VAR Model Estimation And Application Of IRF And FEVD On Currency Exchange Rates, COVID-19 Cases, And WHO Twitter Information In Southeast Asia

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***Abstract*—This paper examines the impact of the COVID-19 pandemic and World Health Organization (WHO) information dissemination through Twitter on the exchange rates of Southeast Asian countries. The study utilizes a VAR model for analysis, incorporating daily positive cases and the percentage of tweets with positive sentiment as proxies for the pandemic and WHO information, respectively. The VAR models are employed for forecasting and estimating impulse response functions (IRF) and forecast error variance decomposition (FEVD). The forecasting performance is evaluated using mean absolute error (MAE), root-mean-square error (RMSE), and R2 metrics, revealing that only Cambodia possesses a reliable forecasting model. The IRF analysis demonstrates varying effects of the pandemic and WHO information across different countries, while the FEVD results indicate distinct contributions of the pandemic and WHO information in each Southeast Asian country. Additionally, the FEVD analysis reveals that exchange rates are mostly influenced by their own past behavior. Overall, this study provides insights into the economic impact of the COVID-19 pandemic and WHO information on exchange rates in Southeast Asia.**

Keywords: Exchange Rates, VAR, Forecasting, IRF, FEVD.

I. INTRODUCTION

ON March 11, 2020, Dr. Tedros Adhanom Ghebreyesus as Director-General of WHO determined the spread of the COVID-19 virus as a global pandemic because the spread of COVID-19 continues to occur throughout the world [1]. The World Bank stated that the COVID-19 pandemic caused the global economy to experience its worst recession since the Second World War [2]. The dissemination of information during the pandemic is crucial, and the World Health Organization (WHO) has been responsible for distributing information about COVID-19 on various types of platforms such as official websites, news, social media, conferences, and others. The information received by countries has played an important role in shaping policies to combat the pandemic, which can have direct and indirect impacts on a country's economy, reflected by its exchange rate.

The foreign exchange market is one of the largest financial markets in the world and is sensitive to unexpected events like the COVID-19 pandemic, making it a useful tool to study the pandemic's effects on Southeast Asian countries. This study aims to analyze the effect of the COVID-19 pandemic and WHO information on the economic conditions of countries in Southeast Asia using daily positive cases and WHO information data processed into a percentage of tweets with positive sentiment. This study will use multivariate time series analysis to estimate parameters and forecast exchange rate returns. Impulse response functions (IRF) and forecast error variance decomposition (FEVD) will be used to analyze the impacts experienced by exchange rates. The currencies of Southeast Asian countries used in this study are those of Brunei Darussalam (Brunei Dollar / BND), Philippines (Peso / PHP), Indonesia (Rupiah / IDR), Cambodia (Riel / KHR), Laos (Kip / Lak), Malaysia (Ringgit / MYR), Singapore (Singapore Dollar / SGD), Thailand (Baht / THB), and Vietnam (Dong / VND), with the USD as the reference currency.

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II. METHODS

In this study, three types of data were used to estimate VAR models for Southeast Asian countries such as exchange rates, WHO Twitter account's positive tweet percentage, and incidence rate of new COVID-19 cases. Daily time series datasets from April 2020 to October 2021 were used for this study. This study aimed to analyze the impacts experienced by exchange rates with respect to WHO positive tweet percentage and incidence rate.

The overall methodology of this study to obtain the results is illustrated in Fig. 1. All processes are done using RStudio and the vars package in R for VAR modeling, forecasting, and calculating IRF and FEVD values [3].

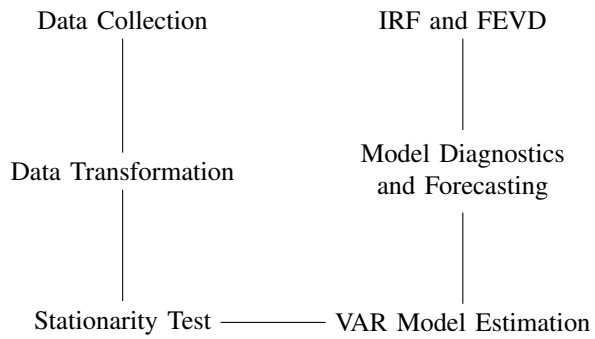


Fig. 1: Research methodology flowchart.

