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MULTIDIMENSIONAL POVERTY AND THE RISK OF COVID-19 IN INDONESIA

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Multidimensional Poverty and the Risk of COVID-19 in Indonesia

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Abstract

The COVID-19 disaster has revealed the extent of Indonesia's capacity to deal with a pandemic. This study analyzes, at a greater depth, the situation of those deprived members of the population who live with multidimensional poverty and the risk of COVID-19 infection. The indicators for the deprivation of drinking water, cooking fuel and toddler nutrition contained in the Indonesian Multidimensional Poverty Index indicator are fatal risk factors affected by COVID-19. This study contributes to strategic policy recommendations, both in its focus and locus, to improve community resilience in facing the current and future pandemic. It is estimated that 176.04 million out of 264 million people or 66.62 percent of the Indonesian population are at risk of being infected with COVID-19. Of the 176 million people in the at-risk groups, at least 21.43 million people or 8.11 percent fall into the category of the multidimensionally poor. We estimate the multidimensional poor population in Indonesia to be 21.58 million people. This shows that most of the multidimensional poor population in Indonesia is vulnerable to COVID-19 infection. On the other hand, there are about 1.27 million multidimensionally poor individuals who are at high risk of being infected with COVID-19. Regionally, the number of people who are more vulnerable to COVID-19 infection tends to be concentrated in Java. Based on geographic characteristics, as many as 93.34 million people or 66.78 percent who live in urban areas are at risk. We also find a strong positive correlation between the number of people at risk and the number of multidimensional poor people in each province in Indonesia. We also conduct simulations using the susceptible, exposed, infectious, and recovered (SEIR) model to estimate the number of people affected in each risk group, based on whether there are social restriction policies or not. We use several simulation scenarios to estimate the impact of the COVID-19 pandemic in a more diverse approach. Our finding shows that effective social restriction policies can significantly reduce the number of people affected by COVID-19. In simulations of the multidimensional poor and at-risk group, if there is no social restriction policy, the number of people in the group who can be infected with COVID-19 reaches1.13 million people, within six months. However, if there is a social restriction policy, the number of people infected in this group can be reduced to 27,348 using a not very effective policy and can be suppressed to reach 830 people with a very effective policy.

Keywords: multidimensional poverty, SEIR simulation, COVID-19.

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Perkumpulan PRAKARSA is an Indonesian think tank that carries out the task of developing and improving policies and ideas in building welfare through independent research and knowledge development. We combine research with policy analysis, communication, and advocacy, transferring knowledge to become actions that promote the creation of justice and public welfare.

1. INTRODUCTION

Measurements of poverty still generally rely on the income or monetary approach. However, those approaches are considered inadequate to dissect poverty thoroughly because poverty is an issue that is more complex and not simply about a lack of money. When measuring poverty, it is necessary that we capture human basic needs such as health, education, and decent living standards. Poverty is seen rather as a multidimensional phenomenon, which cannot be translated as a one-single-cause problem. Measurements using a multidimensional approach are thus required for the optimal development of poverty reduction strategies.

The United Nations defines poverty as not only being based on a lack of income and productive resources to ensure sustainable livelihoods; it is also defined by hunger, malnutrition, limited access to education and other basic services, discrimination and exclusion, as well as the lack of participation in decision-making.[1] This concept of poverty comes from the definition in the Sustainable Development Goals (SDGs) 1, which is aimed at ending any form of poverty, anywhere. This definition follows the notion of poverty based on the capability approach developed by Sen (1999), where poverty is conceptualized as the absence of the capability to realize human potential as a whole.

Based on Sen's capability approach (1999), the Oxford Poverty and Human Initiative (OPHI) in 2010 – and later the United Nations Development Program (UNDP) – developed a poverty measurement approach that looks at a number of indicators, called the Multidimensional Poverty Index (MPI), or *Indeks Kemiskinan Multidimensi* (IKM). Since being developed by the OPHI, the MPI has become a worldwide reference to complement income-based poverty measurements. In the MPI, poverty cases are dismantled through their various aspects to see differences in the characteristics of poverty and the causes of poverty.

Multidimensional poverty includes various deprivations experienced by poor people in their daily lives such as poor health, a lack of education, inadequate living standards, helplessness, poor quality work, threats of violence, and living in dangerous environments. Multidimensional poverty measurements can include a set of indicators that capture the complexity of the phenomena to inform policies aimed at reducing poverty and deprivation in a country. Depending on a country's context and measurement objectives, indicators can be selected to reflect the needs and priorities of the country, provinces, regions, districts/cities and their constituents. With the multidimensional poverty approach, poverty reduction strategies can be better targeted at the poverty problems faced by the poor.

The 2020 COVID-19 pandemic has had a devastating impact on society, in health, social, and economic terms; the latter has especially sparked an increase in the number of poor people. Since it first appeared in China at the end of 2019 to May 2020, COVID-19 has infected up to 4.4 million people worldwide.[2] Some studies suggest that this pandemic has the potential to increase poverty rates (Suryahadi *et al.*, 2020; and Sumner, *et al.*, 2020). The study by Sumner et.al. (2020) estimated the increase in global poverty by applying three scenarios of contractions in per capita household expenditure or income, which are: 5 percent, 10 percent and 20 percent. The estimation results show that in the scenario of extreme per capita household expenditure or income (a contraction of 20 percent), the global poverty rate rises to between 420 and 580 million people. Meanwhile, the calculation by Suryahadi *et al.* (2020)

[1] See https://www.un.org/en/sections/issues-depth/poverty/.
[2] See https://coronavirus.jhu.edu/map.html.

using a monetary approach showed that in severe conditions, the COVID-19 pandemic in Indonesia could increase poverty to 12.4 percent or 8.5 million people by September 2020.

In contrast to Suryahadi *et al.* (2020) and Sumner, *et al.* (2020) who specifically estimated the potential for an increase in poverty due to the COVID-19 pandemic, Alkire *et al.* (2020) discuss the link between COVID-19 and the multidimensionally poor populations. Alkire *et al.* (2020) believe that the deprivations faced by multidimensional poor populations in developing countries can result in their increased vulnerability to COVID-19 infection. Using the data from the Global MPI in 2019, the study finds that 1.3 billion people are experiencing overlapping deprivations in three or more indicators. Deprivations in drinking water, nutrition, and cooking fuel indicators are estimated to increase the risk of individuals being infected with COVID-19. This relates to the condition that being deprived in these three indicators weakens the immune system and respiratory conditions.

As the 2020 COVID-19 pandemic is unlikely to come to an end in the near future, since there is a time lag between the development and distribution of a vaccine for it, there is a growing concern among the general public as to who is most at risk of being infected with COVID-19. In this situation, people who have the potential to be infected with COVID-19 cannot be homogenized because each individual has different health and living conditions. Therefore, unlike the monetary poverty approach, the multidimensional poverty approach is useful to identify them and could be provide complementary information beside the clinical-based approach that is predominantly being used by policymakers in response to the pandemic. For this reason, following Alkire *et al.* (2020), this study estimates the number of citizens who fall into at-risk groups, especially those who are categorized as multidimensionally poor, and attempts to calculate how many of these people would be infected with COVID-19 in relation to their deprivations in the indicators of drinking water, nutrition, and cooking fuel. This study will map the number of people in these at-risk groups who are infected with COVID-19 at the national, provincial, city as well as the village level. On the other side, referring to Atkeson (2020), this study will present simulations of various COVID-19 pandemic scenarios in relation to the increase in the number of people infected with COVID-19 in the at-risk groups in Indonesia.

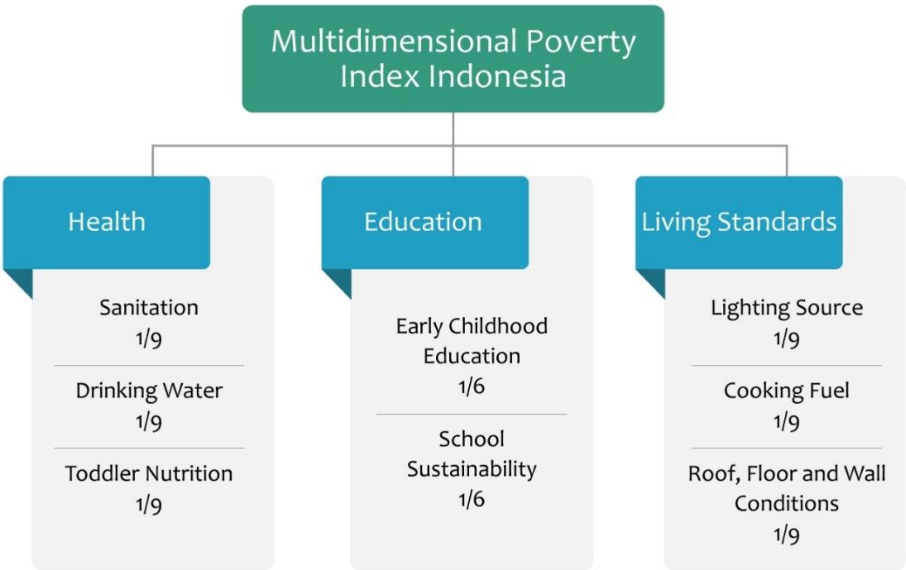
This study aims to inform its readers regarding the aspects of poverty in Indonesia, in relation to the public health crisis. This study is expected to be a subject for discussion by the public, academics, and policymakers to formulate effective mitigation policies in response to the COVID-19 pandemic. In particular, the study attempts to address the conditions of the multidimensionally poor population in the hope that they would not be placed in a more vulnerable position in their efforts to withstand the pandemic.

