

Short-Term Solutions and Human Mobility Changes to Control the Widespread of COVID- 19 in Indonesia

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Abstract

Almost all countries in the world, including Indonesia, have been affected by the spread of COVID-19. As a response, several efforts and solutions have been implemented to avoid the negative impacts of this pandemic. In the context of Indonesia, for example, these include short-term solutions by limiting social contacts and human mobility with national or regional lockdowns. The solutions are surely not an easy way to be implemented in this archipelagic country that has many islands. The initial spread of COVID-19 back in March 2020 had stopped many economic activities in many Indonesian regions, especially in the urban areas. At the end of 2020, when the population mobility was started to be lifted, the spread of Covid-19 became increasingly out of control. Therefore, large-scale social restrictions have once again been implemented, especially in the most populated islands of Java and Bali. This paper aims to investigate the relationship between short-term solutions, human mobility and the spread of Covid-19 in Indonesia. The analyses use data on the trends of Covid-19 cases and human mobility that have been collected by the National Statistical Office (BPS) and the National Task Force (Satuan Tugas/Satgas) on handling Covid-19. The results found that there are strong relationships between human mobility and the increase of Covid-19 cases. Strong enforcement of public policy on how health protocol

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must be adhering in practices has given a remarkable impact on transmitted diseases on transportation.

Keywords: Covid-19, Short-term Solutions, Mobility Impacts, Behavior, Indonesia.

INTRODUCTION

Since the early March 2020, the spread of COVID-19 has reached Indonesia. One of the most challenging issues faced immediately by the government was the choices to prioritize public needs between saving community lives and saving their economic livelihoods. Some argue that prioritizing public health is a moral imperative and after that can be followed by the best economic policy in the long run (Lee et al., 2021). It is not surprising, therefore, several provinces in Indonesia have opted health measures as their first solutions by limiting social contacts and reducing mobility such as the closure of school, businesses and other places that can create crowds, despite the effects of high economic costs in the short term. Evidently, Indonesia experienced a deep economic contraction during 2020. In the second quarter of 2020, the economic growth was minus 5.32 percent, while in the third quarter the situation started to move to minus 3.49 percent (BPS, 2020).

At the end of 2020, having expectations that the spread of Covid-19 is going to have slowed down, the vaccines to combat Covid-19 is going to be available, and the economic growth needs to increase, the government started to lift the restrictions of population mobility and to reopen public places, such as tourist attractions for domestic tourists and shopping centers which coincidentally collides with the same time of long holiday seasons. One of the consequences, unfortunately, was the increase of Covid-19 cases across the regions especially in the most populated island: Java and Bali. Accordingly, the imposition of strict social restrictions was again carried out in early 2021.

In this paper, we argue that when human mobility increases, the spread of Covid-19 in Indonesia will also be in the same direction, bringing the risk of transmission from one region to another. We will certainly build this argument through several representative data sources, the aim of which is to provide suggestions to curb the transmission rate of Covid-19.

LITERATURE REVIEW

Before Covid-19 happens, the strongly two connected interconnected mobility and health are less researched. Prior to the pandemic, quite many sectors of work require flexible mobility. Be it be businessmen

who travel for business negotiations or academics working at their field work, people commute among their working centers to collaborate with others across borders. However, what is considered a pre-requisite of flexibility has now completely changed.

The abrupt change has particularly lead to impacts on network of transportation and mobility. Apart from the suspended activities of human mobility, there are other deeply inside impacts on logistics, technology of infrastructure, and happiness of which their models need to adjust.

One main reason of the mobility limitation or even suspension is to encourage the absence of Corona virus. This is particularly true when health becomes the first priority. However, the definition of health may not cover the human well-being yet. WHO (1946) has stated that "health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity". This argument is supported by the US centre for Disease Control and Prevention (2020) which describes that the issue of well-being intersects with the existence of positive emotions, the absence of negative emotions such as depression as well as over whether people feel satisfied with their life and positive functioning. This implies that the limitation of mobility may successfully avoid the spread of Corona virus, people may be virus free but not contented with their life.