Different types of VAR models were estimated, classified by its variable determination, that is only constant as its determination variables, only trend as its determination variables, both variables, and none of those variables. The mentioned VAR models' equations are defined as:

$$\begin{aligned}
\text{Const} \quad & z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + \phi_0 + a_t, \\
\text{Both} \quad & z_t = \phi_1 z_{t-1} + ... + \phi_p z_{t-p} + \phi_0 + \phi_T + a_t, \\
\text{Trend} \quad & z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + \phi_T + a_t, \\
\text{None} \quad & z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + ... + \phi_p z_{t-p} + a_t,
\end{aligned}$$

The stationary condition of the datasets was checked with the Augmented Dickey-Fuller test, and data transformations were applied to fulfill the stationarity assumption. Four types of VAR models were estimated for each country based on optimal lag selection using Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC) or Schwarz Criterion (SC), Hannan and Quinn (HQ), and Final Prediction Error (FPE). The chosen model was used for forecasting and estimating impulse response functions (IFR) and forecast error variance decomposition (FEVD). The accuracy of the forecasting results was measured with mean absolute error (MAE), root-mean-square error (RMSE), and R-squared (R^2). The goal of estimating IRF and FEVD was to analyze the impacts of exchange rates in relation to COVID-19 incidence rate and WHO positive tweet percentage.

III. RESULT

This study has conducted several steps, including testing for stationarity, VAR model estimation, VAR model diagnosis, forecasting, and lastly IRF and FEVD estimation. The stationary condition is important to make statistical inferences about the structure of a stochastic process. We see that all datasets used in VAR model estimation have fulfilled the stationary condition, shown in Table I below. It has to be confirmed that the data used for VAR model estimation have to reach stationarity concerning that stationarity is needed to make statistical inferences about the structure of a stochastic process on the basis of an observed record of that process [4].

TABLE I: Stationarity Test.

Dataset	P-Value	Stationarity
Positive Tweet Perc.	$< 0,01$	Stationary
Laos IR	$< 0,01$	Stationary
USD/BND	$< 0,01$	Stationary
USD/MYR	$< 0,01$	Stationary
Brunei IR	$< 0,01$	Stationary
Malaysia IR	$< 0,01$	Stationary
USD/PHP	$< 0,01$	Stationary
USD/SGD	$< 0,01$	Stationary
USD/IDR	$< 0,01$	Stationary
USD/THB	$< 0,01$	Stationary
Indonesia IR	$< 0,01$	Stationary
Thailand IR	$< 0,01$	Stationary
USD/KHR	$< 0,01$	Stationary
USD/VND	$< 0,01$	Stationary
Cambodia IR	$< 0,01$	Stationary
Vietnam IR	$< 0,01$	Stationary
USD/LAK	$< 0,01$	Stationary

The VAR model estimation consists of three steps, namely optimal lag selection, model parameter estimation, and optimal model selection. Four criterions mentioned (AIC, BIC / SC, HQ, FPE) are used to determine the best lag for each type of VAR model. The chosen lag is the one with the highest vote and the highest value if there are ties. The results of these steps are shown in Tables II, III, IV, and V.

TABLE II: Optimal Lag For The Type Const.

Country	AIC(n)	HQ(n)	SC(n)	FPE(n)
Brunei Darussalam	4	1	1	4
Philippines	6	1	1	6
Indonesia	7	1	1	7
Cambodia	4	4	1	4
Laos	8	4	1	8
Malaysia	8	1	1	8
Singapore	4	1	1	4
Thailand	4	1	1	4
Vietnam	5	1	1	5

TABLE III: Optimal Lag For The Type Both.

Country	AIC(n)	HQ(n)	SC(n)	FPE(n)
Brunei Darussalam	4	1	1	4
Philippines	6	1	1	6
Indonesia	7	1	1	7
Cambodia	4	2	1	4
Laos	8	4	1	8
Malaysia	8	1	1	8
Singapore	4	1	1	4
Thailand	4	1	1	4
Vietnam	5	1	1	5

TABLE IV: Optimal Lag For The Type Trend.

Country	AIC(n)	HQ(n)	SC(n)	FPE(n)
Brunei Darussalam	4	4	1	4
Philippines	7	4	1	7
Indonesia	7	7	1	7
Cambodia	4	4	1	4
Laos	7	4	1	7
Malaysia	10	4	1	10
Singapore	7	4	1	7
Thailand	4	4	1	4
Vietnam	7	4	1	7

TABLE V: Optimal Lag For The Type None.

