CHAPTER 5

The Measurement of the COVID-19 Pandemic in Cambodia Using the SIR Model

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1. INTRODUCTION

The spread of COVID-19 started at the end of 2019 in Wuhan province of China. The relevant authority hardly controlled the spread of the disease due to the virus being new and infected via the breath, the non-availability of vaccine, the lack of enough Personal Protective Equipment (PPE), the non-availability of adequate testing facilities, including the inadequate hospitalization facilities, such as limited numbers of available beds in hospitals for the patients. The lack of these facilities led to ineffective control of the pandemic. The new daily infected cases in Cambodia, a seven-day rolling average, was 528 (ABVC, 2021). Some strategies were carried out by the authorities in the infected areas to control the transmission of the virus. Those strategies were social distancing (including reducing public transportation, closing schools, banning funerals and weddings, and keeping people out of the streets), wearing masks, a centralized quarantine system, curfew, and lockdown. During the period of the pandemic, lockdown in the infected areas, even though it had a substantial adverse economic impact, was considered one of the most popular policies, generally carried out by government authorities in some countries, such as China and other European nations, such as Italy, Spain, France, and the United Kingdom that the level of infection was very high at the start of the pandemic in the early of 2020.

The government must predict the level of infection of the COVID-19 disease all over the country when it reaches the peak or turning point. To define the turning point of the total infection rate, the SIR model is employed to simulate three observed variables: Susceptible, infected, and recovery or deceased. The simulation of the model can be carried out by estimating two parameters: Contact rate and recovery rate. This chapter further tried to investigate the effectiveness of potential strategies, including curfew, lockdown, vaccination, and social distancing policy, which the Royal Government of Cambodia (RGC) can employ to cope with the COVID-19 pandemic. A multiple regression model is used between total infected cases and the four policies that have just been mentioned. The Ordinary Least Square (OLS) is applied in producing the sample parameters.

The following section of the chapter reviews the empirical studies in this direction. Following this, the chapter discusses the methodology used in this study. The empirical results and discussions, followed by the conclusion, are presented in subsequent sections.

2. LITERATURE REVIEW

The outbreak of COVID-19 first occurred in Wuhan of Hubei province, China. The central government of China imposed a lockdown on Hubei on January 23, 2020, to control the outbreak. The Bass-SIR model was applied to investigate and analyze the spread of the COVID-19 pandemic following Wuhan's lockdown between January 24, 2020, and February 12, 2020. The model used three variables: Cumulative infected cases, cured cases, and death cases in all provinces in China, excluding Hong Kong and Macau. The main objectives of this research were to determine the reproduction numbers and the adequate reproduction numbers to forecast the expected outbreak, the second wave, which might happen shortly. The exogenous impacts of the lockdown policy were also evaluated using the simulation analysis. This study found adequate reproduction numbers around two in Hubei, Heilongjiang, and Guizhou, but the numbers were close to one in other provinces by February 12, 2020. The exogenous force of infection, at 95 percent credible interval (CrI), was found to be 31 percent (CrI: 12-55 percent) and 19 percent (CrI: 5-44 percent) in Fujian and Shanghai despite Wuhan's lockdown. In addition, the second epidemic wave was predicted to occur on February 24, 2020 (Ku *et al.*, 2020).

The study of the outbreak of coronavirus in China, Italy, and France was conducted using the susceptible (S), infected (I), recovered (R), dead (D) scheme (SIRD) model on the period covered from January 22, 2020, to March 15, 2020. Excluding the recovered and dead number, the maximum number of infected individuals was predicted to be 26,000 in Italy, which is expected to happen on March 21, 2020. The result of this study showed a definite universality in the evolution of COVID-19 in China, Italy, and France, as indicated by the time-lag plots of the confirmed infected populations (Fanelli & Piazza, 2020).

Reproduction numbers, Rt, inferring the total population infected or attack rates of COVID-19 had been estimated in 11 European countries using a semi-mechanistic, joint Bayesian hierarchical model. This study further investigates the effectiveness of policies carried out by each country to reduce the mortality rate. The models that represent the number of infections, number of deaths, and number of reproductions were created. Between March 2 and March 20, 2020, government policy intervention had been put into action. Italy began to apply non-pharmaceutical interventions (social distancing encouraged, closing schools and universities, banning public events, case-based isolation, onset of first intervention and lockdown).