All studies on the COVID-19 mostly agree in the profound impacts of this recent pandemic on our lives, especially in our socio-economic and mobility systems. In order to contain the rapid spread of the Covid-19, therefore, many countries have implemented some actions including the new habits of wearing masks, washing hands, social distancing, and lockdowns to limit human mobility. It is not surprising that the travels, both overseas and domestic, have been quickly restricted in many countries including in Indonesia. These human mobility restrictions, for sure, will cause some consequences especially in the most affected regions. The consequences may include economic downturns (due to suspended business and activities) and disruptions in transportations and connectivity (due to limited services and workers availability).

In terms of economy, negative externalities happen to communities when production and consumption impose external costs. Communities outside the market bear it when there is no appropriate compensation is paid. During the corona virus restrictions on mobility, it is undisputed that the global economy has been dented. China as the first few countries making total mobility restrictions has already closed down their Honda and Nissan Motor Factories following the shutdown of Robert Bosch GmbH affecting more than 800 people's livelihood in Wuhan (Dormindo, H, Leung A, 2020).

Another example can be derived from impacts of the international travel ban on tourism. Gossling et.al. (2020) has summarised that many tourism scholars have focused on implications of such restrictions and bans on tourism sustainability. Bali, Indonesia, as one of the primary world class tourist destination has proved that restrictions on international travel mobility have led to their depleting income of livelihood. A rapid assessment done by Kopernik (2020) has shown that 44% tourism workers in Bali have permanently or temporarily laid off, bringing 61% decrease in their income. All of those imply that even though human mobility is strictly restricted to bring a virus free situation, well-being problems may arise from anxiety and future uncertainties.

A recent cross-national study (Medimorec et al., 2020) uses the global mobility data from Google and Apple (i.e. data on their map services and location history, between Februarys to May 2020) describes how the early impacts of the pandemic on global urban mobility have emerged in different countries and income groups. The study particularly confirms that there is a strong decline in the use of public transport with the highest percentage change in the trips to public transport stations. Some reasons are explained, including the number of registered infections and deaths, dates and extent of curfews, lockdowns, and social distancing which affect human mobility in each region.

Some other studies focus more on the relationship between human mobility restriction and the infection rates of Covid-19. Using a global metapopulation disease transmission model, a study led by Chinazzi and colleagues (2020) predicts the impact of human travel limitations on the spread of the Covid-19 epidemic. It is found that the travel quarantine in Wuhan delayed the overall epidemic progression in mainland China by 3 to 5 days. Internationally, it had more effect in which case importations reduced by nearly 80% until mid-February. The sustained 90% travel restrictions to and from mainland China only modestly affect the epidemic trajectory.

The solution of lockdowns to reduce the spread of Covid-19 has been applied in many countries around the world. Tran et al (2020), for example, conduct a study in three different countries (Australia, Sweden and South Korea) with three different models of human mobility restrictions. The study finds out that three distinct patterns of societal reaction to mobility restrictions have different degrees of economic shutdown: near complete lockdown (Australia), relaxed lockdown with preserved workplace activity (Sweden), and minimal lockdown with preservation of both workplace and commercial activity (South Korea). Another study in Italy with the infection rates are among the fast is reported by Bonaccorsi and colleagues (2020). Using a quantitative modelling, the study estimates the main

consequences of human mobility restrictions on Italian economic and social systems during the pandemic. The impacts of mobility restriction is found higher in the richer regions with higher fiscal capacity; meanwhile the mobility restriction is weaker in the poor regions where inequality is higher and income per capita is lower. The pandemic is indeed inducing a reduction of fiscal revenues at national and local governments. At the same time, the most fragile families need to be supported due to the increase of poverty and inequality risks by the lockdown.

