Analysis of Government Policy in Handling Covid-19 in Indonesia

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Abstract. The Covid-19 pandemic has affected the economy in many countries, including Indonesia. Until July 2021, the Government has implemented social activity policies for the community, starting from Large-Scale Social Restrictions in the first semester of last year to PPKM Level 4 to stop the spread of Covid-19. Responding to the Covid-19 pandemic, Google released data from people who access google applications using mobile devices. The Google Mobility report shows changes in population activity and mobility in several locations. This study aims to examine the effect of the PSBB and PPKM policies in Indonesia on the decline in COVID-19 cases in Indonesia using the Google Mobility Index and their impact on the economy in Indonesia. The analysis uses graphs and Pearson Correlation and Long Short-Term Memory (LSTM) method to predict Covid-19 cases and mobility data. The result shows that the mobility of people to five places has a significant effect on the number of daily cases of Covid-19, while there is a significant effect on three places of community mobility on Indonesian economic. As the results, controlling the spread of Covid-19 is better prioritized than economic condition.

1. Introduction

The government implemented a semi-lockdown policy to limit the movement of people to suppress the spread of the virus with the increase in active cases of COVID-19 in Indonesia. Starting from Large-Scale Social Restrictions (PSBB) in the first semester of last year to the implementation of micro-based Community Activity Restrictions (PPKM) since March, emergency PPKM at the end of June, and PPKM level 4 at the end of this July (PPID, 2021). The purpose of several activity restriction policies is to contain the spread of the virus and reduce the Bed Occupancy Rate [7].

The government eased restrictions on March 9 with the implementation of micro PPKM. Several public places such as shopping centers, cinemas, offices, restaurants, and places of worship have reopened with a capacity of 50 percent of visitors by implementing health protocols. However, in mid-June, there was a spike in COVID-19 cases due to the spread of the Delta variant from India. The government took a firm policy to close all teaching, office, and other public activities. Some of these activities are temporarily online. Data from covid19.go.id as of July 30, 2021, confirmed cases of COVID-19 reached nearly 3.4 million cases with a death toll of 92,311 cases. The addition of the number of COVID-19 cases in Indonesia is one of the highest in the world. According to experts, virus transmission can occur through droplets or breathing, so reducing the level of direct community interaction, can reduce the rate of virus spread [3].

By implementing strict social distancing in various activities, people's movements are very limited [2]. Several studies were conducted to find out what variables affect transmissions such as transportation access, demographic conditions, and mobility patterns [3]. Woskie [1] in 2020 examined the effect of social distancing policies in 27 countries on the European continent with population mobility and COVID-19 infection using two linear mixed effect models. The result is that since implementing the stay-at-home policy, population mobility has fallen by 70 percent. Changes in mobility significantly affect changes in the growth of COVID-19 cases. For example, a 10 percent reduction in mobility will reduce COVID-19 cases by 11.8 percent.

Google [4] released data from people who access the Google application using mobile devices to respond to the pandemic. The Google Mobility report shows changes in population activity and mobility in some locations, compared to before the spread of COVID-19 [4]. This data is useful for measuring activity and movement [5]. This report provides an opportunity for researchers to conduct a study on the correlation between mobility and active cases of COVID-19. The question is whether the government's social restriction policies are effective in suppressing the spread of the virus. Research conducted by Sulyok and Walker in 2020, found that globally, a decrease in population activity has a correlation with a decrease in COVID-19 cases using the Kendall correlation. Wang [2] also used the mobility index to measure the effect of social distancing on virus transmission and made a model to predict Covid-19 cases with the help of population mobility activity data from the Google Community Mobility report. They determine the best and most accurate model using Partial Differential Equation (PDE). As a result, social distancing can reduce the spread of the virus. According to Wellenius [7], there is a strong relationship between decreasing mobility and Covid-19 case growth. The research used regression discontinuity analysis on google mobility data.