2. METHODOLOGY AND DATA

2.1 The Calculations of Multidimensional Poverty and Risk Groups Potentially Infected with COVID-19

The multidimensional poverty calculations in this study are derived from the Indonesian Multidimensional Poverty Index (MPI) developed by the PRAKARSA (2020), which is based on the Alikre-Foster's method (2007, 2011). The Indonesian MPI calculates the deprivations simultaneously experienced by an individual, in various indicators in three dimensions, namely the dimensions of health, education, and living standards. The calculations begin at the household level and are then detailed at the individual level, allowing for an understanding of the kinds of poverty experienced by the individual. Graph 1 shows the Indonesian MPI indicators in each dimension, where the health dimension is composed of three indicators, the education dimension of two indicators, and the living standards dimension of three indicators. The index gives the same weight to each dimension and indicator in its calculation.

Graph 1. The Dimensions and Indicators of the Indonesian Multidimensional Poverty Index



Source: PRAKARSA (2020)

Each individual will be identified as to whether or not they fall into the multidimensionally poor category, based on the number of deprivations they experience, as reflected in the deprivation score. The range of the deprivation score is 0 to 1. An individual is said to be multidimensionally poor if they have a deprivation score greater than the poverty cutoff (poverty line limit), which, based on PRAKARSA (2020), is 0.333, or when the individual is deprived in at least three of the eight indicators. The justifications for the deprivations in each indicator are described in Appendix 1 and the example of the deprivation calculation is in Appendix 2.

Alkire *et al.* (2020) state that the concept of the MPI, which calculates poverty based on deprivations simultaneously experienced by an individual, can be used to measure the level of individual risk/vulnerability to COVID-19 infection. According to the study, deprivation indicators related to drinking water, nutrition, and cooking fuel are representative measures of the individual risk level for COVID-19 infection.

Unhygienic drinking water increases the risk of disease because it weakens the immune system (WHO, 2019; Gao *et al.*, 2019; Pal *et al.*, 2011). Similarly, malnutrition is closely related to a weakened immune system, which triggers conditions that make people vulnerable to illness and even death, especially in the toddler age group (WHO, 2020; Macari *et al.*, 2005; Dowd *et al.*, 1984). Cooking with unclean fuels, such as firewood and charcoal, creates air pollution and causes respiratory disease (Gordon *et al.*, 2014; Ezzati *et al.*, 2001; Smith *et al.*, 2011). Meanwhile, several recent studies such as those of Geier *et al.* (2020), Giamarellos-Bourboulis *et al.* (2020) and Guan *et al.*(2020) show that COVID-19 is the type of disease that attacks the respiratory system. Thus, those individuals who are deprived in these indicators are more at risk of being infected with COVID-19 compared to those who are not.

This study follows Alkire *et al.* (2020) to map population groups that are more vulnerable to COVID-19 infection. However, since PRAKARSA (2020) does not measure a general nutrition indicator in the Indonesian MPI, this study changes the indicator for nutrition with toddler nutrition. Malnutrition affects young children more significantly (Victora *et al.*, 2008), so the nutritional intake of children is more crucial to identify people who have the potential to be infected with COVID-19. This study classifies people who are at risk of COVID-19 infection into three groups, namely:

1. **At-Risk**
   An individual is included in the at-risk group if he/she is deprived in one of the indicators related to COVID-19 (drinking water, toddler nutrition, and cooking fuel).
2. **Multidimensionally Poor At-Risk**
   An individual is included in the multidimensionally poor and at-risk group if he/she is deprived in at least three of the eight multidimensional poverty indicators, one of which is an indicator related to COVID-19. People who fall into this group are also part of the at-risk group.
3. **Multidimensionally Poor At High Risk**
   An individual is included in the multidimensionally poor and at highrisk group if he/she is deprived in at least three of the eight multidimensional poverty indicators where there are three indicators related to COVID-19 simultaneously. People who fall into this group are also part of the multidimensionally poor at-risk group and the at-risk group.

The calculations of multidimensional poverty and risk population groups in the study use the data from the National Socio-Economic Survey (Susenas) issued by the Central Statistics Agency (BPS). The study leverages the 2018 data, which had a sample of 297,276 households consisting of a total of 1,131,825 individuals. The use of the 2018 data has implications for the possibility of a slight overestimation in describing the conditions of multidimensional poverty and at-risk groups in 2020. This is because in 2019 BPS announced that Indonesia's poverty rate (measured in monetary/income terms) had decreased, compared to 2018. On the other hand, PRAKARSA’s studies (2020, 2015) show that the changing trends in monetary poverty and multidimensional poverty in Indonesia go hand in hand.

2.2 Simulations of Possible Infections of COVID-19 in the Risk Groups

Simulations are designed based on the estimation results of the multidimensional poverty and risk groups calculations. This study uses the susceptible, exposed, infectious, and recovered (SEIR) simulation model developed by Atkeson (2020), which divides the population into four large groups at each time. The assumptions used in the simulations are that the level of unreported cases is very small and the disease testing has been carried out in very large numbers. The population is normalized into one, so the model produces a ratio of the population groups to the population. This also causes the four population groups to be summed into one at that moment. The population groups consist of susceptibles (without immunity) *S*, exposed *E*, infected *I*, and recovered (or dead) *R*. The developmentof the four population groups can be written as follows:

$$\frac{dS}{dt} = -\beta_t \frac{S}{N} I \quad (1)$$

$$\frac{dE}{dt} = \beta_t \frac{S}{N} I - \sigma E \quad (2)$$

$$\frac{dI}{dt} = \sigma E - \gamma I \quad (3)$$

$$\frac{dR}{dt} = \gamma I \quad (4)$$

$$\beta_t = R_t \gamma \quad (5)$$

The parameter γ shows the length of time taken (per day) for an infected individual to recover or die. In this study, it is assumed that γ = 1/17, which is derived from the estimated duration of COVID-19 disease for 17 days. The parameter σ shows the length of time taken (per day) for people exposed to the disease to become sick, assumed to be σ = 1 / 5.5. This value indicates the estimated incubation period of COVID-19 for 5.5 days.

The parameter β_t indicates the rate at which an infected individual can transmit the disease to others. The ratio S/N is the group of people who are vulnerable to the people who have been exposed to the disease, hence, they can be said to be in transition to the group of people who have first been exposed to the disease. The parameter R_t is the combined ratio of the β_t rate and the recovery rate + death γ at time t. This parameter can show the ratio of the rate of people who are susceptible to infection and the people who are infected but expected to recover or die for a certain amount of time. This parameter can be controlled or changed if there is a quarantine or social restriction policy.

Following the measures taken by Atkeson (2020), this study attempts to show the impact of implementing a quarantine or social restriction policy. In addition to the estimation carried out by Atkeson (2020), this study tries to simulate the impact on at-risk groups that are vulnerable to the effect of COVID-19 by assuming a constant proportion.

The impact of a quarantine or social restrictionpolicy is measured by breaking down the parameter R_t.

$$R_{1t} = R_{1,0} \exp(-\eta_1 t) + (1 - \exp(-\eta_1 t))\overline{R_1} \quad (6)$$

$$R_{2t} = R_{2,0} \exp(-\eta_2 t) + (1 - \exp(-\eta_2 t))\overline{R_2} \quad (7)$$

$$R_t = \frac{R_{1t} + R_{2t}}{2} \quad (8)$$

$R_0 = (R_{1,0} + R_{2,0})/2$ is the initial value of R_t, which shows the initial distribution value of the disease. The parameter $\overline{R_\iota}$ for $i = 1.2$ shows the long-term value when R_{it} cones to a value. The long-term value of R_t cones to $(\overline{R_1} + \overline{R_2})/2.$ R_{1t} and has a declining function, and R_{2t} has an ascending function to get a U-shaped pattern of R_t. The parameter η_i indicates that the rate of R_{1t} decreases to $\overline{R_1}$. The parameter η_2 shows that the rate of R_{2t} increases to $\overline{R_2.}$

The description of the parameter R_t in equations (6) through (8) forms three differential equations as follows:

$$\frac{dR_{1t}}{dt} = -\eta_1(R_{1t} - \overline{R_1}) \tag{9}$$

$$\frac{dR_{2t}}{dt} = -\eta_2(R_{2t} - \overline{R_2}) \tag{10}$$

$$\frac{dR_t}{dt} = -\frac{1}{2}\eta_1(R_{1t} - \overline{R_1}) - \frac{1}{2}\eta_2(R_{2t} - \overline{R_2}) \tag{11}$$

The initial condition used is $R_{i,0}$.

The first step in estimating is to determine the initial values of a few parameters. The initial value of parameter I is 1/67 million, which shows the initial cases of four of Indonesia's total population of 268 million by 2020. The initial value of $E = 51I$, which indicates that 204 people are suspected of being carriers of the virus but have not yet transmitted it. This value comes from the data collected from the Ministry of Health in March 2020.