Effective policies aim to reduce the death rate to the lowest level. The death rate was observed until May 4, 2020. The initial average of Rt across all countries was estimated to be 3.8, with a credible interval between 2.4 and 5.6. This number is reduced owing to the combined non-pharmaceutical interventions. As of May 4, 2020, the highest attack rate was found in Belgium, at 8 percent of the total population. The rates were 5.5 percent and 4.6 percent in Spain and Italy, respectively. The lowest attack rate was found in Germany, estimated to be 0.85 percent of the total population. Two models were developed, with and without intervention, to predict deaths in 11 European countries. Had appropriate intervention policies been carried out at the start of the pandemic, the cause of the deaths would have been reduced by 3.1 million people across the 11 European countries. This research further revealed that the predicted infection rate was higher than reported. The deviation might have come from the test to detect COVID-19 infection. The high uncertainty of infection estimated here may be due to the focus on hospital test settings that miss out on mild or asymptomatic cases in the community. Reproduction numbers were reduced by 81 percent at the credible interval between 75 percent and 87 percent if a lockdown was implemented (Flaxman *et al.*, 2020).

One of the most famous mathematical models, the SIR model, was constructed to analyze the COVID-19 outbreak in the Kingdom of Saudi Arabia (KSA). The basis of the SIR model was created on the fundamentals of three subsets: Susceptible (S), Infected (I), and Recovered (R). Ordinary Differential Equation (ODE) was developed under these subsets. Two parameters, effective contact and recovery rates, were derived by solving ODE. The main objective of the study was to predict the pandemic situation in the next 700 days. Three scenarios were imposed: no action, lockdown, and new medicine. The implementation of the lockdown scenario was compared with the no-action and new medicine scenarios. This research found that lockdown intervention delays the peak point of the infection. The simulation prediction from the model showed that the highest infection cases would occur between 15 and 30 November 2020. The outbreak had been predicted to be under complete control after June 2021. The reproductive rate indicates that the lockdown and isolation of individuals still not be the best policy options to stop the spread of COVID-19. The study recommended that authorities implement a strict long-term prevention strategy as soon as possible to successfully reduce the size of the outbreak (Alanazi *et al.*, 2020).

A time-dependent SIR model was employed to investigate the number of infected persons in China. The infected persons were classified into detectable and undetectable persons. Daily data was used between January 15, 2020 and March 2, 2020. The National Health Commission (NHC) of the People's Republic of China collected the dataset. The reproductive rate was greater than 1, which considered that there was an outbreak. The reproductive numbers were reduced by adopting effective social distancing based on analysis of the independent cascade model, the so-called IC model for disease propagation in a configuration random network. The effectiveness of social distancing worked not just in China; this study found that it also worked in the case of Japan, Singapore, South Korea, Italy, and Iran (Chen *et al.*, 2020).

A discrete-time stochastic model using binomial distribution was developed to study the epidemic of COVID-19 in China. The study period was between January 11 and February 13, 2020 in China. Two main things were estimated to evaluate government policies implemented to control the transmission of the disease: The contact rate and effective reproductive numbers. Based on the current control policy option, the peak was predicted to be the end of February 2020 under the simulation technique generated from the model (He *et al.*, 2020).

Artificial Intelligence (AI) algorithms were incorporated into the SIR model with time-dependent parameters, and deep learning was applied to study the COVID-19 pandemic in South Korea. Datasets were collected from the Korea Centers for Disease Control and Prevention (KCDC). The critical parameters of the SIR model were estimated using the Runge-Kutta (RK4) method, a traditional numerical algorithm (Jo *et al.*, 2020).

The Susceptible-Exposed-Infectious-Removed (SEIR) model was applied with an AI approach to investigate the COVID-19 epidemic in China. Migration populations before and after January 23 were taken into account to measure and evaluate the effectiveness of policies employed, such as large-scale quarantine, strict controls on travel, and extensive monitoring of suspected cases. The highest number of infections might be in February 2020, as predicted by the model. The total number of infections would have increased threefold in mainland China if the government had taken inadequate policies and actions (Yang *et al.*, 2020).