Country	AIC(n)	HQ(n)	SC(n)	FPE(n)
Brunei Darussalam	4	4	1	4
Philippines	7	4	1	7
Indonesia	7	7	1	7
Cambodia	4	4	1	4
Laos	8	4	1	8
Malaysia	10	4	1	10
Singapore	7	4	1	7
Thailand	4	4	1	4
Vietnam	5	4	1	5

After determining the optimal lag for each type of VAR model, the next step is to estimate the parameters. This involves estimating the parameters for all observed countries in Southeast Asia, and producing a log-likelihood score that measures the goodness of fit of each estimated model. Using the log-likelihood score for every type of VAR model, the optimal model will be selected based on the highest score. Table VI highlights the models selected for each observed country in Southeast Asia.

TABLE VI: Log-Likelihood Score and Optimal Model.

Country	Const	Both	Trend	None	Optimal Model
Brunei Darussalam	2738.207	**2749.238**	2718.791	2706.765	Both
Philippines	5880.446	**5882.952**	5855.571	5852.961	Both
Indonesia	6214.081	**6216.309**	6193.404	6190.512	Both
Cambodia	2367.18	**2385.969**	2334.126	2334.985	Both
Thailand	3935.853	**3943.387**	3914.032	3906.015	Both
Malaysia	5055.845	**5058.192**	5022.607	5021.021	Both
Singapura	4320.994	**4323.148**	4292.495	4290.32	Both
Laos	3070.914	**3071.748**	3038.201	3031.042	Both
Vietnam	5670.198	5674.157	**5678.261**	5639.006	Trend

The selected models will undergo diagnosis using residual analysis, which consists of four steps. The first step, called serial correlation test or Portmanteau test, checks for serial correlation in the residuals. The second step is the autoregressive conditional heteroscedasticity test or ARCH-LM, which checks for multivariate ARCH effects among the residuals. The third step is the residual normality test or Jarque-Bera test, which checks if the residuals are normally distributed. Lastly, the structural stability test or OLS-CUSUM tests if there are any structural changes within the estimated models. Results from each test are provided in Table VII.

After completing the model diagnosis, the estimated models are ready for use in forecasting and estimating IRF and FEVD. Even though the results obtained are not as expected, forecasting will still be done considering that significance test is not necessarily needed for business forecasting [5]. This study applies a method of forecasting which writer called ”N-Roll” because of mean-reverting behavior that a stationary VAR models have [6]. The results of this method are evaluated using MAE, RMSE, and R^2. The Table VIII shows a comparison between mean, standard deviation, MAE, RMSE, and R^2, and it is concluded that only Cambodia's VAR model provides good forecasts.

The impulse response functions (IRF) illustrate the effect of a shock on one variable on the movement of another variable, while the forecast error variance decomposition (FEVD) shows the contribution of variables influenced by themselves and other variables. In this study, the exchange rate returns are used as response variables and both positive tweet percentage and respective incidence rate are used as the impulse variables to analyze the impact of COVID-19 and WHO on the economic condition of each country in Southeast Asia. The results of IRF and FEVD are presented in Table IX and Table X below, showing that all the exchange rates in the observed Southeast Asian countries were mostly affected by their own past performance.