3. ANALYSIS

3.1 Multidimensional Poverty and Risk Groups Calculations

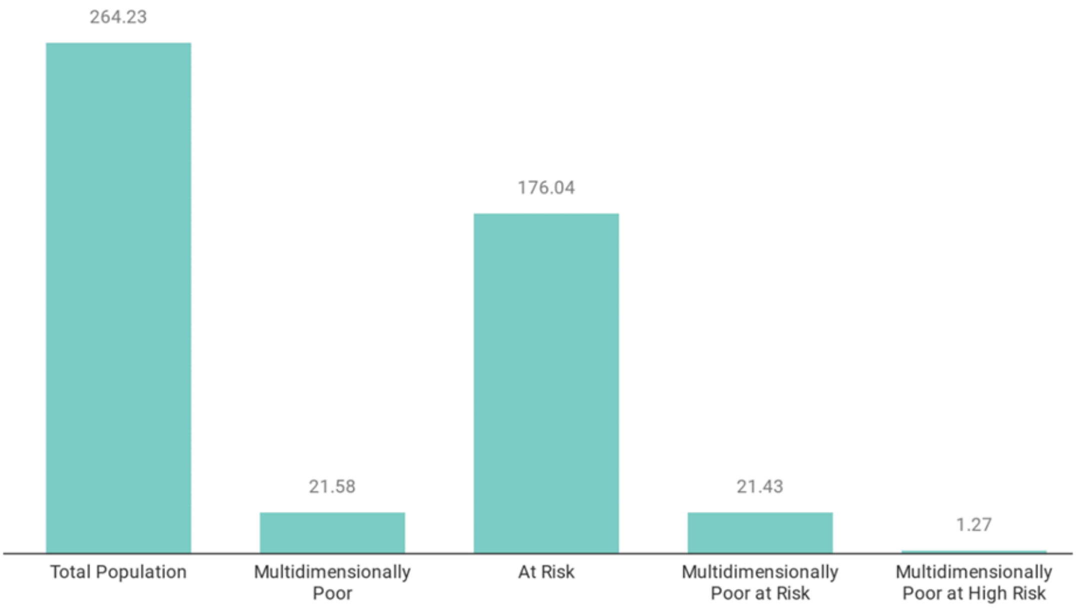
Graph 2 shows that of the 264.23 million Indonesians spread across 34 provinces, an estimated 21.58 million people lived in a multidimensionally poor condition in 2018. As a percentage, this equals 8.17 percent of the total population. The multidimensionally poor are deprived in at least one-third of the indicators in the dimensions of health, education, and standard of living. These people may not have proper sanitation, school sustainability, cooking fuel, and so on.

It is estimated that 176.04 million Indonesians or 66.62 percent of the total Indonesian population are at risk of COVID-19 infection. This number of people are deprived in one of the three deprivation indicators related to COVID-19, which is either drinking water, toddler nutrition, or cooking fuel. Of these three indicators, deprivation in the drinking water indicator is the main factor for them to be included in the at-risk groups. Drinking water contributes 70 percent, toddler nutrition 5 percent, and cooking fuel 25 percent in the at-risk groups' deprivation composition.

Of the 176 million people in the at-risk groups, at least 21.43 million people or 8.11 percent of the population fall in the category of the multidimensionally poor. This shows that around 99 percent of the multidimensionally poor population in Indonesia is vulnerable to being infected with COVID-19. Only about 150 thousand multidimensionally poor people in Indonesia are relatively resistant to the risk of being infected with the virus. On the other hand, there are about 1.27 million multidimensionally poor people who are at high risk of being infected with COVID-19. This is because these 1.27 million individuals live with poor quality drinking water, child malnutrition, and highly polluting cooking fuels simultaneously.

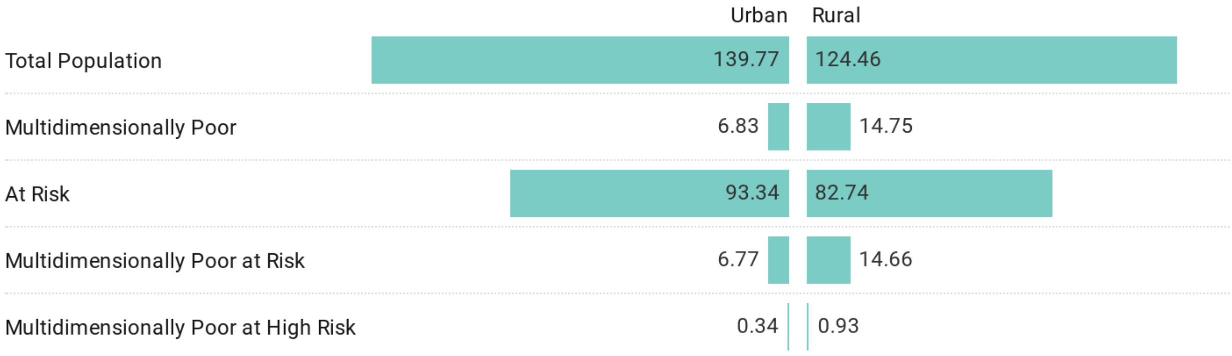
Graph 3 shows that the majority of the Indonesian population live in urban areas. However, the multidimensionally poor individuals mostly live in rural areas. It is estimated that there are around 14.75 million multidimensionally poor people living in villages and around 6.83 million multidimensionally poor people living in cities.

Graph 2. Multidimensional Poverty and Risk Groups (million people)



Source: the authors' estimation.

Graph 3. Multidimensional Poverty and Risk Groups Based on Urban-Rural (million people)

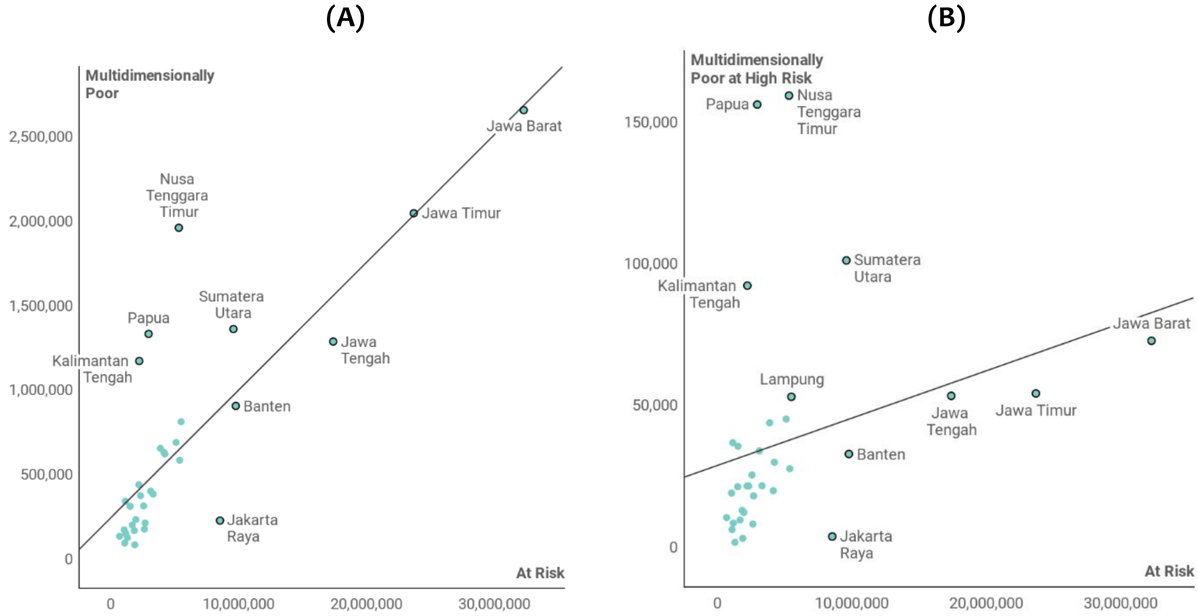


Source: the authors' estimation

Although the multidimensionally poor population in the villages accounts for around 80 percent of the total multidimensionally poor population in Indonesia, people who fall into the group at risk of COVID-19 infection mostly live in urban areas. As many as 93.34 million individuals or 66.78 percent who live in the cities are at risk. The number of individuals in the at-risk groups in the cities is higher than in the at-risk groups in the villages because 88 percent of people in the at-risk groups in the cities are deprived in the indicator of drinking water, while only 73 percent of individuals in the at-risk group in the villages are deprived in the same variable.

The number of the multidimensionally poor population in Indonesia that is relatively resistant to the risk of being infected with COVID-19 is more or less evenly distributed between the cities and the villages. However, the number of people in the multidimensionally poor at-risk groups in the villages is twice as high as in the cities, while the number of people in the multidimensionally poor at high risk group in the villages is almost three times higher than in the cities. This results in the possibility that many multidimensionally poor people in Indonesia who are infected with COVID-19 will be concentrated in the villages.

Graph 4. The Correlation between At-Risk Groups and Multidimensional Poverty (people)



Source: the authors' estimation.

Graph 4A shows that there is a strong, positive correlation between the number of people at risk and the number of multidimensionally poor people in 34 provinces in Indonesia. The greater the number of people there are at risk in a province, the greater the number of multidimensionally poor people there are. As shown in Graph 2, almost all multidimensionally poor people in Indonesia are at risk of COVID-19 infection.

Graph 4B shows that there is a positive correlation between the number of people at risk and the number of multidimensionally poor people at high risk. The greater the number of people there are at risk in a province, the greater the number of multidimensionally poor people there are who have a high risk of being infected with COVID-19. Therefore, provinces that have a greater number of people at risk of COVID-19 infection need to be a top priority in plans for the prevention and treatment of COVID-19.

Table 1 shows that at the provincial level, the number of people at risk of contracting COVID-19 is largely concentrated in Java. This is because people in these at-risk groups are deprived in one indicator related to COVID-19, which is drinking water or toddler nutrition or cooking fuel. The concentrated Javanese provinces include West Java (32.3 million people), East Java (23.7 million people), Central Java (17.4 million people) and Banten (9.7 million people). North Sumatra is an area on the island of Sumatra which is included in the top five regions with the highest number of people at risk, reaching 9.6 million people. Meanwhile, DKI Jakarta is in sixth position with the number of residents at risk reaching 8.5 million. These facts need to be made aware to policymakers, considering that those provinces (until May 2020) have had the largest number of cases of COVID-19 in Indonesia, especially DKI Jakarta, which has been the epicenter for the spread of the virus.

Table 1 also shows that Java is the region with the highest number of multidimensionally poor, at-risk people in Indonesia. This is prompted by the deprivations experienced by people in the multidimensionally poor at-risk groups, which score in at least three of the eight multidimensional poverty indicators, where one of them is related to COVID-19 (drinking water or toddler nutrition or cooking fuel). The provinces in Java that have the highest number of multidimensionally poor at-risk people include West Java (2.6 million people), East Java (2 million people), and Central Java (1.2 million people), while other regions outside the Island that have the highest number of multidimensionally poor, at-risk populations comprise East Nusa Tenggara (1.9 million people), Papua (1.3 million people) and Central Kalimantan (1.1 million people)..