The social distancing policy in each country is different. President Joko Widodo stressed that he would not issue a lockdown policy because it would have a bad impact on the economy. According to Putra [8], there is strong positive correlation between people’s mobility and economic growth in Indonesia. Therefore, it is interesting to examine the effect of the PSBB and PPKM policies in Indonesia on the decline in COVID-19 cases in Indonesia using the Google Mobility Index and their impact on the economy in Indonesia. Previous research using Long Short Term Memory (LSTM) and mobility data from Google and Apple showed that daily cases of COVID-19 in Indonesia were influenced by the mobility trend of the previous eight days [3].

2. Methodology

2.1. Pearson correlation

This study uses a descriptive analysis of data on changes in mobility, daily positive cases of COVID-19, and the impact of the economy in Indonesia through graphs, tables, and Pearson correlations. This Pearson correlation analysis uses to determine the close relationship between the variables of changes in mobility and confirmed cases of COVID-19. The magnitude of the close relationship ranged between -1 to 1. If the value is closed to -1 or 1 , the relationship between the two variables is getting stronger. Otherwise, if it is closed to zero, the relationship between the two variables is weaker. The following is the Pearson correlation formula [9]:

$$r_{xy} = \frac{n\sum XY - \sum X \sum Y}{\sqrt{n\sum X^2 - (\sum X)^2}\sqrt{n\sum Y^2 - (\sum Y)^2}} \quad (1)$$

Notes:
r_{xy} = correlation value,
X = variable X,
Y = variable Y.

2.2. The Long short term memory

In addition, this study also uses a method, namely Long Short Term Memory (LSTM). LSTM is one of the most common forms of RNN. LSTM stores information on patterns in the data. LSTM can learn data that will be stored and discarded because each LSTM neuron has a gate structure that regulates the memory of each neuron itself. This method can process and predict time series data. Architecture of LSTM consist of three layer that are input layer, output layer, and hidden layer. The hidden layers are set of memory cell that have input gate, forget gate, and output gate [10]. The diagram can be shown in figure below.

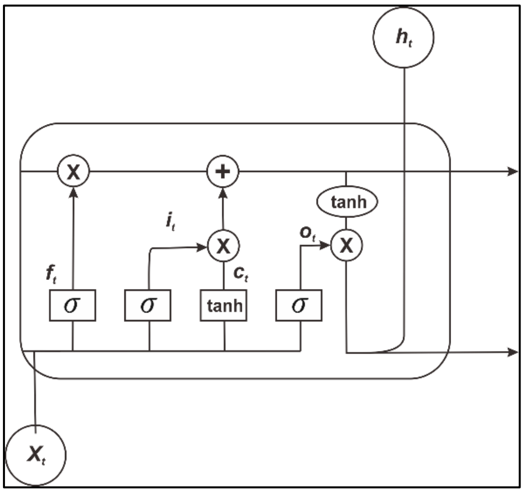

Figure 1. LSTM diagram of memory cell

1. Input gate (i_t)
   This gate controls the information that saves in a memory cell. That information is an output of the previous memory cell and has passed the sigmoid layer. The formula of this gate can be shown below.

$$i_t = \sigma(W_i S_{t-i} + W_i X_t) \tag{2}$$

Note:
W_t = weight of input gate
S_{t-i} = previous (t-1) state
X_t = input in current time (t)
σ = sigmoid function

2. Forget gate (f_t)
   This gate controls the extent to which the value remains in the memory cell. This gate is a sigmoid layer that takes output in t-1 and input in t, the output of this gate is 0 or 1. If the forget gate (f_t) is 0 then the previous state will be forgotten, while if the forget gate (f_t) is 1 then the previous state is not changed, and the following formula is:

$$f_t = \sigma(W_f S_{t-i} + W_f X_t) \tag{3}$$

Note:
W_t = weight of forget gate
S_{t-i} = previous (t-1) state
X_t = input in current time (t)
σ = sigmoid function