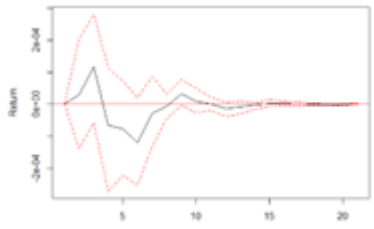
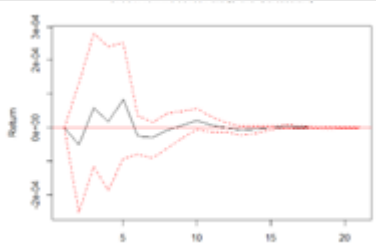
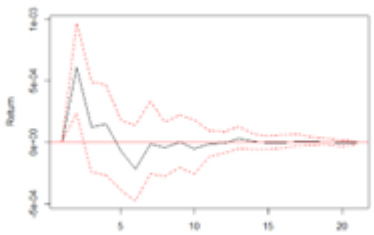
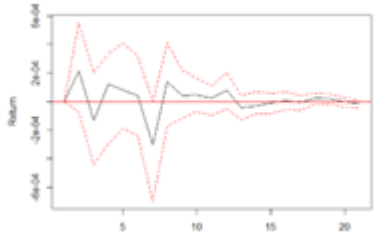
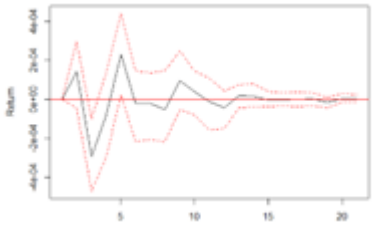
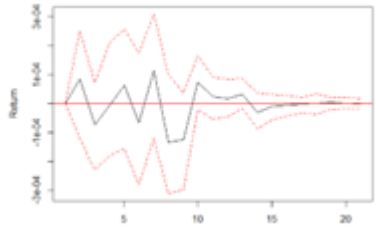
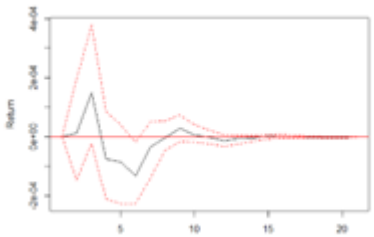
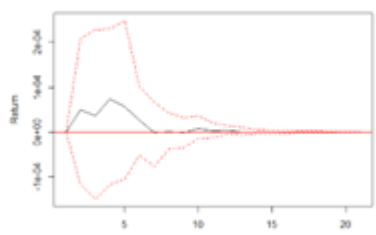
TABLE VII: Test Results.

Country	Portmanteau		Multivariate ARCH-LM		Jarque-Bera	
	P-Value	Serial Correlation	P-Value	ARCH Effect	P-Value	Residuals Normality
Brunei Darussalam	0.03163	Present	4.055×10^{-4}	Present	$< 2.2 \times 10^{-16}$	Absent
Philippines	0.3225	Absent	5.896×10^{-2}	Absent	$< 2.2 \times 10^{-16}$	Absent
Indonesia	0.1968	Absent	$< 2.2 \times 10^{-16}$	Present	$< 2.2 \times 10^{-16}$	Absent
Cambodia	0.03032	Present	2.696×10^{-6}	Present	$< 2.2 \times 10^{-16}$	Absent
Laos	0.4007	Absent	3.154×10^{-4}	Present	$< 2.2 \times 10^{-16}$	Absent
Malaysia	0.7266	Absent	5.039×10^{-13}	Present	$< 2.2 \times 10^{-16}$	Absent
Singapore	0.01257	Present	3.843×10^{-5}	Present	$< 2.2 \times 10^{-16}$	Absent
Thailand	0.3491	Absent	1.744×10^{-5}	Present	$< 2.2 \times 10^{-16}$	Absent
Vietnam	0.002133	Present	1.414×10^{-9}	Present	$< 2.2 \times 10^{-16}$	Absent

TABLE VIII: Comparison Between Mean, Standard Deviation, MAE, RMSE, and R^2.

Country	Mean	StdDev	MAE	RMSE	R^2
Brunei Darussalam	0.00002233	0.001771147	0.001317327	0.001840595	-0.088811195
Philippines	0.000275117	0.003532624	0.002602102	0.003666109	-0.085828393
Indonesia	-0.000187233	0.0017316	0.001381759	0.001974453	-0.310823227
Cambodia	-0.00001802	0.001526186	0.0007308501	0.001303358	0.2647108735
Laos	0.00068656	0.003510873	0.002151295	0.003723831	-0.13421429
Malaysia	0.000021578	0.001692784	0.001252358	0.001770012	-0.102286286
Singapore	0.000022333	0.001772484	0.001319126	0.001843419	-0.090508448
Thailand	0.00031623	0.003386142	0.002409353	0.003405277	-0.019623314
Vietnam	-0.000938015	0.000466377	0.0002761188	0.000500237	-0.1599078494

TABLE IX: IRF.