Table 2 shows that, if seen from the proportion of the total population, provinces outside Java and especially those in eastern Indonesia have the highest percentage of the population at risk of COVID-19. These provinces comprise Papua, North Maluku, West Papua and East Nusa Tenggara, with a percentage of more than 99 percent. Meanwhile, the region in fifth position for the highest percentage is Central Kalimantan, which amounts to 93.7 percent. This shows that compared to the respective total populations, these areas are vulnerable to an outbreak that is getting worse with the presence of at-risk populations who are deprived in one indicator related to COVID-19. If these situations are not addressed by policymakers, these areas may become the new epicenters of the spread of COVID-19.

Table 2 also shows that the provinces with the highest percentage of people at risk are also the areas with the highest number of multidimensionally poor at-risk people. The province with the highest percentage of multidimensionally poor, at-risk people is Central Kalimantan with 49.05 percent. After that, it is followed by Papua (44.75 percent), East Nusa Tenggara (36.63 percent), West Papua (29.72 percent), and North Maluku (20.34 percent). As with the at-risk groups, the number of people in the multidimensionally poor at-risk groups is close to half the total population in an area – and if not handled seriously by policymakers – can transform into new sources for the spread of the virus and worsen the condition of the COVID-19 pandemic.

Table 1. The Number of At-Risk and Multidimensionally Poor At-Risk People by Provinces (thousand people)

	Provinces	At Risk	Multidimensionally Poor at Risk
1	Jawa Barat	32,300	2,622
2	Jawa Timur	23,700	2,030
3	Jawa Tengah	17,400	1,277
4	Banten	9,785	896
5	Sumatera Utara	9,601	1,349
6	Jakarta Raya	8,550	224
7	Lampung	5,509	808
8	Riau	5,391	581
9	Nusa Tenggara Timur	5,329	1,960
10	Sulawesi Selatan	5,119	683
11	Kalimantan Barat	4,244	617
12	Sumatera Selatan	4,164	622
13	Sumatera Barat	3,893	651
14	Aceh	3,324	381
15	Nusa Tenggara Barat	3,126	397
16	Papua	2,970	1,332
17	Sulawesi Utara	2,695	211
18	Bali	2,644	176
19	Sulawesi Tenggara	2,579	309
20	Jambi	2,335	373
21	Kalimantan Tengah	2,235	1,170
22	Kalimantan Selatan	2,207	438
23	Kalimantan Timur	1,963	232
24	Yogyakarta	1,891	84
25	Kepulauan Riau	1,850	167
26	Sulawesi Tengah	1,691	200
27	Maluku Utara	1,531	312
28	Maluku	1,517	310
29	Kalimantan Utara	1,307	125
30	Bengkulu	1,186	149
31	Papua Barat	1,147	342
32	Bangka-Belitung	1,099	94
33	Sulawesi Barat	1,058	171
34	Gorontalo	695	133

Source: the authors' estimation

Table 2. The Percentage of At-Risk and Multidimensionally Poor At-Risk People by Provinces

	Provinces	At Risk	Multidimensionally Poor at Risk
1	Papua	99.76%	44.75%
2	Maluku Utara	99.75%	20.34%
3	Papua Barat	99.60%	29.72%
4	Nusa Tenggara Timur	99.59%	36.63%
5	Kalimantan Tengah	93.70%	49.05%
6	Kepulauan Riau	87.17%	7.86%
7	Kalimantan Barat	85.17%	12.39%
8	Kalimantan Utara	83.08%	7.97%
9	DKI Jakarta	81.85%	2.14%
10	Riau	79.58%	8.57%
11	Kalimantan Selatan	77.93%	15.48%
12	Banten	77.49%	7.09%
13	Sulawesi Utara	76.75%	6.02%
14	Bangka-Belitung	75.67%	6.46%
15	Sulawesi Tengah	75.50%	8.94%
16	Sumatera Barat	72.54%	12.13%
17	Sulawesi Barat	70.89%	11.45%
18	Maluku	70.57%	14.41%
19	Gorontalo	67.51%	12.95%
20	Sumatera Utara	66.78%	9.38%
21	Jawa Barat	66.57%	5.40%
22	Lampung	65.98%	9.68%
23	Jambi	65.66%	10.49%
24	Sulawesi Selatan	65.14%	8.69%
25	Kalimantan Timur	64.44%	7.61%
26	Sulawesi Tenggara	64.35%	7.71%
27	Aceh	63.22%	7.24%
28	Nusa Tenggara Barat	62.54%	7.95%
29	Bali	61.75%	4.12%
30	Bengkulu	60.65%	7.63%
31	Jawa Timur	60.08%	5.14%
32	Jawa Tengah	50.53%	3.71%
33	Sumatera Selatan	49.90%	7.45%
34	DI Yogyakarta	49.84%	2.21%

Source: the authors' estimation

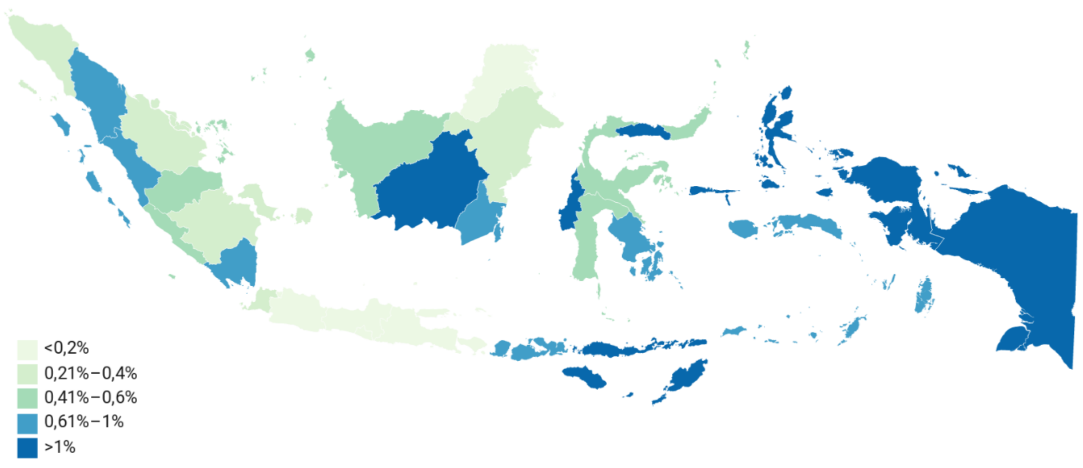
Graph 5. The Distribution of People in Multidimensionally Poor At High Risk Groups (people)

Source: the authors' estimation

Graph 5 shows that the number of multidimensionally poor populations with a high risk of COVID-19 infection generally tends to be concentrated in Java. Notably, West Java, Central Java and East Java are the provinces with the highest number of individuals who fall into the multidimensionally poor, at high risk groups. Beyond Java, North Sumatra, Central Kalimantan, East Nusa Tenggara, and Papua are the provinces that have relatively high numbers of multidimensionally poor populations at high risk in Indonesia. The details of the multidimensionally poor at high risk populations are provided in Appendix 3.

Graph 6 shows that, when viewed as a percentage, the distribution of populations in multidimensionally poor at high risk groups tend to be concentrated in eastern Indonesia. In Papua Province, the percentage of the multidimensionally poor, at high risk people is around 5.24 percent of the total population. Meanwhile, the multidimensionally poor at high risk populations in the provinces of West Papua and North Maluku are around 3.2 percent and 2.32 percent of the respective total populations.

Graph 6. The Distribution of People in Multidimensionally Poor At High Risk Groups (percent)



Source: the authors' estimation

In terms of the number of people, it is estimated that Java has more multidimensionally poor population at high risk of being infected with COVID-19. However, since the population of the island is the largest in Indonesia, the percentage of multidimensionally poor residents at high risk in Java tends to be relatively small. Of the five provinces with the fewest multidimensionally poor, high risk populations in the country, four are in Java. The details of the percentage of multidimensionally poor at high risk populations are provided in Appendix 3.

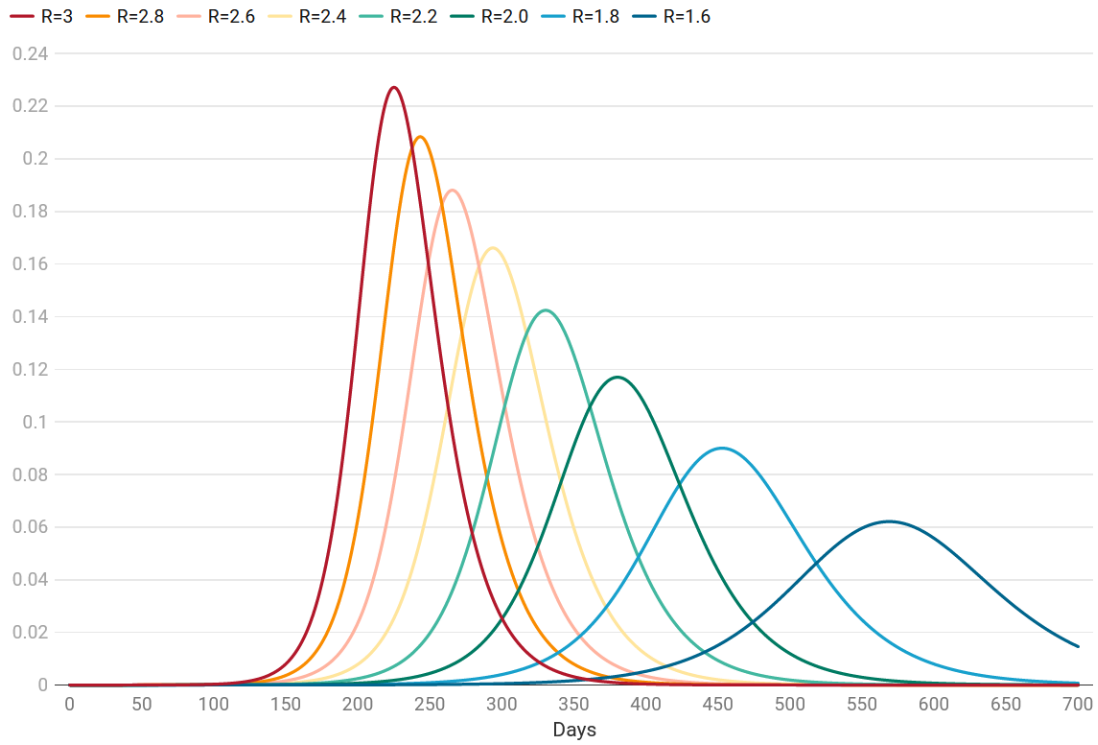
3.2 Simulations of Possible Infection of COVID-19 in the Risk Groups

