------------|------|------|
| Dickey-Fuller  | -9.6779 | -10.2 |
| Lag order      | 8    | 8    |
| P-value        | <0.01 | <0.01 |

4.1. The ARIMAX Modeling
The first step in ARIMA modelling is by regressing the returns with exogenous variable, which is the dummy variable for election (D). Table 4 gives information of the summary of regression of dummy variable on JKSE and SRTG returns.
Table 4. The summary of regression coefficients

| Return                    | Variable | Coefficient | P-value |
|---------------------------|----------|-------------|---------|
| JKSE with intercept       | Constant | 0.000482    | 0.1527  |
|                           | D        | -0.001904   | 0.2798  |
| JKSE without intercept    | D        | -0.001422   | 0.4110  |
| SRTG with intercept       | Constant | -0.000357   | 0.7382  |
|                           | D        | 0.002590    | 0.6428  |
| SRTG without intercept    | D        | 0.002233    | 0.6835  |

Based on Table 4, the dummy variable of election does not significantly affect both returns. The regression with and without intercept (constant) were conducted but the results had the same conclusion, i.e. the effect of election was not significant. One possibility to explain these is that the time period of the election vibe should be longer as the election time is still in 2019, which is the next five months. Extending the time period may result in significant effect of election. Besides, additional dummy variable of the election day may also be useful.

Because the effect of exogenous variable was not important, the returns will be modelled using ARIMA model. In this paper, we only went through one of returns, which was the more volatile SRTG return, since the forecasting steps were similar. First, the ACF and PACF plots are presented in Figure 4.

![Figure 4: ACF and PACF plots](a)
According to Figure 4, the possible orders for ARIMA are AR(1), MA(1), and ARMA(1,1). After trying to run those models, only AR(1) with zero mean is significant (see Table 5). However, at the next steps (residual diagnostic), Table 6 reveals that the residual does not satisfy white noise assumption. Furthermore, not only residual but also the squared residual were not white noise. Thus, the model that could capture non-constant volatility was needed. In this study, we would consider ARCH and GARCH models.

Table 5. The AR(1) coefficients of SRTG return

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|----------|-------------|------------|-------------|-------|
| AR(1)    | -0.238325   | 0.036454   | -6.537765   | 0.000 |

Table 6. The ACF, PACF, Ljung-Box statistic of residual and squared residual of AR(1)

| Lag | Residual | Squared Residual |
|-----|----------|------------------|
|     | AC       | PAC   | Q-Stat | Prob | AC       | PAC   | Q-Stat | Prob |
| 1   | -0.014   | -0.014 | 0.1395 |       | 0.134   | 0.134 | 12.784 |       |
| 2   | -0.082   | -0.082 | 4.9084 | 0.027 | 0.155   | 0.139 | 29.86  | 0     |
| 3   | -0.111   | -0.114 | 13.683 | 0.001 | 0.017   | -0.02 | 30.059 | 0     |
| 4   | -0.071   | -0.083 | 17.249 | 0.001 | 0.113   | 0.095 | 39.141 | 0     |
| 5   | -0.068   | -0.094 | 20.584 | 0     | 0.049   | 0.026 | 40.839 | 0     |
| 6   | 0.044    | 0.013  | 22.001 | 0.001 | 0.195   | 0.165 | 68.2   | 0     |
| 7   | 0.005    | -0.027 | 22.014 | 0.001 | 0.069   | 0.022 | 71.594 | 0     |
| 8   | 0.085    | 0.067  | 27.238 | 0     | 0.028   | -0.039| 72.168 | 0     |
| 9   | -0.013   | -0.016 | 27.365 | 0.001 | 0.065   | 0.059 | 75.252 | 0     |
The results for ARCH-GARCH modelling is depicted in Table 7. Based on Table 7, the chosen order was GARCH(1,1). In other words, the final model was AR(1)-GARCH(1,1) which had significant coefficients (see Table 7). Moreover, as can be seen in Table 8, the white noise assumption for residual and the squared residual was satisfied. Besides, the model residual was normally distributed. Therefore, this model is the fixed model for SRTG return prediction.

Table 7. The AR(1)-GARCH(1,1) coefficients of SRTG return

| Variable   | Coefficient | Std. Error | z-Statistic | Prob. |
|------------|-------------|------------|-------------|-------|
| AR(1)      | -0.116291   | 0.040197   | -2.893003   | 0.0038|
| Variance Equation |
| C          | 1.35E-05    | 9.77E-07   | 13.82882    | 0.0000 |
| RESID(-1)^2| 0.206127    | 0.009261   | 22.25810    | 0.0000 |
| GARCH(-1)  | 0.842232    | 0.003755   | 224.2944    | 0.0000 |
| Akaike info criterion | -4.80543 |
| Hannan-Quinn criter. | -4.795506 |
| Schwarz criterion | -4.779739 |
| S.E. of regression | 0.027347 |