3. Output gate (o_t)
   The output gate decides how much value is in the memory cell to calculate the output. This gate also controls how many states pass to the output and works in the same way as any other gate.

$$\sigma_t = \sigma(W_o S_{t-i} + W_o X_t) \tag{4}$$

Note:
W_o = weight of output gate
S_{t-i} = previous (t-1) state
X_t = input in current time (t)
σ = sigmoid function

In this study, the COVID-19 case data compares with mobility data with a 14-days time difference. The use of this time difference is because Covid-19 does not directly affect population mobility. Testing whether the model used to train the dataset is good or not using a graphic diagram that compares the training loss and validation loss on the implementation of the model to the dataset. If the training loss and validation loss decrease to stability point and the gap between them is small, the model used to train the data is suitable for that dataset.

2.3. Data and sources

This study uses 2020 to 2021 data of Indonesia from the Statistics of Indonesia, covid19.go.id, and Google Community Mobility Report. The mobility change data collected includes:

1. *Retail and Recreation*
2. *Grocery and Pharmacy*
3. *Parks*
4. *Transit Station*
5. *Workplace*
6. *Residential*

3. Results and Discussions

3.1. Descriptive Analysis

Figure 2 shows the mobility of people to work and residential areas for the number of confirmed COVID-19 from February 2020 to July 2021. This graph also shows that positive cases of COVID-19 from June 2021 increased quite significantly. This phenomenon caused by mobility activities to the workplace starts to increase and made office clusters. Meanwhile, the increasing triggered by the discovery of the Delta variant in May 2021 in Indonesia. On the other hand, the increase of community mobility to residential areas at the end of June was in line with the implementation of the emergency PPKM due to the increase in confirmed cases of COVID-19.

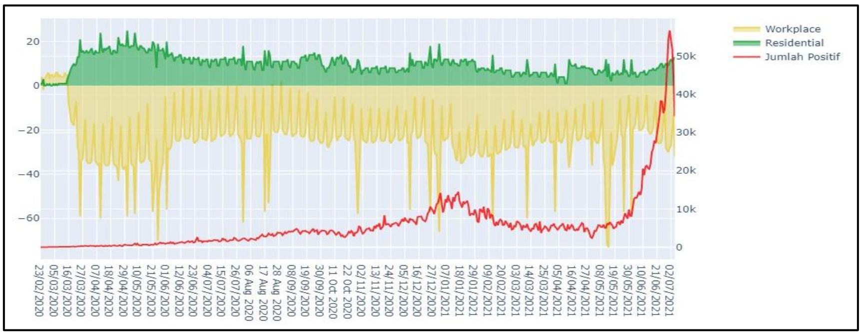

Figure 2. Comparison between workplace and residential mobility to Covid-19 Cases.

Based on Figure 3, the number of confirmed COVID-19 cases from February 2020 to July 2021 is directly proportional to the mobility of people to parks and public transportation centers. In December 2020, there are Christmas and New Year holidays, which makes mobility to parks and public transportation increase and make COVID-19 cases growing up. This phenomenon also occurred during Ramadan and Eid Fitri.

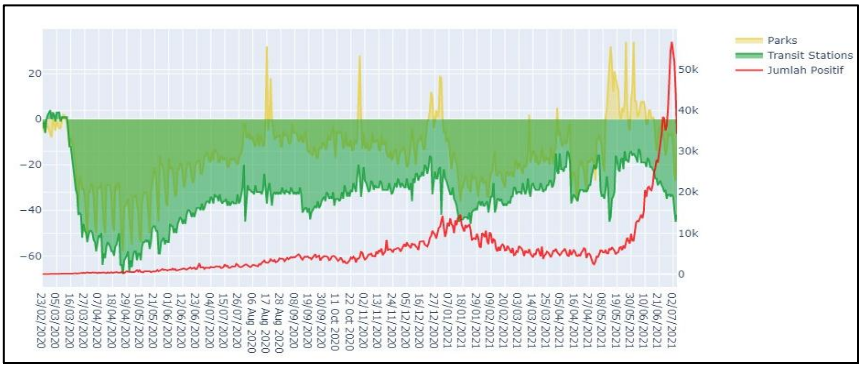

Figure 3. Comparison between parks and transit station mobility to Covid-19 Cases.