3.2.1 Simulation 1: there are constant mitigations for 20 months

Simulation 1 assumes that the characteristics of COVID-19 in Indonesia do not change and there are constant disease mitigations for 20 months. Following the estimation measure carried out by Atkeson (2020), the simulation in this section assumes a value of $R_t = R_0$ with an interval of 1.6; 1.8; 2.0; 2.2; 2.4; 2.6; 2.8; and 3.0. Each R_t value indicates the difference in mortality rates in various mitigation scenarios. The value $R_t = 1.6$ indicates the best scenario; a higher value indicates a worse scenario.

Graph 7 shows the ratio of COVID-19 infected population in Indonesia with various scenarios. Indonesia's government claimed that the nation's health facilities, as of April 27, 2020, were able to accommodate 10,000 patients.[3] The hospitals expect be overwhelmed by the increasing number of people infected with COVID-19. Graph 7 shows that each scenario R_t produces a pandemic peak that exceeds the estimated capacity of the health facilities. This simulation also provides evidence that efforts to "flatten the curve" will have a positive impact on the ratio of the population infected with COVID-19. In the worst- case scenario, reaching a peak of 0.22 of the infected population takes 225 to 250 days. When the curve can be maintained as a slope, the number of days needed increases to 575 to 600 days with a peak ratio of the infected population of 0.062.

Graph 7. The Ratio of COVID-19 Infected Population



Source: the authors' estimation

[3] See https://katadata.co.id/berita/2020/04/27/kapasitas-rs-mampu-tangani-10-ribu-pasien-corona-saat-ini-terisi-80.

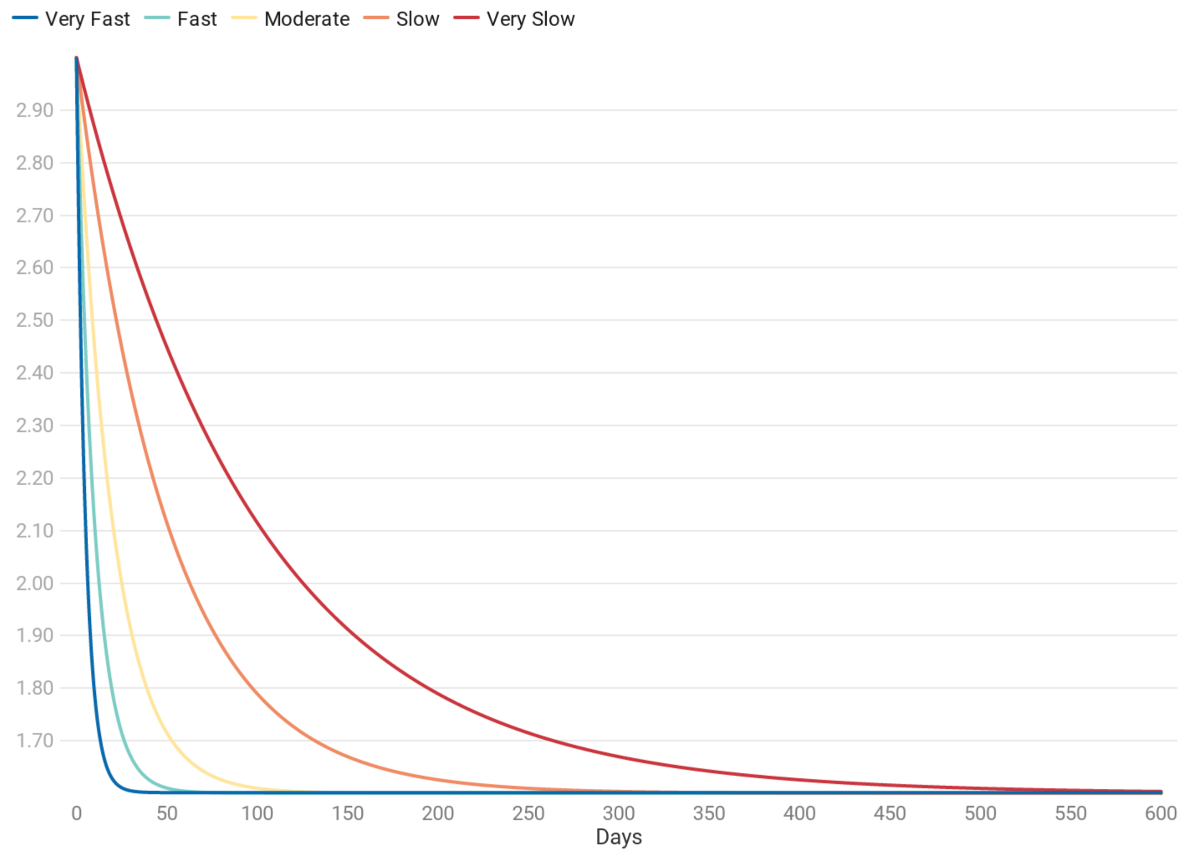
3.2.2 Simulation 2: implementations of quarantineor social restriction policy

In Simulation 2, we try to estimate the implementation of quarantine or a social restriction policy by changing the rate of R_t. This section divides the success scenarios of a quarantine or social restriction policy into five groups: very fast, fast, moderate, slow, and very slow. The estimation is done by making the interval R_t, which in the previous section has a continuous-discrete value where $R_0 = 3.0$ and $R_\infty = 1.6$. As explained in the methodology and data section, determining the values of R_0 and R_∞ indicates values that are increasingly conical in long-term conditions.

Graph 8 shows changes in the rate of R_t in for each effectiveness scenario of the social restriction policy. The figure shows that the more effective the social restriction policy is, the faster the rate of change is for R_t to become conical in its long-term value. Conversely, when the effectiveness of a social restrictions policy is very slow, the rate of change in R_t tends to be slower than other scenarios.

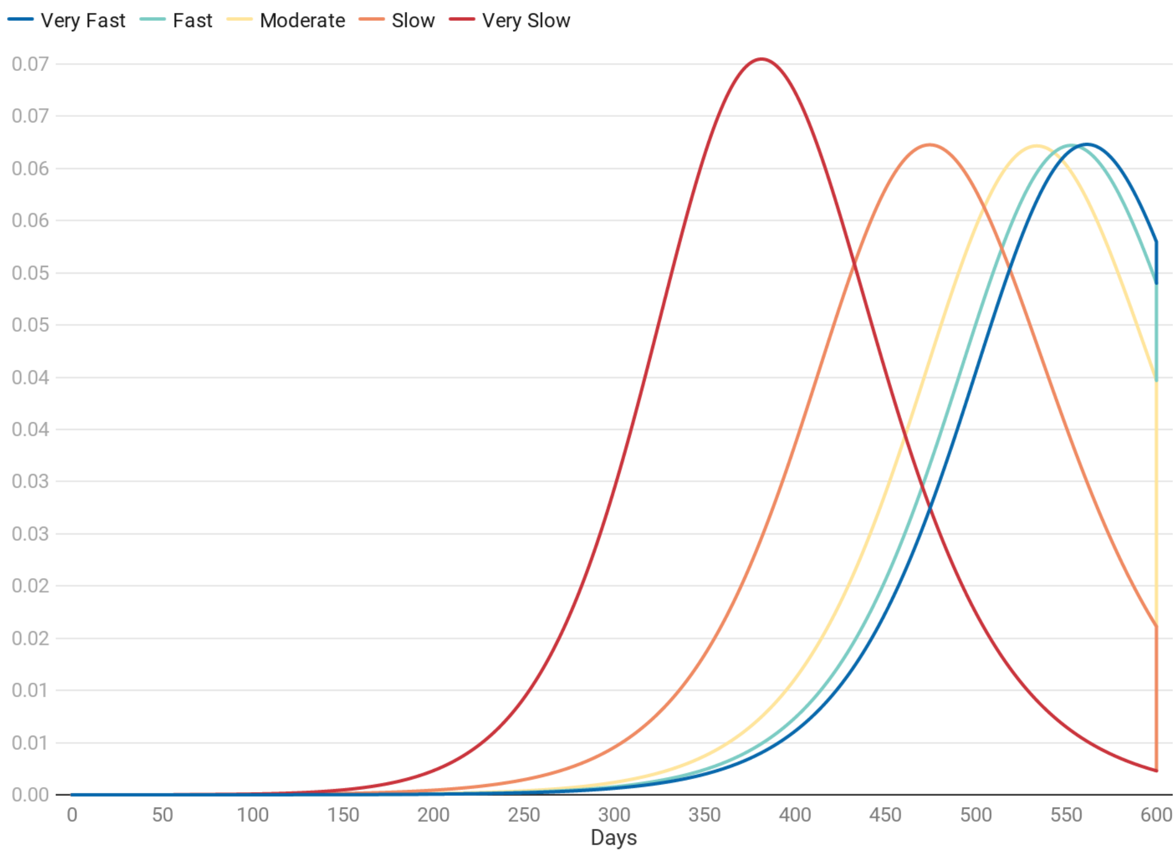
Graph 9 shows the ratio of the population infected with COVID-19 under the effectiveness scenario of a social restrictions policy. All social restriction policy scenarios show that this policy can reduce the ratio of populations infected with COVID-19. In the slowest policy effectiveness scenario, this policy can decrease the population ratio to 0.07 and requires 380 to 390 days. The values of each scenario have not been able to suppress the ratio below 1 percent, which is an estimated number for health facilities not to be overwhelmed. Other effectiveness scenarios of a social restriction policy can reduce the population ratio at the peak of the pandemic to reach 0.061 to 0.062 at 480 to 560 days.