Table 8. The ACF, PACF, Ljung-Box statistic of residual and squared residual of AR(1) GARCH(1,1)

| Lag | AC  | PAC  | Q-Stat | Prob |
|-----|-----|------|--------|------|
| 1   | -0.007 | -0.007 | 0.0317 |       |
| 2   | -0.03  | -0.03  | 0.6943 | 0.405 |
| 3   | -0.032 | -0.032 | 1.4238 | 0.491 |
| 4   | -0.044 | -0.046 | 2.8148 | 0.421 |
| 5   | 0.002  | -0.001 | 2.8169 | 0.589 |
| 6   | -0.034 | -0.038 | 3.6354 | 0.603 |
| 7   | -0.032 | -0.035 | 4.3603 | 0.628 |
| 8   | -0.031 | -0.036 | 5.0462 | 0.654 |
| 9   | -0.013 | -0.018 | 5.1671 | 0.74  |
| 10  | 0.001  | -0.007 | 5.1676 | 0.819 |
| 11  | -0.069 | -0.076 | 8.5895 | 0.571 |
| 12  | -0.006 | -0.014 | 8.6117 | 0.658 |
| 13  | -0.035 | -0.045 | 9.4847 | 0.661 |
| 14  | 0.015  | 0.004  | 9.6451 | 0.723 |
| 15  | -0.079 | -0.095 | 14.203 | 0.435 |

| Lag | AC  | PAC  | Q-Stat | Prob |
|-----|-----|------|--------|------|
| 1   | 0.014 | 0.014 | 0.1481 |       |
| 2   | -0.02  | -0.02  | 0.4308 | 0.512 |
| 3   | -0.02  | -0.019 | 0.7056 | 0.703 |
| 4   | -0.002 | -0.002 | 0.709  | 0.871 |
| 5   | -0.03  | -0.031 | 1.3666 | 0.85  |
| 6   | 0.009  | 0.009  | 1.4217 | 0.922 |
| 7   | 0.077  | 0.075  | 5.6443 | 0.464 |
| 8   | 0.067  | 0.065  | 8.9004 | 0.26  |
| 9   | -0.024 | -0.022 | 9.2993 | 0.318 |
| 10  | -0.031 | -0.026 | 9.9736 | 0.353 |
| 11  | -0.01  | -0.007 | 10.046 | 0.436 |
| 12  | -0.036 | -0.034 | 11.007 | 0.443 |
| 13  | -0.003 | -0.001 | 11.015 | 0.528 |
| 14  | 0.014  | 0.026  | 11.158 | 0.674 |
Based on Table 7, the model can be written mathematically as

\[ r_t = -0.116291 r_{t-1} + a_t \]

where \( a_t = \sigma_t \epsilon_t \)

\[ \sigma_t^2 = 1.35 \times 10^{-5} + 0.206127 \sigma_{t-1}^2 + 0.842223 r_{t-1}^2 \]

\( \epsilon_t \sim N(\mu, \sigma^2) \).

For JKSE return, the best model according to minimum AIC is ARIMA(3,0,2) with zero mean.

**Table 9.** The results of JKSE return modeling

| Variable | ar(1) | ar(2) | ar(3) | ma(1) | ma(2) |
|----------|-------|-------|-------|-------|-------|
| Coefficient | -0.0202 | 0.7424 | -0.0606 | 0.0437 | -0.8048 |
| s.e. | 0.1237 | 0.1153 | 0.0405 | 0.1185 | 0.1046 |
| AIC | -4712.73 | BIC | -4680.75 | RMSE | 0.008753429 |

4.2. **VARX Modeling**

Multivariate modelling is considered since the correlation among returns is (although not high but) significant (see Table 2). For the order of VAR, we firstly model it by using lag order 1 (p=1). The results are given in Table 10.

**Table 10.** The results of VAR modeling

| Variable | Estimate | Std. Error | T | P-value |
|----------|----------|------------|---|---------|
| rtkjse(t) | rtkjse(t-1) | 0.0290679 | 0.0377742 | 0.77 | 0.442 |
| rtsrtg(t-1) | -0.0055921 | 0.0118984 | -0.47 | 0.639 |
| Const | 0.0004678 | 0.0003376 | 1.386 | 0.166 |
| D | -0.0018262 | 0.0017653 | -1.034 | 0.301 |
| R-squared: 0.002716 |

| rtsrtg(t) | rtkjse(t-1) | 0.0326046 | 0.1163738 | 0.28 | 0.779 |
| rtsrtg(t-1) | -0.2396307 | 0.0366564 | -6.537 | 0* |
| Const | -0.0004518 | 0.0010402 | -0.434 | 0.664 |
| D | 0.0032228 | 0.0054384 | 0.593 | 0.554 |
| R-squared: 0.05738 |

Based on Table 10, the dummy variable of pre-election vibe is not significant. In addition, it seems that there is no role of a series in predicting another series. Thus, univariate model is more suitable in predicting these returns.

5. **Conclusion**

To conclude, JKSE return is less volatile than SRTG return. Both series are stationary based on ADF test so that differencing is not needed. The effect of election vibe is still not pronounce as the dummy variable is not significant for these two returns. The best univariate model for JKSE index and SRTG returns are ARIMA(3,0,2) with zero mean and AR(1)-GARCH(1,1) with zero mean. Furthermore, the
multivariate VAR model is not recommended because there is no relation between the two series. The future work of this study may be done by Extending the time period to a period after the election day and adding a dummy variable of the election day.

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