Figure 4 describes mobility to retail and recreational areas similar to restaurants and pharmacies with the number of COVID-19 cases. This is due to an increase in people's income (from the provision of holiday allowances and salaries), which pushes aggregate demand to move up. Moreover, the easing of community activities to stimulate the economy. This can be seen from June 2021, community activities to entertainment venues have begun to increase, increasing in COVID-19 cases in Indonesia.

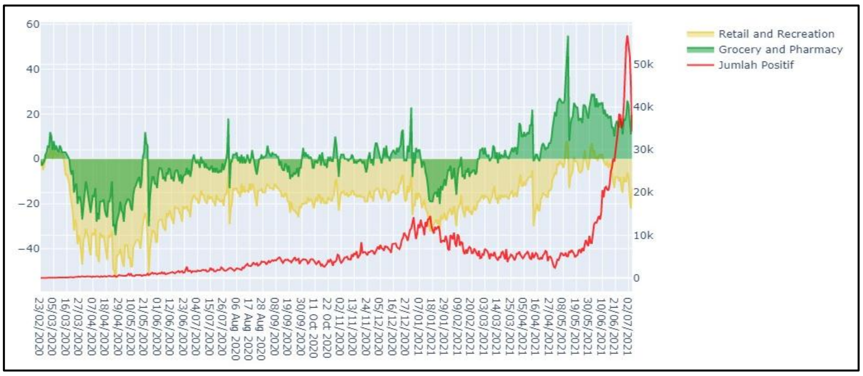

Figure 4. Comparison between retail & recreation and groceries & pharmacy mobility to Covid-19 cases.

3.2. Correlation Analysis

3.2.1. Relation between mobility to Covid-19 cases

Community mobility is one of the factors that affect the number of COVID-19 cases in Indonesia, this is because community mobility involves interactions between communities which indirectly have an impact on the spread of the Covid-19 virus. Reporting to kompas.com 99% of infected people show symptoms within 14 days, so in this study, the COVID-19 data was compared with community mobility data from the previous 14 days. This can be seen from the table of Pearson correlation results between mobility and daily cases of COVID-19.

Table 1. Correlation between mobility and Covid-19 cases

		Covid-19 Cases	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Covid-19 Cases	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	499						
Retail and recreation	Pearson Correlation	.273**	1					
	Sig. (2-tailed)	.000						
	N	499	499					

		Covid-19 Cases	Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential
Grocery and pharmacy	Pearson Correlation	.425**	.881**	1				
	Sig. (2-tailed)	.000	.000					
	N	499	499	499				
parks	Pearson Correlation	.221**	.838**	.743**	1			
	Sig. (2-tailed)	.000	.000	.000				
	N	499	499	499	499			
Transit stations	Pearson Correlation	.143**	.899**	.698**	.701**	1		
	Sig. (2-tailed)	.001	.000	.000	.000			
	N	499	499	499	499	499		
workplace	Pearson Correlation	-.032	.300**	.111*	.001	.490**	1	
	Sig. (2-tailed)	.481	.000	.013	.979	.000		
	N	499	499	499	499	499	499	
residential	Pearson Correlation	-.138**	-.727**	-.576**	-.453**	-.833**	-.579**	1
	Sig. (2-tailed)	.002	.000	.000	.000	.000	.000	
	N	499	499	499	499	499	499	499

Notes:
**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The table shows a relationship between the mobility variable and Covid-19 cases, indicated by a significance value <0.05 except for the mobility variable to work. The strongest correlation between mobility and Covid-19 case growth is grocery and pharmacy mobility, that is 0.425. That means if number of people coming to grocery and pharmacy increase, then the number of Covid-19 cases also increase.