Graph 8. Changes in the rate of R_t



Source: the authors' estimation

Graph 9. Infection Ratio and Social Restriction Policy



Source: the authors' estimation

3.2.3 Simulation3: the proportion of constant risk groups and constant mitigations

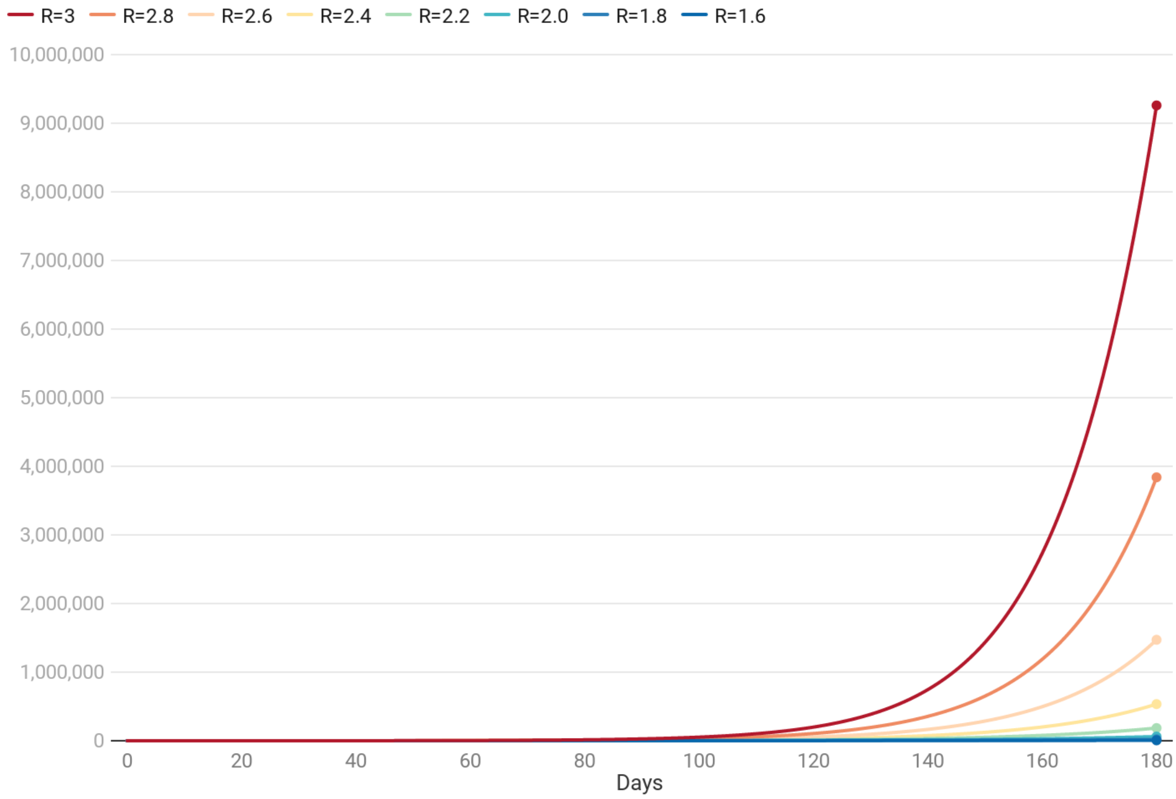
Simulation 3 assumes that the proportion of the populations divided into risk groups does not change and the COVID-19 mitigation is constant. Graph 10, Graph 11, and Graph 12 show the results of simulations of the populations of at-risk; multidimensionally poor, at-risk; and multidimensionally poor, at high risk groups who are estimated to be infected with COVID-19.

Over six months, the populations in the at-risk groups infected with COVID-19 are estimated to reach 9.26 million people in the worst-case scenario ($R_t = 3$). In the best-case scenario ($R_t = 1.6$), the affected population can be reduced to 5,845 people. In the median scenario ($R_t = 2.2$), the number of people affected is 185,232. This shows that the suppression of the value of R_t has a big impact within six months.

In the same span, the population included in the multidimensionally poor groups potentially infected with COVID-19 is estimated to reach 1.13 million people in the worst-case scenario. In the best scenario, the affected population can be reduced to 711 people. In the median scenario, the number of people affected is 22,547.

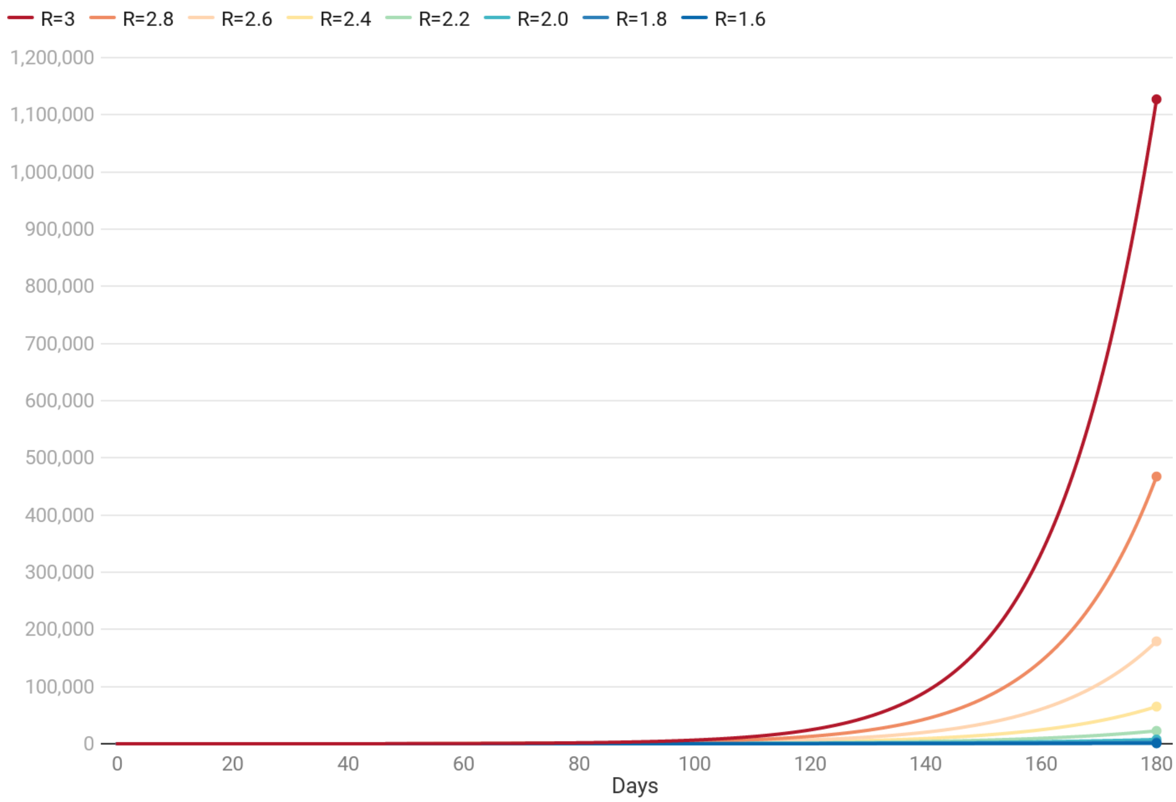
The population in the multidimensionally poor, at high risk groups potentially infected with COVID-19 are estimated to reach 66,914 people in the worst-case scenario. In the best scenario, the affected population can be reduced to only 42 people. In the median scenario, the number of people affected is 1,339. The sharp decrease in the affected people is very dependent on the decrease in the rate of R_t

Graph 10. The Number of COVID-19 Infected Populations in the At-Risk Groups (people)



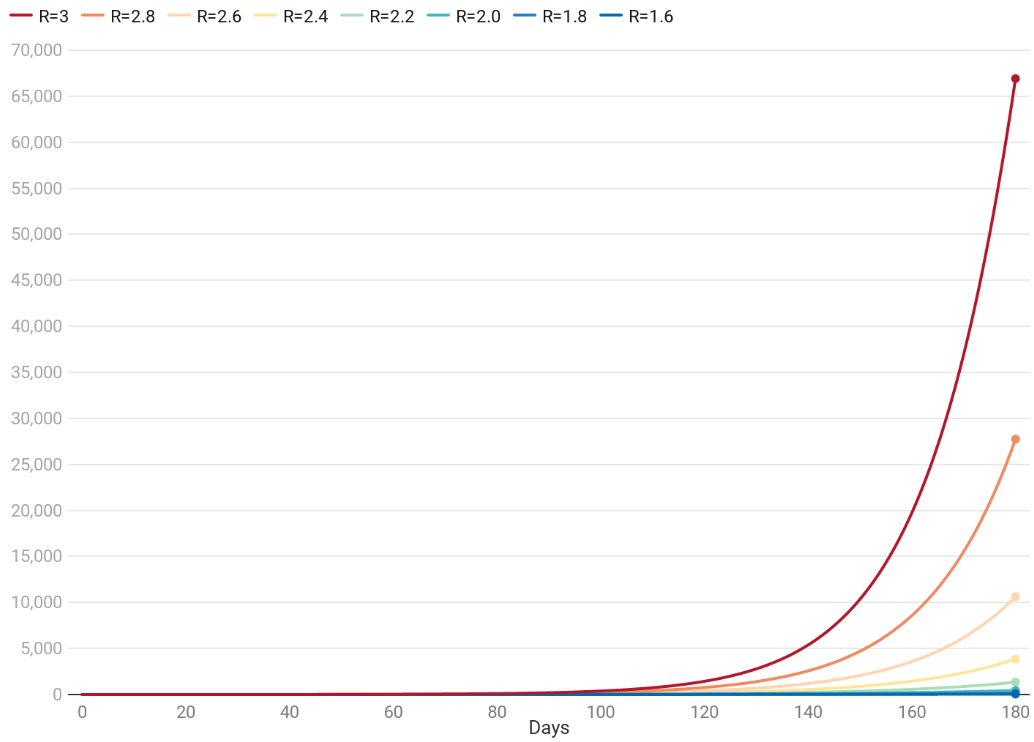
Source: the authors' estimation

Graph 11. The Number of COVID-19 Infected Populations in the Multidimensionally Poor At-Risk Groups (people)