A Markov Chain Monte Carlo technique and SEIR model were used to predict reproductive numbers caused by the COVID-19 pandemic in Italy and Hunan, China. Daily time-series data were applied from January 22, 2020, to April 2, 2020. As indicated by the posterior mean with 95 percent CrI, the reproductive number of COVID-19 was estimated to be 4.34 at 95 percent CrI in the range between 3.04 and 6.00, and 3.16 at 95 CrI in the range between 1.73 and 5.25, for Italy and Hunan, respectively. The endpoint in Italy was predicted to be on August 5, 2020 (Wangping *et al.*, 2020).

The SIR model was one of the best models for predicting the transmission of COVID-19 disease (Cooper *et al.*, 2020). A nonlinear SIR model was developed to study the COVID-19 epidemic in Germany, Spain, Italy, France, Algeria, and Morocco. The main objective of this research was to evaluate the social distancing policy introduced by the government in each respected country. This research showed that the numerical simulation technique creates an effective tool for forecasting the transmission of COVID-19 disease (Gounane *et al*., 2021).

SEIR model was extended to be susceptible (S), exposed (E), infectious (I), quarantined (Q), recovered (R), deaths (D), and vaccinated (V) (SEIQRDV) to investigate the spread of COVID-19 disease in KSA by taking into account vaccination compartment. The ensemble Kalman filter (EnKF) method was used to improve the efficiency of parameter estimation. In a short-term prediction, two weeks ahead, the level of recovered, deaths, and confirmed cases were simulated from the model, and the prediction error was a minor deviation compared to accurate data. The pandemic was being affected by vaccination, as revealed by this research (Ghostine *et al*., 2021). The analysis of the COVID-19 pandemic was started with a basic epidemical model developed by Kermack-McKendrick. The model was extended to observe the heterogeneity in the spread of the disease, especially to study the effectiveness of policy options that any government might have used to control the pandemic, such as non-pharmaceutical interventions, lockdown strategy, potential approaching of herd-immunity levels, and optimal deploying of COVID-19 vaccines. This research was theoretical (Saldana & Velasco-Hernandez, 2021).

SEIR model was extended by including the asymptomatic isolated, in short, it was called SEIR-AQ, to conduct performance measurement prevention and control strategies for the COVID-19 pandemic in China, America, India, and Brazil. Instead of dividing the population into four: Susceptible people (S), Exposed (E), Infected (I), and Removed (R), the SEIR-AQ included four more in the model, such as isolation of susceptible people (Sq), isolation of contacts (Eq), isolation of infected people (Iq), asymptomatic patients (A), and hospitalized patients (H). The parameters of the model were calculated using the Euler method. The transmission of COVID-19 disease was affected significantly through the effective implementation of isolation and medical tracking isolation regarding the theoretical analysis. Studies have shown that in containing the spread of the COVID-19 pandemic, the local government's swift precaution and control measures are vital to minimize direct contact among people to reduce the exposure rate and ensure proper isolation rate (Yu *et al*., 2021).

The literature review shows studies measuring the COVID-19 pandemic in different countries and the policy options for the government to prevent and control infections. In the presence of quite a limited number of studies, this chapter aims to significantly contribute to the current discussion and measures to control the pandemic in the Kingdom of Cambodia.

3. METHODOLOGY

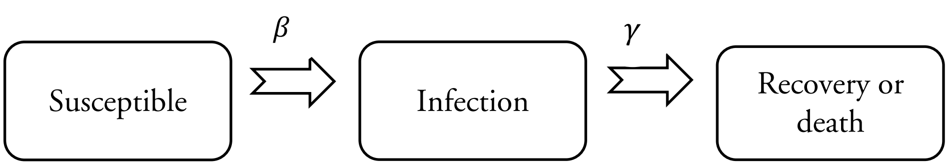
The methodology part of this chapter is divided into two parts: The first part describes the Susceptible-Infected-Recovery model, known as SIR model, which is developed aiming to determine the maximum number of infective of COVID-19 and when this number is going to happen, while the second part of the methodology represents a multiple regression between dependent variable, total infected COVID-19 cases, and the independent variables indicate policy options, which have been carried out by the government in order to fight with the infection. The SIR model is one of the epidemiologic models to understand the spread of an infectious disease. There are three observed variables: Susceptible (S), infected (I), and recovery (R), which means the total population is classified into three components. The model specification is presented in the following three equations:

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \gamma I$$

$$\frac{dR}{dt} = \gamma I$$

Where β is the probability of infecting a contact in a specified time, and$\gamma$is the rate at which an infected recovers and moves into the resistance phase. This model had three key assumptions. The first assumption is that individuals are never infected and can catch the disease. The second compartment is that infected individuals can spread the disease to susceptible individuals, and the third one is that individuals are assumed to be immune for life or death. The diagram shows these assumptions.