3.2.2. Relation between mobility to Gross Domestic Regional Product (GDP) at Constant Price

The government's policy in handling Covid-19 in Indonesia avoided lockdown had quite an effect on the economy in Indonesia, where Indonesia had experienced a recession in the third quarter of 2020. In the next quarter, the Indonesian economy showed a slow increase. The relationship between changes in community mobility and the government's economy of 2020-2021 is in the following table.

Table 2. Correlation between mobility and GDP of Indonesia

		Retail and recreation	Grocery and pharmacy	Parks	Transit stations	Workplaces	Residential	GDP
Retail and recreation	Pearson Correlation	1						
	Sig. (2-tailed)							
	N	6						
Grocery and pharmacy	Pearson Correlation	.836	1					
	Sig. (2-tailed)	.038						
	N	6	6					
parks	Pearson Correlation	.935	.877	1				
	Sig. (2-tailed)	.006	.022					
	N	6	6	6				
Transit stations	Pearson Correlation	.921	.585	.769	1			
	Sig. (2-tailed)	.009	.223	.074				
	N	6	6	6	6			
workplace	Pearson Correlation	.623	.110	.435	.830	1		
	Sig. (2-tailed)	.186	.836	.389	.041			
	N	6	6	6	6	6		
residential	Pearson Correlation	-.884	-.613	-.703	-.954	-.686	1	
	Sig. (2-tailed)	.019	.196	.119	.003	.132		
	N	6	6	6	6	6	6	
GDP	Pearson Correlation	.910	.907	0.963	.705	.313	-.707	1
	Sig. (2-tailed)	.012	.013	.002	.118	.546	.116	
	N	6	6	6	6	6	6	6

The correlation shows the relationship between GDP and people's mobility to retail and recreation places, retail stores, food, and pharmacies also parks with a significance below 0.05 with a Pearson correlation close to one, which means it has a strong relationship.

3.2.3. Forecasting

Based on the figure and correlations between variables, a daily number of Covid-19 cases was forecast based on multivariable community mobility using the LSTM approach. The best model uses 4 LSTM layers with 128 units in each layer, activation function using Rectified Linear Unit (ReLU), dropout layer 0.01, dense layer, and a learning rate of 0.05. The following is the learning curve model obtained.

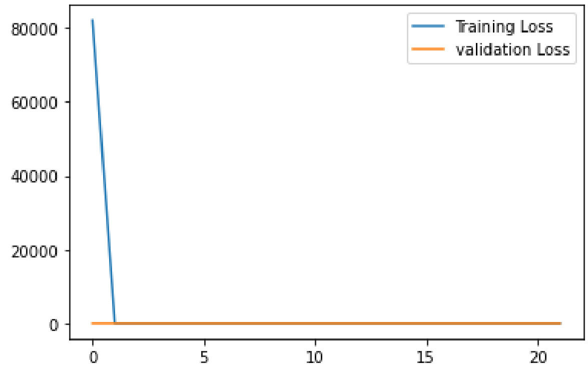

Figure 5. Learning Curve Model

The graph above shows that the model used is suitable for training datasets and predicting the y variable (number of Covid-19 cases). Comparison of actual and predictions data from this model is in the following graph.