METHODOLOGY

3.1. Methodology of data collection and analysis

The abbreviation for United against Covid-19 (BLC), stands for the name of the dashboard. The United against COVID-19 Dashboard (BLC) is a dashboard that was built and used by the Task Force for Handling COVID-19 in the Behaviour Change Sector in monitoring the activities of Behavior Change Ambassadors in the field as well as monitoring the situation of changes in community behavior in real time. Based on reports from the Behaviour Change Ambassadors as well as officers working in the field, it is spread in all regencies and cities that have a number of reports of infected residents. BLC Dashboard is an application that volunteers use to monitor behaviour changes. The methodology applied is: snowball at the location where each volunteer is on duty. This sampling applied with limitations there are no specific frames related to how many locations should be. All data collection in the field, moves from volunteers without any special assignments/placements.

Name of Online Survey conducted: Dashboard reporting of the Covid-19 condition system, using partners who are paid (10%) and 90% voluntarily with, coordinating among others universities, community/NGOs, and police. Announced weekly and monthly events zoom online with artists. The report has good criteria with the following criteria: completeness of the report, photos and activities. Priority is given to District Boundaries as the first stage on the Dashboard. The people who served in each of the selected districts/cities were selected, then developed many partners massively to carry out campaigns. The number of partners in each district/city was selected in the range of 20 to 100 people.

The data analysis method applied is descriptive and statistical inference with ARIMA for economy analysis.

3.2. Data Source

Data Source

Facing the COVID-19 crisis, the Indonesian government through related parties has carried out a number of data collection innovations. Among them, online surveys and the development of a Covid-19 handling dashboard. The Covid-19 impact survey was conducted by the Central Statistics Agency (BPS) with two types of respondents, individuals and business actors. Surveys are carried out several times to see the impact of Covid-19 on a regular basis. Meanwhile, the development of the data dashboard by the task force (Satgas) for handling Covid-19 through the BLC application aims to accommodate case information and behavior changes through the implementation of health protocols. In addition, the availability of mobility data from Google Mobility is quite helpful in parsing the initial picture in this paper. For example, seeing the initial picture of abnormal changes in mobility and activity patterns that require attention, and also allows the exchange of data between different stakeholders in a timely manner (James et al., 2020).

Population Mobility

We use the relationship between population mobility and the positivity rate to see where the number of cases increases. Generally, population mobility, which improves connectivity between and within cities, is considered a key factor contributing to the spread of infectious diseases (Connolly et al., 2020). This is also confirmed in research on the relationship between patterns of mobility and the spread of the virus in various parts of the world. Thus, population mobility is one of the determinants of the spread of Covid-19.

Table 1. Correlation between Population Mobility by Positivity Rate of Infected covid-19

	Retail & recreation	Grocery & pharmacy	Parks	Transit stations	Workplaces	Residential	Mean
Confirmation Positif	0.269	0.443	0.411	0.123	-0.053	-0.192	0.252
<i>Positivity Rate</i>	0.310	0.220	0.203	0.351	0.185	-0.289	0.296

Source: Calculated from Google Mobility Report, 2nd March - 22 December 2020 and Monitoring Application of BLC Behaviour Changes

The results of the correlation analysis show that the mobility of the population for shopping and recreation needs; and transit areas of public transport have a positive and greatest correlation with the positivity rate of Covid-19. In this condition, the higher the mobility of the population in shopping and recreation areas as well as public transportation stations has the potential to increase the daily

positivity rate. Meanwhile, increased population mobility in housing can reduce the daily positivity rate. The positivity rate data is a comparison of the number of individuals confirmed with Covid-19 per number of individuals tested daily on the condition of October 21, 2020 to December 26, 2020. Data on the level of washing hands, using masks and maintaining distance are calculated and obtained from the Behavior Change Monitoring Application.

Unfortunately, domestic migration is a weaker predictor of transmission, as the correlation results show only 0.3 points. This is in line with the information conveyed (Lee et al., 2021), however, domestic migrants returning to their hometowns and villages are the focus of local fears and national policy debates. In fact, the flow of migration between cities and islands, which have natural boundaries as territorial isolation, is not taken into account in the strategy for the spread of the pandemic in Indonesia by policy makers in this regard. In this condition, the prediction of the number of cases is not measured accurately and the worst is that many residents do not undergo a massive test to identify the infection of every individual in the community, because it is expensive. So it becomes a question and a problem if many people are asymptomatic but infected with Covid-19 and are free to do activities in public spaces as a source of spreading Covid-19 between humans.