Solving the three differential equations above, we get:

Susceptible	*Infected*	*Recovered*
$dS = (-\beta SI)dt$	$dI = (\beta SI - \gamma I)dt$	$dR = \gamma I dt$
$S_{i+1} - S_i = (-\beta S_i I_i)dt$	$I_{i+1} - I_i = (\beta S_i I_i - \gamma I_i)dt$	$R_{i+1} - R_i = \gamma I_i dt$
$S_{i+1} = S_i - (-\beta S_i I_i)dt$	$I_{i+1} = I_i + (\beta S_i I_i - \gamma I_i)dt$	$R_{i+1} = R_i - \gamma I_i dt$

This research also tried to evaluate the performance of government policies that are being implemented to cope with the level of infection of the disease in the country. The assessment is carried out through a multiple regression analysis between total infected cases, *TC* (dependent variables), and independent variables, such as curfew (*CF*), lockdown (*LD*), vaccination (*PVCIN*), and stringency index (*SINDEX*) measured based on school and workplace closures; restrictions on public gatherings; transport restrictions; and stay-at-home requirements.

$$TC_t = \theta_1 CF_t + \theta_2 LD_t + \theta_3 PVCIN_t + \theta_4 SINDEX_t + \varepsilon_t$$

Where $\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$is a vector of slope parameters to be estimated, ε is a residual or error term, and t represents the time. Curfew and lockdown represent dummy variables, where one indicates the days of the curfew or lockdown zero otherwise. The study period covers from February 20, 2021, to August 20, 2021. All data are collected from the Ministry of Health, Royal Government of Cambodia.

This research employs time series data; hence, to avoid spurious results, Unit root tests are conducted on all data series except dummy variables. The estimated method is Ordinary Least Square (OLS). In order to fulfill the assumptions of OLS, diagnostic tests, such as multicollinearity, autocorrelation, and heteroscedasticity, are carried out. The detection of multicollinearity is conducted through a correlation matrix. Any pair of variables with a correlation coefficient greater than -0.9/+0.9 is omitted from the regression analysis. The autocorrelation is detected using the Durbin-Watson statistic. The variance of the residual terms is assumed to be constant, so-called homoscedasticity, as indicated by OLS techniques. One of the most popular tests of heteroscedasticity is the Breusch-Pagan-Godfrey (BPG) test. The null hypothesis of the test is homoscedasticity.

4. EMPIRICAL RESULTS AND DISCUSSIONS

The interpretation of research findings is classified into three different parts. The first part concerns descriptive statistics on daily COVID-19 and total infected cases. The forecasting of daily susceptible, infected, and recovered or deceased is presented in the second part. The empirical results, which explain the effectiveness of government policies, curfew, lockdown, vaccination, and social distancing policies, on total COVID-19 infected cases, are shown in the last part of this section.

Throughout the study, 182 days, the average daily and total infected were 482 and 31,933 cases, respectively. The minimum daily infected case is zero, while the maximum infected cases are 1130. Daily new cases' standard deviation is 310, and the standard deviation of total cases is 29019. The maximum total number of infected cases is 88,242. In addition, the two data series are not distributed as normal distributions regarding the estimated result of the Jarque-Bera (JB) tests. The probability of the tests for both NC and TC is lower than the level of significance of 1 percent, which claims that the null hypotheses are rejected. The movement of the two data series can be seen more precisely through Figure 5.1 and Figure 5.2.