Positive Tweet Percenatge	Incidence Rate
Brunei Darussalam	
	
Indonesia	
	
Laos	
	
Singapore	
	

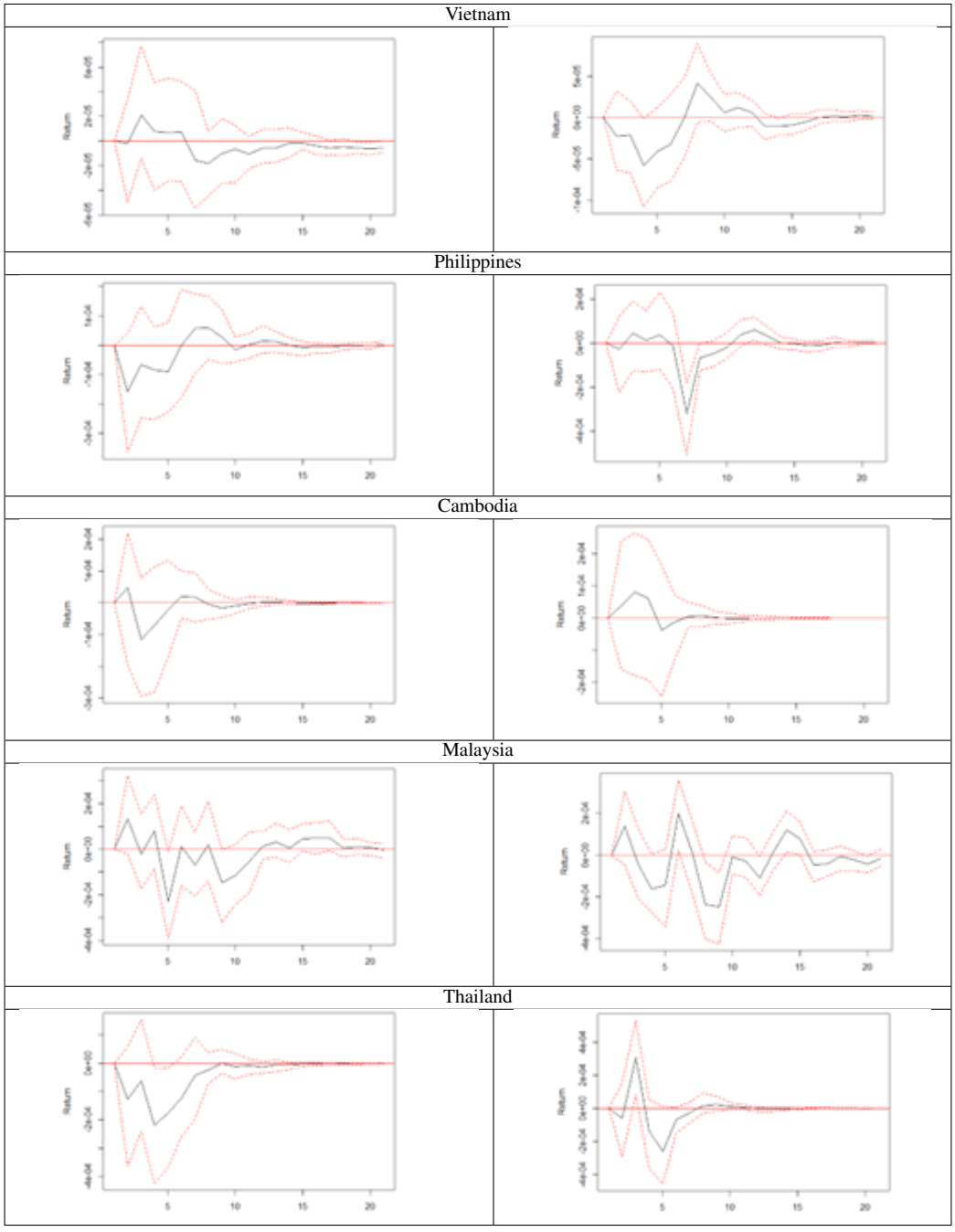

Vietnam
Philippines
Cambodia
Malaysia
Thailand

TABLE X: FEVD Return.