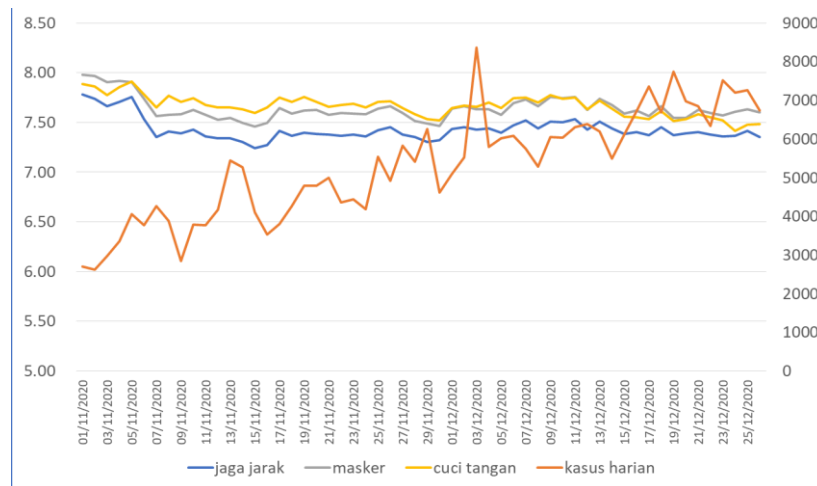
RESULTS AND DISCUSSION

Results

1 Health Protocol

In daily practices, in fact, there has been a decrease in the implementation of health protocols while the daily cases of Covid-19 are increasing. In general, the trend of compliance behavior of the people in Indonesia to the 3M protocol (which stands for wearing masks, washing hands and keeping distance) shows a decline. Consequently, during the same period, there was an increasing trend in the number of daily Covid-19 cases.

Figure 1. Obedience Trend of 3M Behaviour and Daily Total Prevalence



Source: Calculated from Monitoring Application of BLC Behaviour Changes

COVID-19 has shown on how fast an infectious disease can spread, and how vulnerable each community is (Connolly et al., 2020). Observing the decreased trend in the implementation of health protocols, it can be assumed that the level of confidence that arises in the community about the effectiveness of vaccines is increasing. However, this is still a presumption that needs to be studied further. Because referring to existing data, the decline in the implementation of health protocols is in line with the increase in Covid-19 cases recently.

2 Econometrics Analysis

ARIMA

ARIMA is a method that generates forecasts based on the synthesis of historical data patterns. This ARIMA completely ignores the independent variable because this model uses the present value and past values of the dependent variable to produce accurate short-term forecasting. For long-term forecasting, the accuracy of the forecast will usually tend to be flat (horizontal / constant) for a fairly long period.

In making forecasts, this model completely ignores the independent variables because this model uses the present and past values of the dependent variable to produce accurate short-term forecasting. The Box-Jenkins method can only be applied, explained, or represented a stationary series or has been made stationary through a differencing process. Because the stationary series does not have a trend element, what this method wants to explain is the remaining element, namely error.

In general, ARIMA $(p, d, q)(P, D, Q)^S$ model for x_t time series is (Hamilton, 1994); :

$$\Phi_p B^S \phi_p(B)(1 - B)^d(1 - B^S)^D x_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t$$

with:

B : lag operator.

p, q : Nonseasonal autoregressive order and nonseasonal moving average order.

P, Q : Seasonal autoregressive order and seasonal moving average order.

d : nonseasonal differencing order.

D : seasonal differencing order.

S : seasonal period, for monthly data ($S = 12$), quarter data ($S = 4$), daily data.

$\phi_p(B)$: nonseasonal autoregressive component.

$\Phi_p B^S$: seasonal autoregressive component.

$\theta_q(B)$: nonseasonal moving average component.

$\Theta_Q(B^S)$: seasonal moving average component.

$(1 - B)^d$: nonseasonal differencing.