Table 5.1: Daily New Infected Cases and Total Infected Cases

	New Infected Cases (NC)	*Total Infected Cases (TC)*
Mean	482.1868	31933.68
Median	549.0000	24401.00
Maximum	1130.000	88242.00
Minimum	0.000000	533.0000
Std. Dev.	310.1169	29019.29
Skewness	-0.204741	0.528999
Kurtosis	1.892583	1.882224
Jarque-Bera	10.57154	17.96325
Probability	0.005063	0.000126
Sum	87758.00	5811929.
Sum Sq. Dev.	17407216	1.52E+11
Observations	182	182

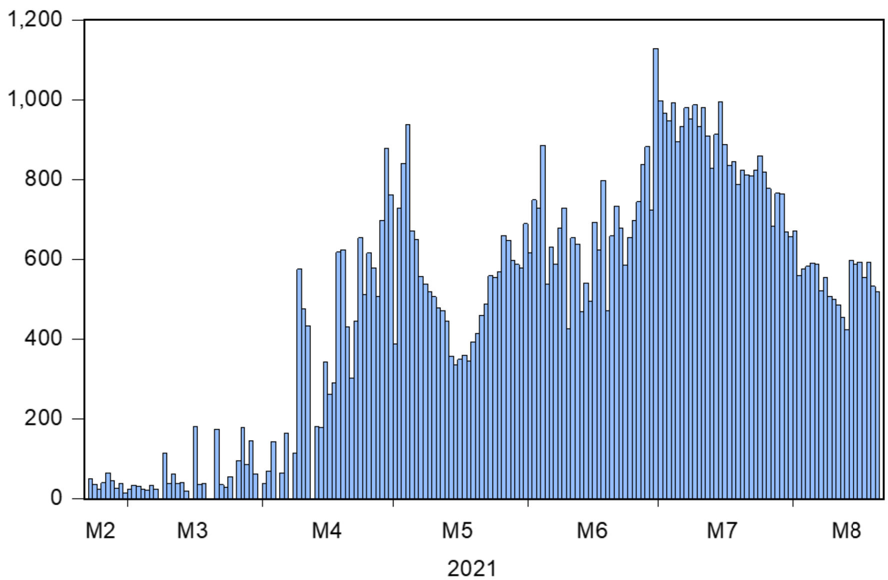


Figure 5.1: Daily Infected Cases, February 20, 2021 – August 20, 2021

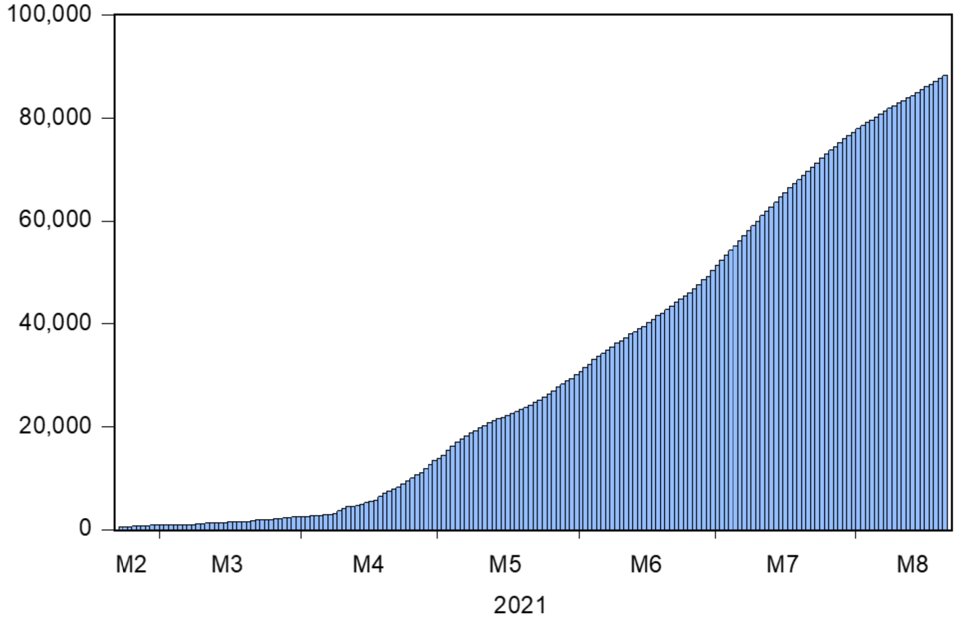


Figure 5.2: Total Infected Cases, February 20, 2021 – August 20, 2021

The observed time series data combined with the estimated probability infected infecting a contract in a specific time and the rate that an infected recovers and moves into the resistance phase, the out-of-sample forecasting of susceptible, infected, and recovered as a proportion to the total population in the country which derived from the Ordinary Differential Equation (ODE) are revealed. The simulation of the SIR model indicated that the infection of COVID-19 would be expected to peak on July 2, 2022, which is regarded as a turning point.