Source: the authors' estimation

Graph 12. The Number of COVID-19 Infected Populations in the Multidimensionally Poor At High Risk Groups (people)



Source: the authors' estimation

3.2.4 Simulation 4: the proportion of constant risk groups and the application of social restriction policy

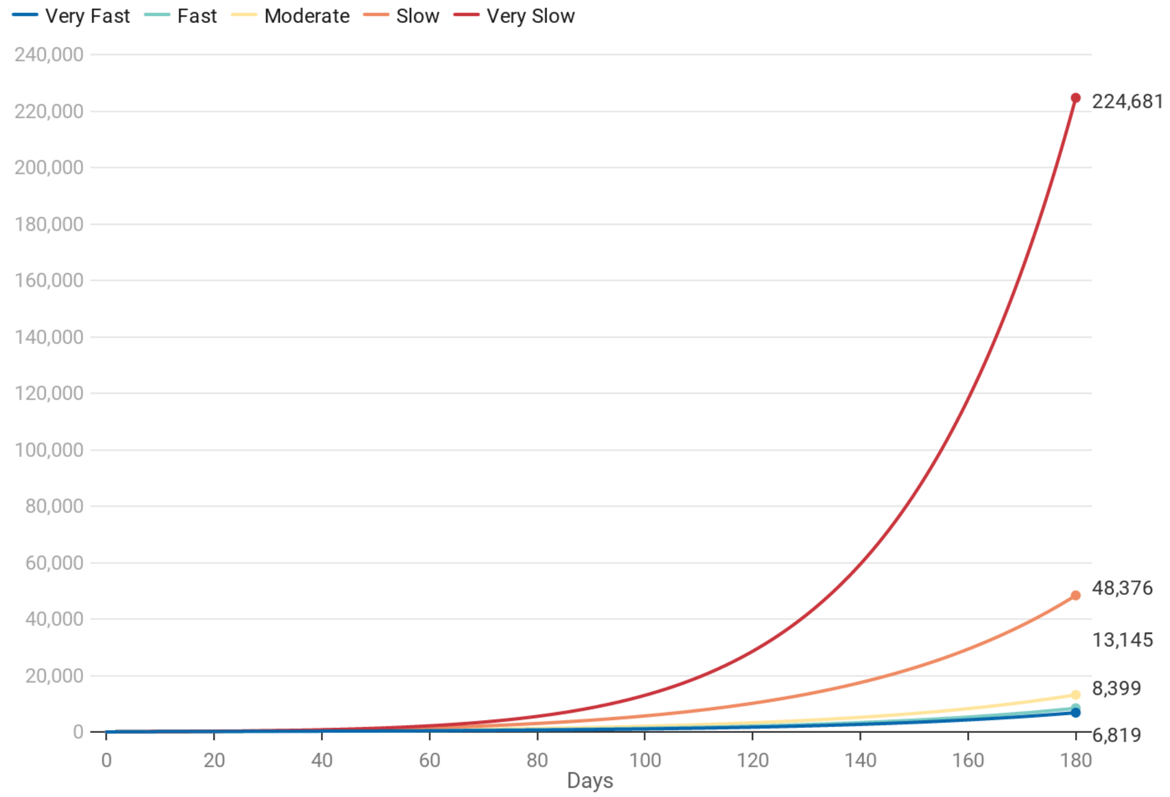
Simulation 4 assumes that the proportion of the population divided into risk groups does not change and there is a social restriction policy. Graphs 13, 14, and 15 show the results of simulations of the populations in at-risk; multidimensionally poor,at-risk; and multidimensionally poor at high risk groups who are estimated to be infected with COVID-19. A social restriction policy with various scenarios of effectiveness can reduce the growth rate of the infected people in each risk group.

In the very slow policy effectiveness scenario, the number of infected people in the at-risk groups is estimated to be reduced to 224,681 people. If there is no social restriction policy, the number may reach 9.26 million people. In the best effectiveness scenario, the number of infected people in the at-risk groups can be reduced to 6,819. Meanwhile, in the moderate scenario, the number of people affected is 13,145.

The number of infected people in the multidimensionally poor, at-risk groups is estimated to be reduced to 27,348 people in the very slow policy effectiveness scenario. If there is no social restriction policy, the number of infected people may reach 9.26 million. In the most effective scenario, the number of the infected people in the multidimensionally poor, at-risk groups can be reduced to 830. Meanwhile, the number of people affected in the moderate scenario is 1,600.

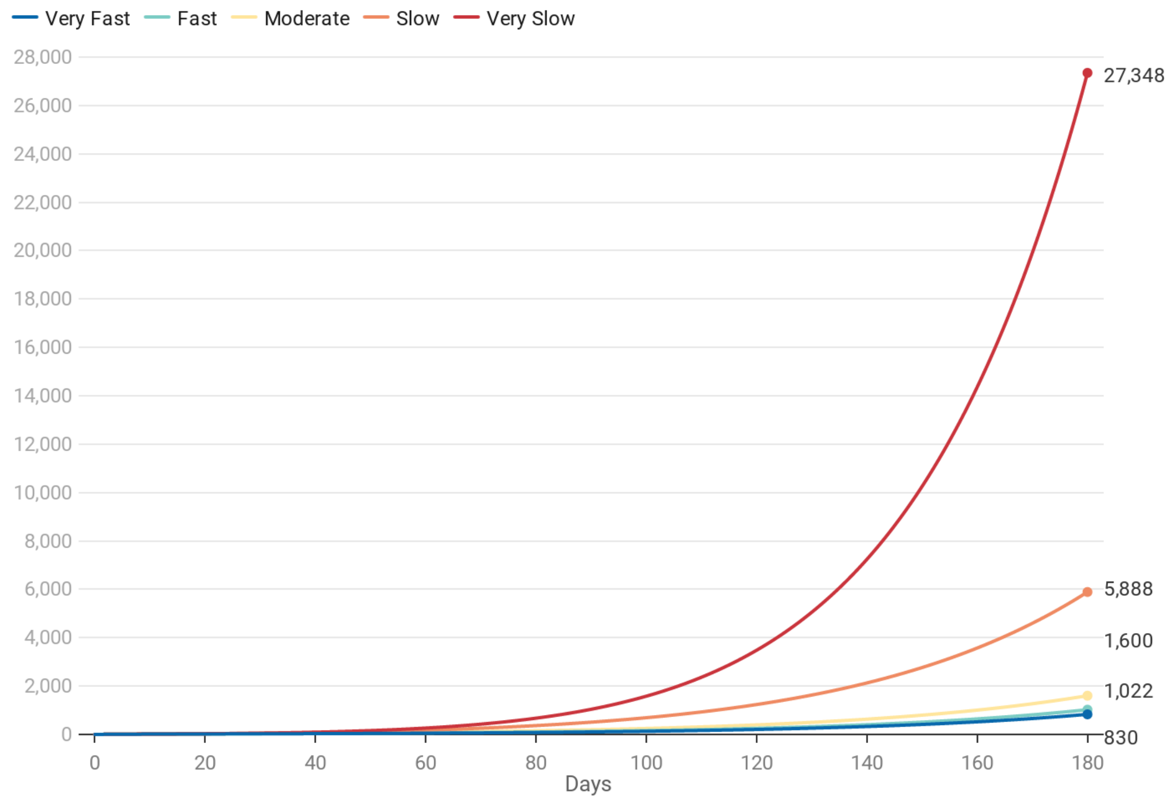
In the multidimensionally poor, at high risk groups, in the very slow policy effectiveness scenario, the number of infected peopleis estimated to be reduced to 1,624. If there is no social restriction policy, the number of infected people may reach 66.914 million. In the most effective scenario, the number of the infected people in the multidimensionally poor, at high risk groups can be reduced to 830. Meanwhile, the number of people affected in the moderate scenario is 95.