$(1 - B^S)^D$: seasonal differencing.

ε_t : Error term.

ARIMA model parameter estimation could be done by using maximum likelihood method. The best ARIMA model is determined by choosing a model with the lowest AIC. AIC is calculated with the following formula:

$$AIC = -2 \times \log \text{maximum likelihood} + 2 \times \text{the number of parameter in a model}$$

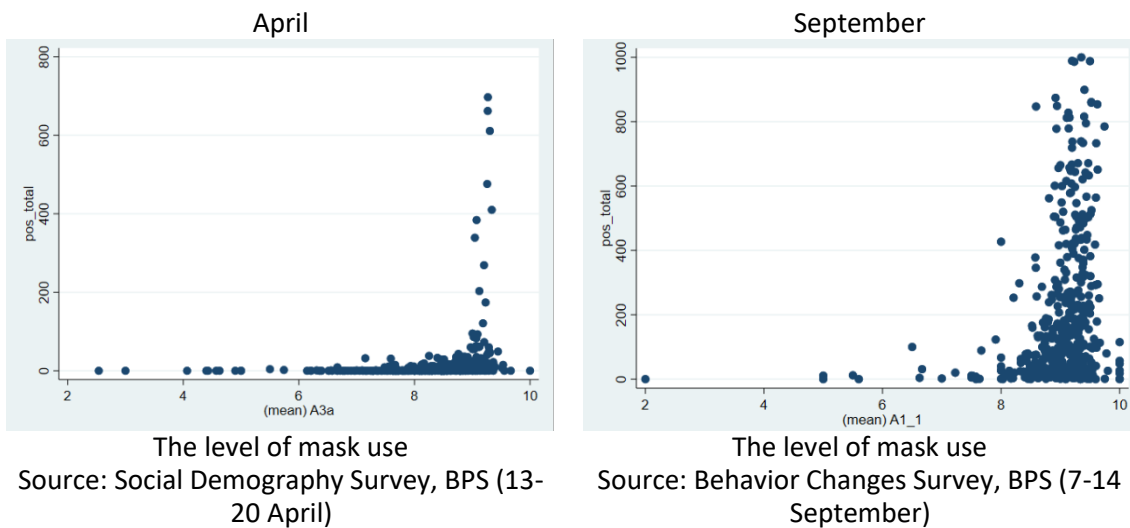
In the research ARIMA model used to not accommodative to the seasonal component.

The econometric model of which we use is the auto regressive moving average (ARMA) model. In this paper, the results of the study are faced with the limited data available, so they do not refer to a specific framework. However, econometric analysis needs to test the stationarity of the data first. So that, what we produce in this paper is considered stationary and free from spikes. The results of the stationarity test are attached in this paper.

Of the many ARMA tests, we took the best four testing out of the many steps we produced. First, the relationship between using masks in the previous period and the positivity rate of Covid-19. Second, the relationship between hand washing and the positivity rate of Covid-19. Third, maintaining a distance between one and two previous periods reduces the positivity rate of Covid-19. Fourth, the relationship of mobility in the market and the workplace to the positive rate of Covid-19.

First, wearing masks at one period earlier reduces the positivity rate of Covid-19. Table 2 point (a) shows that using a mask at one period earlier reduced the positivity rate of Covid-19 with a significance value of 0.0031, below 5 percent. The use of masks is part of a comprehensive package of preventive and control measures that can limit the spread of certain respiratory viral diseases, including COVID-19 (WHO, 2020). Masks can be used to protect a healthy person (worn to protect oneself in contact with an infected individual) or for source control (worn by an infected individual to prevent further transmission) and both. However, the use of hoods alone is not sufficient enough to provide an adequate level of protection for an uninfected individual or prevent transmission. Other measures are needed for prevention and control to prevent human-to-human transmission of SARS (WHO, 2020).