$\beta = 0.0461$ (Contact rate)
$\gamma = 0.0061$ (Recovery rate)

The data series used in this research are time series. The unit root tests are applied to avoid spurious results. One of the most famous unit root tests, the Augmented-Dickey Fuller (ADF) test, is selected to assess all the data series except the dummy variables, CF and LD. The null hypothesis of the test is that the series has a unit root. The result of the ADF tests presented in Table 5.2 indicated that TC, PVCIN, and SINDEX are all integrated of order one, I(1), which means that each individual series has a unit root at level but has no unit root at first difference. Therefore, a regression between dependent and independent variables can be performed at the level. However, a co-integration test must be conducted to check whether all data series are co-integrated or have a long-run relationship. Engle and

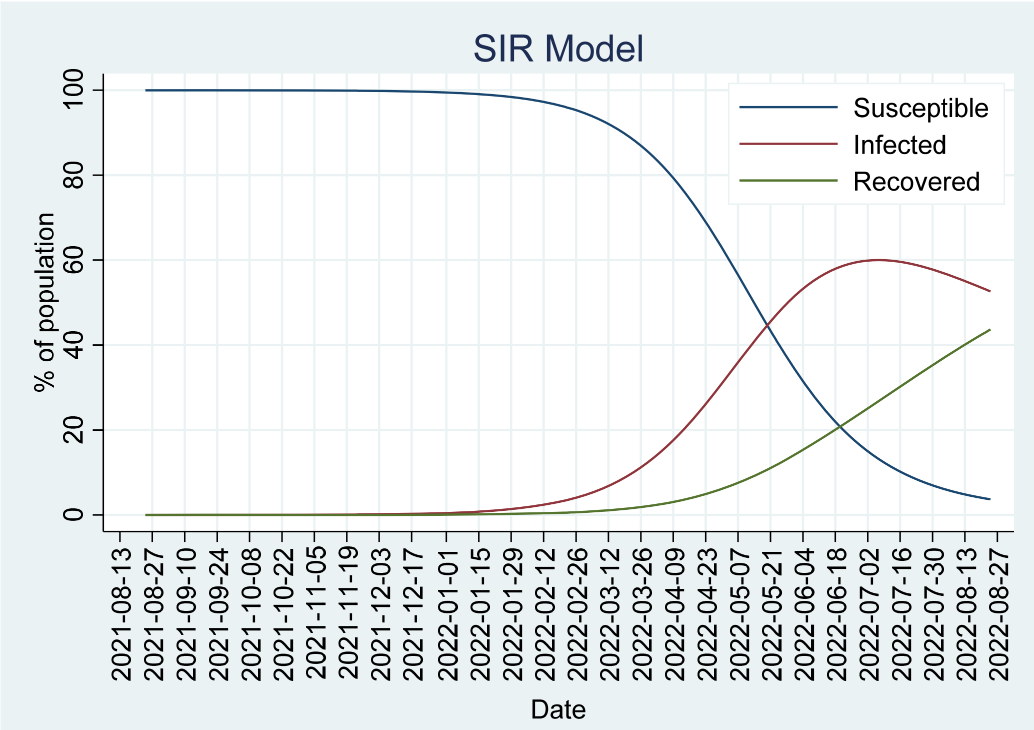


Figure 5.3: SIR Model, Out-of-Sample Forecasting

Granger's two-step co-integration test is applied. In the first step, a multiple regression is carried out to get all estimated parameters, which will be used to predict the residual terms. The co-integration among variables under investigation does exist if the residual series is stationary or has no unit root. Instead of avoiding spurious regression results, the fulfillment of the assumptions of OLS, no multicollinearity among dependent variables, no first-order autocorrelation of the residual terms, and variance of the error term must be constant, or homoscedasticity is also needed to investigate.

After analyzing the correlation between all independent variables in the model, a multiple regression analysis is implemented and presented in the correlation matrix below. As indicated in Table 5.3, the correlation coefficient of all pairs of variables is no less than -0.9 or no more than +0.9, which claims that high or perfectly positive or negative correlations between variables in the model are not detected. On the other hand, the multicollinearity in the model is not detected, which means that none of the variables is omitted.