Period (Days)	USD/BND (Brunei Darussalam)			USD/PHP (Philippines)			USD/KHR (Cambodia)		
	Return	PosTweet	Inc. Rate	Return	PosTweet	Inc. Rate	Return	PosTweet	Inc. Rate
1	0.9993244	0.0001984445	-0.0005757103	0.9927471	0.00706398	0.0001654144	0.9944281	0.00344599	0.0002744343
2	0.9995882	0.0031012425	0.0013150121	0.9913023	0.00827461	0.000768035	0.9968631	0.02122659	0.0016165435
3	0.99947528	0.0040551967	0.0013702348	0.9890875	0.01101059	0.0008188845	0.9885176	0.01226563	0.0012171764
4	0.99157707	0.0033388567	0.0020948627	0.9868684	0.01262217	0.0016616544	0.9882299	0.0083720809	0.003035014
5	0.9882299	0.0083720809	0.003035014	0.9865176	0.01226563	0.001217176	0.9882299	0.0083720809	0.003035014
6	0.9838238	0.0085573007	0.0032030969	0.9825843	0.01379448	0.002974254	0.9838238	0.0085573007	0.0032030969
7	0.9822114	0.008556905	0.0032114622	0.9772194	0.01379448	0.002974254	0.9822114	0.008556905	0.0032114622
8	0.9979915	0.0088769204	0.0032023906	0.9557212	0.01397419	0.003304427	0.9979915	0.0088769204	0.0032023906
9	0.9878784	0.0089006970	0.0032023880	0.955516	0.013999124	0.003404927	0.9878784	0.0089006970	0.0032023880
10	0.9878784	0.0089006970	0.0032023880	0.955516	0.013999124	0.003404927	0.9878784	0.0089006970	0.0032023880

Period (Days)	USD/IDR (Indonesia)			USD/LAK (Laos)			USD/SGD (Singapore)		
	Return	PosTweet	Inc. Rate	Return	PosTweet	Inc. Rate	Return	PosTweet	Inc. Rate
1	0.9702463	0.02469336	0.003206384	0.9944475	0.00404889	0.001140857	0.9994347	0.000392741	0.0005269806
2	0.9682665	0.02729714	0.004457322	0.9776767	0.02075956	0.002467291	0.9994189	0.000321725	0.000504629
3	0.9657534	0.02973918	0.005073744	0.9707641	0.01521449	0.00241678	0.9991844	0.000313917	0.000484837
4	0.9650415	0.02056900	0.005092445	0.9648512	0.03146752	0.003141391	0.9991455	0.000207456	0.000460795
5	0.9645812	0.03201526	0.006021598	0.9626408	0.02414763	0.003019608	0.9988103	0.000186989	0.000449775
6	0.9559473	0.03318319	0.012611383	0.9211835	0.02358238	0.003344742	0.9986193	0.000184658	0.000445349
7	0.9547572	0.03181513	0.013915133	0.9246476	0.03336297	0.003207562	0.9984527	0.000190563	0.000445293
8	0.9645812	0.03184152	0.00314552	0.9264172	0.03382639	0.002694187	0.9983621	0.000184624	0.000445373
9	0.9543370	0.03200080	0.013669227	0.9283718	0.03382617	0.002741696	0.9982964	0.000184624	0.000445433
10	0.9530481	0.03205800	0.014669227	0.9308194	0.03382456	0.002794373	0.9982931	0.000185700	0.000446133

Period (Days)	USD/VND (Vietnam)		
	Return	PosTweet	Inc. Rate
1	0.9980014	0.0000413557	0.001984473
2	0.9948136	0.001619007	0.003567407
3	0.9826475	0.007198341	0.0155542
4	0.9644052	0.00194449	0.021308184
5	0.9736728	0.002069720	0.024257513
6	0.9728992	0.002884875	0.024222188
7	0.9638959	0.004448006	0.031656118
8	0.9604622	0.003984472	0.02976923
9	0.9640527	0.003416229	0.03163104
10	0.9638959	0.004448006	0.031656118

IV. CONCLUSIONS

This study utilized an autoregressive vector (VAR) model to analyze the effect of the COVID-19 pandemic and WHO information through Twitter on the exchange rates of Southeast Asian countries. The VAR models were estimated and used for both forecasting and estimating impulse response functions (IRF) and forecast error variance decomposition (FEVD). The forecasting process was evaluated using mean absolute error (MAE), root-mean-square error (RMSE), and R^2, and it was found that only Cambodia had a reliable model for the forecasting process. The IRF analysis showed that the effects of the COVID-19 pandemic and WHO information were different for each country, while the FEVD results showed that the COVID-19 pandemic and WHO information had a different proportion of contributions in each Southeast Asian country. The FEVD results also showed that the exchange rate of a currency was most selfinfluenced in the past.

APPENDIX

Appendixes should appear before the acknowledgment.

ACKNOWLEDGMENT

References are important to the reader; therefore, each citation must be complete and correct. If at all possible, references should be commonly available publications.

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