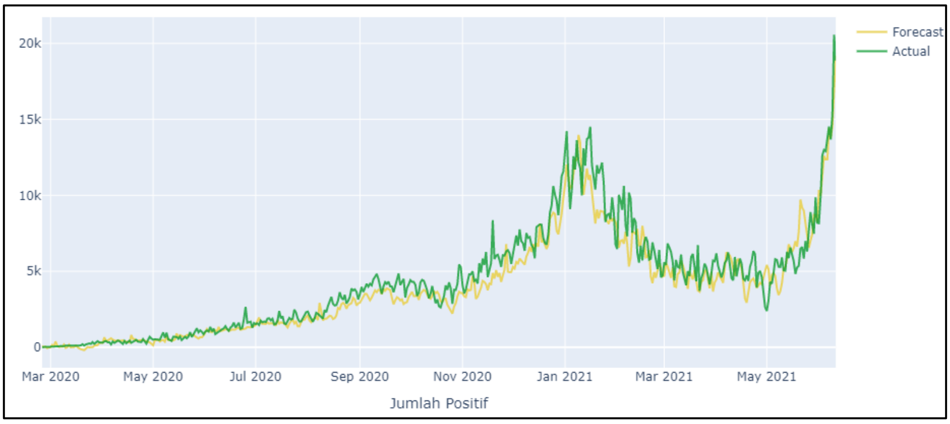

Figure 6. Comparison prediction and actual data of covid-19 cases

According Figure 7 below, from the condition of community mobility which has declined again due to PPKM policies and vigilance against delta variants, the number of daily COVID-19 cases will experience a significant decline in August and September then they return to fluctuating conditions.

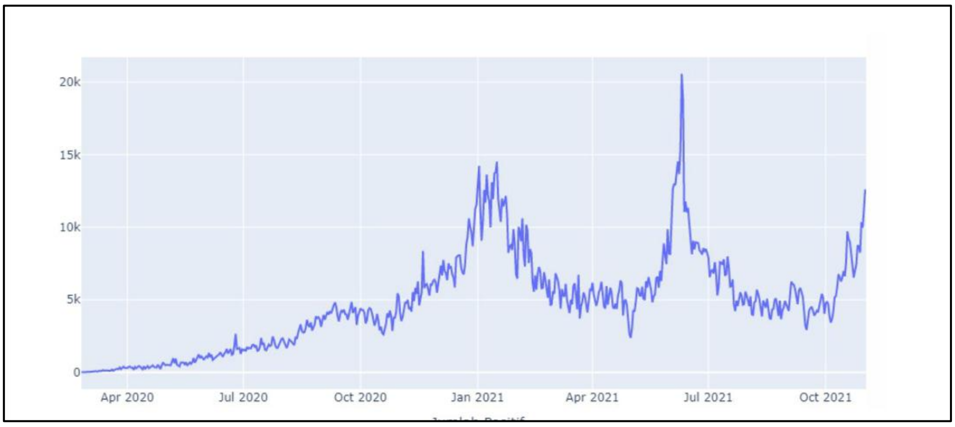

Figure 7. Prediction of covid-19 cases from current google mobility

4. Conclusion

The government's policy in terms of limiting people's mobility as a step to minimize the potential for the spread of COVID-19 in Indonesia is quite good because the daily number of COVID-19 is in line with community mobility from the previous 14 days. The correlation between community mobility and the daily increase in the number of COVID-19 also shows the significance of less than 0.05 except for the variable of community mobility to work. Meanwhile, the correlation between people's mobility and Indonesia's GDP has a strong correlation with people's mobility to retail and recreation areas, grocery stores, food and pharmacies, and parks.

The best LSTM model for predicting the number of daily Covid-19 cases based on community mobility consists of 4 LSTM layers with 128 units in each layer, function activation using Rectified Linear Unit (ReLU), dropout layer 0.01, dense layer, and using a learning rate of 0.05. The results of the prediction with the LSTM model obtained show that the number of daily Covid-19 cases will begin to decline along with the decline in community mobility, although there will still be cases of daily increase in cases because the graph shows volatile conditions.

It can be concluded from the graph of the prediction of the daily number of Covid-19, that the policy in reducing community mobility in to reduce the risk of the spread of Covid-19 is better prioritized in line with the delta variant which spreads faster than the previous variant. In recovering the economy, the government can provide capital injections in retail and recreation areas, grocery stores, food, and pharmacies, especially after the spread of Covid-19 can be controlled.

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