Table 5.2: ADF Tests

	At Level			
		TC	*PVCIN*	*SINDEX*
With Constant	t-Statistic	4.1197	–0.5901	–1.1024
	Prob.	***0.4619***	***0.8686***	***0.7147***
		n0	n0	n0
With Constant and Trend	t-Statistic	–3.1581	–2.6122	–0.8219
	Prob.	***0.7964***	***0.2755***	***0.9608***
		n0	n0	n0
Without Constant and Trend	t-Statistic	7.6411	0.7694	–0.8095
	Prob.	***0.6285***	***0.8789***	***0.3641***
		n0	n0	n0
	At First Difference			
		d(TC)	d(PVCIN)	d(SINDEX)
With Constant	t-Statistic	–2.3383	–4.5358	–13.3725
	Prob.	***0.1612***	***0.0002***	***0.0000***
		n0	***	***
With Constant and Trend	t-Statistic	–3.4877	–4.5224	–13.6025
	Prob.	***0.0437***	***0.0018***	***0.0000***
		**	***	***
Without Constant and Trend	t-Statistic	–0.6388	–4.4568	–13.3791
	Prob.	***0.4394***	***0.0000***	***0.0000***
		n0	***	***

Note: ***, **, significant at 1% and 5% levels, respectively.

Table 5.3: Correlation Matrix

	CF	*LD*	*PVCIN*	*SINDEX*
CF	1			
LD	–0.1824	1		
PVCIN	–0.4766	0.1860	1	
SINDEX	–0.2347	0.1941	0.1322	1

As indicated by the ADF unit root test of the predicted residual series from the regression model, the null hypothesis, which stated that the residual series has a unit root, is highly rejected since the MacKinnon one-sided probability value or p-value is less than 1 percent significant level. The series is stationary. As such, all series in the model are co-integrated.

Table 5.4: ADF Unit Root Test, Residual Series

Null Hypothesis: RESID01 has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag =13)

			t-Statistic	*Prob.**
Augmented Dickey-Fuller test statistic			–5.861930	0.0000
Test critical values:	1% level		–3.466994	
	5% level		–2.877544	
	10% level		–2.575381	

*MacKinnon (1996) one-sided p-values

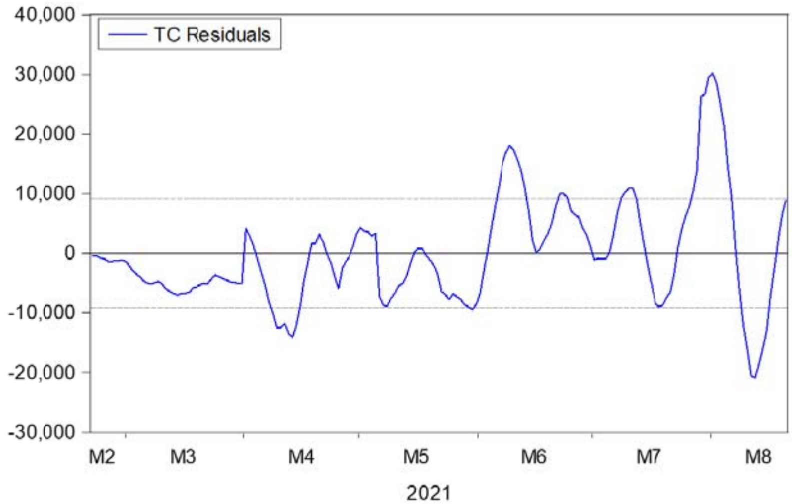


Figure 5.4: Regression Residual Series

The result of the ADF unit root test presented in Table 5.4 is consistent with the trend of the regression residual series in Figure 5.4, that the series has a mean-reverting process characteristic of a stationary process. The assessment of spurious regression results has been completed. The next issue is the detection of the first-order autocorrelation of the residual series. Since the Durbin-Watson statistic, known as the d-statistic derived from the regression result, is 0.087, the difference between the two indicates that the first-order autocorrelation of the residual terms is detected. The next step is to check whether the variance of the error terms is constant or not using the Breusch-Pagan-Godfrey heteroscedasticity test. The null hypothesis of the test is homoscedasticity, which means that the variance of the residual terms is constant.