Figure 2. The Relationship between the Level of Mask Use and Positive Cases of Covid-19 in April and September 2020



The level of mask use
Source: Social Demography Survey, BPS (13-20 April)

The level of mask use
Source: Behavior Changes Survey, BPS (7-14 September)

A trend was identified that the greater the number of positive cases of Covid-19, the greater the level of mask use and in vice versa. The use of masks is closely related to the positive incidence of Covid-19. In the early days of the pandemic, wearing masks was not really related to the number of Covid-19 case. Meanwhile, in September 2020 the two of them were strong related.

Table 2. Relationship of Using Masks, Washing Hands and to the Positivity Rate of Covid-19

Using a Mask for the Previous Period Lowers the Positivity Rate of Covid-19					Washing Hands Reduces the Positivity Rate of Covid-19				
Dependent Variable: PR Method: Least Squares Date: 12/27/20 Time: 16:16 Sample (adjusted): 10/23/2020 12/26/2020 Included observations: 65 after adjustments Convergence achieved after 20 iterations MA Backcast: 10/22/2020					Dependent Variable: PR Method: Least Squares Date: 12/27/20 Time: 16:38 Sample (adjusted): 10/22/2020 12/26/2020 Included observations: 66 after adjustments Failure to improve SSR after 23 iterations MA Backcast: 10/20/2020 10/21/2020				
Variable	Coefficient	Std. Error	t-Statistic	Prob.	Variable	Coefficient	Std. Error	t-Statistic	Prob.
MASKER	0.023323	0.007584	3.075479	0.0031	CTANGAN	-0.030776	0.017693	-1.739409	0.0869
AR(1)	0.973908	0.053999	18.03552	0.0000	AR(1)	1.003866	0.001421	706.2111	0.0000
MA(1)	-0.750004	0.123919	-6.052391	0.0000	MA(1)	-0.714340	0.121567	-5.876123	0.0000
					MA(2)	-0.285448	0.121505	-2.349275	0.0220
R-squared	0.385977	Mean dependent var	0.159700		R-squared	0.509832	Mean dependent var	0.159289	
Adjusted R-squared	0.366170	S.D. dependent var	0.039294		Adjusted R-squared	0.486115	S.D. dependent var	0.039133	
S.E. of regression	0.031283	Akaike info criterion	-4.046401		S.E. of regression	0.028053	Akaike info criterion	-4.250756	
Sum squared resid	0.060676	Schwarz criterion	-3.946045		Sum squared resid	0.048792	Schwarz criterion	-4.118050	
Log likelihood	134.5080	Hannan-Quinn criter.	-4.006804		Log likelihood	144.2750	Hannan-Quinn criter.	-4.198318	
Durbin-Watson stat	1.581087				Durbin-Watson stat	2.030759			
Inverted AR Roots	.97				Inverted AR Roots	1.00			
Inverted MA Roots	.75				Estimated AR process is nonstationary				
					Inverted MA Roots	1.00	-.29		
(a)					(b)				
ARMA (1,1)					ARMA (1,2)				

Firstly, Hand Washing Reduces the Positivity Rate of Covid-19. Table 2 point (b) shows that Hand Washing Reduces the Positivity Rate of Covid-19 at a 10 percent significance level, which is a probability value of 0.0869 point. The Covid-19 pandemic has increased to hand hygiene and awareness of hand hygiene, even the Center for Disease Control (CDC) has advocated washing hands frequently with soap and water (Rundle et al., 2020). Because of health workers and the community in public generally focus on strict hand hygiene.

Secondly, maintaining a distance between one and two previous periods reduces the positivity rate of Covid-19. Table 3 point (a) shows a significance value of 0.0499 point which is below 5 percent. In contrast to the research of Olivera-La Rosa et al. (2020) who provide the fact that social anxiety and social trust do not predict social distancing (in opposite directions). One possibility is that the social distancing scale is a more indirect measure than the one used to assess confidence and disease predictions. In this condition, of course, additional research is needed with the desired alternative measure of social distance.