Table 5.5: Heteroscedasticity Test: Breusch-Pagan-Godfrey

F-statistic	24.36488	Prob. F (4,177)	0.0000
Obs*R-squared	64.62750	Prob. Chi-Square (4)	0.0000
Scaled explained SS	108.0612	Prob. Chi-Square (4)	0.0000

The calculated F-statistic of the Breusch-Pagan-Godfrey test is 24.36 based on 4 degrees of freedom and 177 observations, and since the probability of the calculated F-statistic is 0.0000, which is far less than 1 percent significant level, the null hypothesis of homoscedasticity is rejected, which claimed that heteroscedasticity does exist.

Table 5.6: Regression Results

Dependent Variable: TC

Method: Least Squares

Sample: 2/20/2021 - 8/20/2021

Included observations: 182

HAC standard errors and covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
CF	–9286.751	5260.985	–1.765211	0.0792
LD	–10362.02	1918.662	–5.400651	0.0000
PVCIN	–6.668291	0.350045	–19.04981	0.0000
SINDEX	–6.700497	29.69047	–0.225678	0.8217
R-squared	0.902006	Mean dependent var		31933.68
Adjusted R-squared	0.900354	S.D. dependent var		29019.29
S.E. of regression	9160.432	Akaike info criterion		21.10491
Sum squared residual	1.49E+10	Schwarz criterion		21.17533
Log likelihood	–1916.547	Hannan-Quinn criterion		21.13345
Durbin-Watson stat	0.087266			

Two assumptions of OLS were found to be violated: First-order autocorrelation and heteroscedasticity. Due to these violations, the test of statistic generated from the regression results is unreliable since each individual standard error of the t-statistic is significant, which turn out that the calculated t-test is small. In order to remedy first-order autocorrelation and heteroscedasticity problems, heteroscedasticity and autocorrelation consistent (HAC) standard error and covariance are employed to produce robust standard errors for hypotheses testing. The regression result is presented in Table 5.6. The adjusted R-squared is 0.90, which is considered high, meaning the model fits the data well. The estimated slope parameter of CF is -9286, and the null hypothesis that the population parameter of CF is zero is weakly rejected since the p-value is 0.0792, which is less than a 10 percent significant level. A one-day curfew is expected to reduce the number of infected cases by 9286. More interestingly, the estimated slope coefficient of LD is -10362 and highly statistically significant at a 1 percent level, which is greater than the p-value of 0.0000. The number of infected cases would reduce by 10362 if the government announced a lockdown by one day. The number of vaccinated people has also helped reduce the spread of the disease. A one-vaccinated person would help prevent the infection of the disease by about seven people, and the estimated result is highly significant at the 1 percent level since the probability of the calculated t-test is low. Despite the estimated slope coefficient of SINDEX being -6.700497, which is negative, the null hypothesis failed to be rejected because the p-value of 0.8217 is greater than the significance level of 5 percent.

5. CONCLUDING REMARKS

This research aims to study the interaction between susceptible, infected and recovered COVID-19 using the Ordinary Differential Equation to conduct the out-of-sample forecast. Another objective is to assess government policies in fighting the spread of the disease nationwide. Regarding the estimated contracted rate and the recovery rate, which were 0.0461 and 0.0061, respectively, the simulation of the SIR model indicated that the total infected COVID-19 cases were predicted to reach the peak point that is regarded as a turning point on July 2, 2022. From August 20, 2021, the present time or end of the sample data point of this study, to July 2, 2022, which was predicted to be a peak point of the total infected cases as proportion to the total population, which has about ten months and a half for the government to establish effective policies, such as curfew, lockdown, vaccination, and social distancing policy in order to cope with COVID-19 pandemic. Among the four policies employed, lockdown is considered to be one of the most effective strategies to fight the pandemic since a one-day lockdown is expected to decrease the total infected cases by 10362, followed by curfew, which helped reduce the spread of the disease by about 9287 cases per day. In contrast, the last policy is vaccination, which prevented the infection by about seven cases per day. Of course, executing government policies, especially lockdowns and curfews, would help prevent the spread of the disease. However, it harmed the economy, and therefore, it needs to be carefully implemented prudently by the government and its agencies.

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