Thirdly, mobility in the market and the workplace increases the positive rate of covid-19. Table 3 point (b) shows the significance value for mobility in the market of 0.0632 point below 10 percent, and 0.0011 point in the workplace. The data shows that systematically predicting the pattern of confirmed COVID-19 cases by the end of 2020 can be described by population mobility. This is in line with the findings of the study by Lee et al., (2021). Furthermore, Number of Passenger

of Railways Transportation is compiled data by BPS Statistics Indonesia which is obtained from the source: Head Office of State Owned Railways Company and Jabodetabek Commuter Area, PT Kereta Api Indonesia dan PT. KAI Commuter Jabodetabek has decreased significantly about 34.134 million (2020) and 35.122 million (2019) passenger. Whilst for the number of Passenger Flight at Main Airports is also compiled data by BPS Statistics Indonesia which is obtained from the source : PT (Persero) Angkasa Pura I and II on the contrary increased from 3.204 million (2020) and 3.139 million passenger at Domestic airport, and for international airport also increased by more or less 100,000 passengers.

Table 3. The Relationship of Maintaining Distance, Mobility in the Market and Workplace, to the Positivity Rate of Covid-19

Maintaining a Distance of One and Two Previous Periods Reducing the Positivity Rate of Covid-19	Mobility in the Market and Workplace increases the Positive Rate of Covid-19																																																																	
Dependent Variable: PR Method: Least Squares Date: 12/27/20 Time: 16:12 Sample (adjusted): 10/22/2020 12/26/2020 Included observations: 66 after adjustments Convergence achieved after 17 iterations MA Backcast: 10/20/2020 10/21/2020	Dependent Variable: PR Method: Least Squares Date: 12/27/20 Time: 19:13 Sample (adjusted): 10/24/2020 12/23/2020 Included observations: 61 after adjustments Convergence achieved after 126 iterations MA Backcast: 10/22/2020 10/23/2020																																																																	
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Discussion

The main results use data on mobility patterns and health protocols to predict the pattern of COVID-19 cases occurring at the end of 2020. The potential concern is that there is a correlation between increased mobility, decreased health protocols, and increased cases of COVID-19. Mechanical bias can occur through at least three sources.

While national and local Government policy were being implemented to public transport in some cities seems difficult to follow the rule particularly in a populated region/ cities such as: Jakarta, Surabaya and Bandung. Those three biggest megapolitan cities are very population

with a great massive transportation as public transport facilities. However, the strict regulation on how to keep a limited social distancing are not easy as the design formulation though for practices. The low level awareness and unknowledge community on how to obey the health protocol in public transport is on the contrary with the public transport SOP and daily operation. Even all regulation and policy been developed to be helpful while adhering to our stringent privacy protocols and protecting people's community health from transmitted diseases. Regarding the trend of passenger to all type of transportation since 2019 – 2020 monthly, shows that in April 2020 had plunged dramatically after been applied the social distancing and clean of covid-19 test for passenger. The number of passenger getting increase during holiday season and end of the year.

Firstly, especially at the start of a pandemic, governments are selective in determining who can be tested. People without symptoms don't generally get tested, nor do people with symptoms get tested. Conversely, at least since the time of PSBB, people with symptoms are more likely to self-test if they are traveling between regions, or are in close contact with someone who is positive for Covid-19. These screening criteria could mechanically create a strong correlation between mobility and an increase in confirmed COVID-19 cases. Secondly, testing centers may be more likely to be located in mobility destinations with a higher population, such as Jakarta. This could once again drive the mechanical correlation between mobility and the incidence of COVID-19. Thirdly, a correlation can be created by the entry of immigrants from outside the region during the holidays, as well as the opening of tourist and shopping places at the end of 2020. The problem is that the implementation of health protocols is deemed to have decreased, so that increased mobility tends to increase the number of Covid-19 cases.

CONCLUSIONS

This research proves that there is a relationship between increased mobility and decreased health protocols leading to increased cases of COVID-19. Mechanical bias can occur on, at the start of a pandemic due to the unclear of standard operating procedure and knowledge of society on who and what should do tested on Covid-19. The mechanical correlation between mobility and the incidence of COVID-19. Lastly, the increased mobility and release border among in-out migrants tends to increase the number of Covid-19 cases. For those findings, it high demand to ceate a new short solution and policy strategy on handling this Covid-19 spread.

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