Graph 13. The Number of COVID-19 Infections in Social Restrictions in the At-Risk Groups (people)



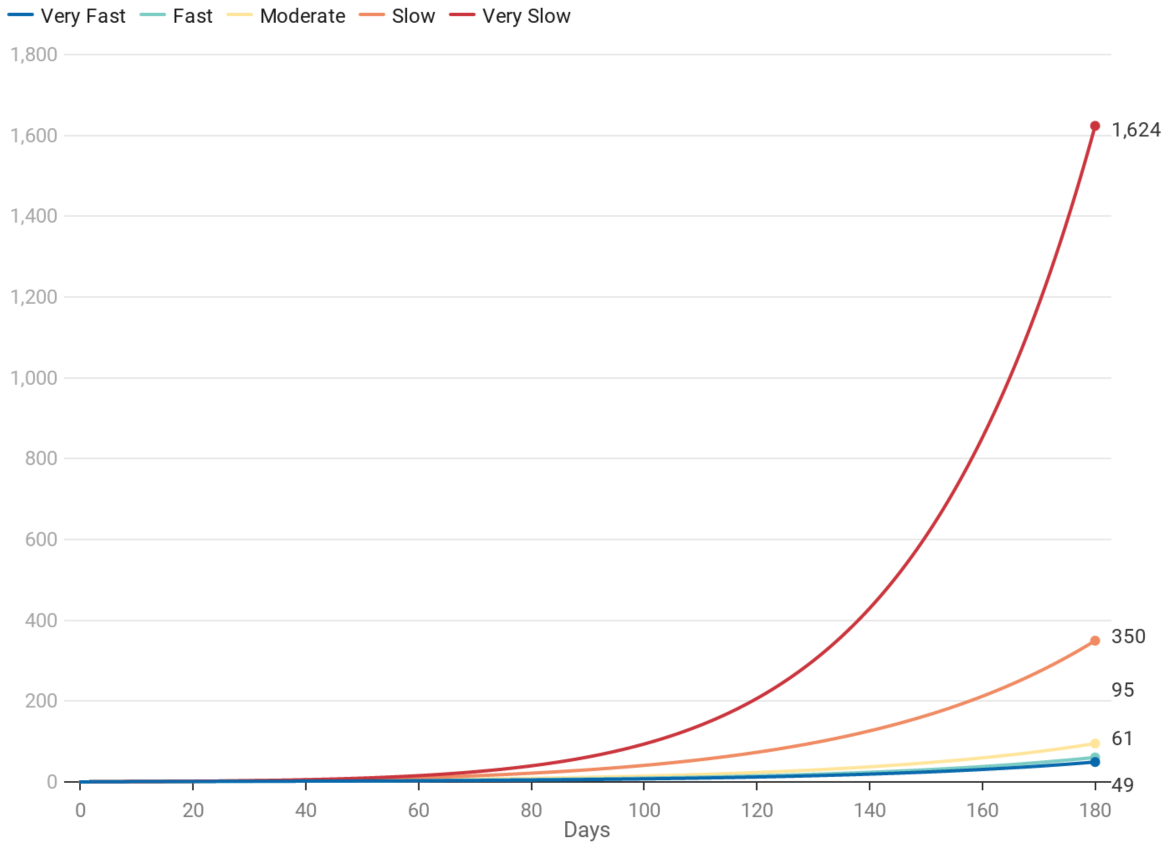
Source: the authors' estimation

Graph 14. The Number of COVID-19 Infections in Social Restrictions in the Multidimensionally Poor At-Risk Groups (people)



Source: the authors' estimation

Graph 15. The Number of COVID-19 Infections in Social Restrictions in the Multidimensionally Poor At High Risk Groups (people)



Source: the authors' estimation

4. CONCLUSION AND POLICY RECOMMENDATIONS

Based on the results ofthe analyses obtained from the calculations related to multidimensional poverty, risk groups, and the relationship and distribution between the two, it can be concluded that there is a strong correlation between the possible number of people at risk of being infected with COVID-19 and the number of people experiencing multidimensional poverty in Indonesia.

The results of the analyses have shown that in general, 66.62 percent of the Indonesian population are at risk of COVID-19 infection. Moreover, 8.17 percent of Indonesia's total population or 21.58 million people live in multidimensionally poor conditions, of which 21.43 million people are at risk of COVID-19 and only 1 percent or 150,000 people have resistance to the risk of infection. The positive correlation between the number of people at risk of COVID-19 infection and the number of people living in multidimensionally poor conditions implies that the greater the number of people there are at risk of COVID-19 infection in a province, the greater is the number of multidimensionally poor people who have a high risk of being infected with the virus.

It should be noted that around 99 percent of the poor population in Indonesia are vulnerable to being infected with COVID-19 and 70 percent of people become part of the group at risk of being infected due to the unavailability of hygienic drinking water. Also, the results of the analyses found that although the multidimensionally poor population in the villages accounts for around 80 percent of the total multidimensionally poor population in Indonesia, people who are classified as at risk of being infected with COVID-19 mostly live in urban areas. This finding provides a new perspective on the process of slowing the spread of COVID-19 in Indonesia, which can be predicted to have been less effective so far,because the public has not been disciplined in complying with the social restriction policy.

The effectiveness of the social restriction policy greatly influences the slowing down of the spread of COVID-19. This can be proven in the simulations that the more effective the social restriction policy is, the faster the rate of change is in the ratio of the rate of people susceptible to infection and people infected to recover or die to cone at its long-term value. Conversely, when the effectiveness of social restrictions policy is very poor, the rate of change in the ratio tends to be slower. Therefore, the control of policymakers regarding the implementation of this social restriction policy is crucial to ensure the slowing down of the spread.

If efforts to slow down the spread are unsuccessful, health facilities face major obstacles in providing services to patients with COVID-19 infection. The Indonesian government stated that health facilities, as of April 27, 2020, were able to accommodate 10,000 patients. The estimated growth in the number of beds available in the health facilities is not able to keep the pace with the growth in the numbers infected with COVID-19.

Other simulations carried out in this study also show that in the worst-case scenario, within six months, the populations in the at-risk groups are infected, with the number of infected individuals reaching 9.26 million; 1.13 million of whom are from the poor groups and 66,914 are from poor and at high risk groups. Therefore, the decline in the R_t rate greatly affects the decrease in the number of people infected and a decline in the R_t rate can only be realized through the implementation of an effective social restriction policy. The simulation results also show that social restriction policies with various effectiveness scenarios can suppress the growth rate of infected people in each risk group.

Based on the analyses results above, several recommendations can strengthen the policies that have been implemented by policy makers, as follows:

1. Policymakers need to prioritize provinces that have a number of people at risk of COVID-19 infection in their prevention and management plans for COVID-19. The results of the analyses show that the number of multidimensionally poor people at high risk of being infected with COVID-19 generally tends to be concentrated in Java (in West Java, Central Java, and East Java) but also outside Java, namely in the provinces of North Sumatra, Central Kalimantan, East Nusa Tenggara and Papua, which also have relatively large numbers of multidimensionally poor, at high risk populations.

2. Policymakers need to pay special attention to the issues of unhygienic drinking water, highly polluting cooking fuels, and child malnutrition experienced by some Indonesians. The food and hygiene kit distribution program that has been implemented during the pandemic needs to be complemented with another program that promotes and provides drinking water and the use of fuels that are safer for humans and the environment.

3. If the social restriction policy–known as Large-Scale Social Restrictions (PSBB) – is still relatively loose and inconsistent, the rate of slowing of the COVID-19 infection will be unstable, and it will be difficult to predict with certainty when it will end. Therefore, it is necessary to evaluate the implementation of PSBB and measure their effectiveness. Measuring the effectiveness of PSBB is critical to make changes (for policy strengthening) in order to slow down COVID-19 infection rates.

4. Policymakers at the central and regional levels need to cooperate and have a voice regarding the implementation of the homecoming ban policy. This policy is very crucial, considering the results of the analyses which show that people who are at risk of COVID-19 infection mostly live in urban areas. Therefore, PSBB relaxation efforts that can encourage the mobilization of residents from cities to villages (in this case, Lebaran homecoming) need to be carefully examined. Such an action could potentially increase the number of poor people at risk of COVID-19 infection.

5. Policymakers at the central level need to create a transparent blueprint for handling COVID-19 so that awareness can arise from each party directly involved, especially the health facilities and local governments, in preparing for the worst situation of COVID-19's spread.

6. Policymakers need to consider large-scale investment in health infrastructure, especially in areas with a high number and distribution of multidimensionally poor at high risk populations to improve the toddler nutrition and living standards of the populace, thereby reducing their risk of being infected with COVID-19.

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Appendix 1

Health Dimension

1) **Indicator of Sanitation**
An individual is said to be deprived in the sanitation indicator if they do not have either public, shared, or private bowel facilities and their type of toilet is not a gooseneck one.

2) **Indicator of Drinking Water**
An individual is said to be deprived in the drinking water indicator if they use or consume clean water that is not from a metered source. An individual can also be said to be deprived if they do not use drinking water from pumps, protected wells or protected springs that are less than 10 metres from the septic tank. This assumption is used because if the protected springs are less than 10 metres from the septic tank, there is a possibility that their drinking water can be contaminated with elements that come from the septic tank in the form of solid or liquid waste.

3) **Indicator of Toddlers' Nutrition**
A toddler (a baby under five years old) is said to be deprived if its nutritional intake is less than the required intake. Table 3 shows the minimum nutritional needs of toddlers, based on age groups between the ages of 0 to 1 years old, 1 to 3 years, and 4 to 5 years, based on the Regulation of the Ministry of Health No. 75 of 2013 concerning Nutrition Adequacy Rates Recommended for Indonesians.

Table 3. Balanced Nurtrition for Toddlers

Age	Energy (kkal)	Protein (g)	Fat (g)	Carbohydrate (g)
< 1 year	637.5	15	35	70
1–3 years	1,125	26	44	155
3–5 years	1,600	35	62	220

Education Dimension

1) **Indicator of Early Childhood Education (PAUD)**
Individuals (children) are said to be deprived if those aged 3 to 6 years old do not have access to preschool education services, such as PAUD, other PAUD equivalent posts, kindergartens (TK) or equivalent, playgroups, and other types of preschool education.

2) **Indicator of School Sustainability**
Individuals (children) are said to be deprived if they are of primary or secondary school age but are unable to complete their education up to the senior high school level, such as SMA (High School), SMK (Vocational High School), or MA (Madrasah Aliyah) or equivalent.

Living Standards Dimension

1) **Indicator of Lighting Source**
An individual is said to be deprived when they use electricity for lighting that does not come from the National Electric Company (PLN), but rather from petromax/aladine, lamps/flashlights/torches, or other sources of lighting.

2) **Indicator of Cooking Fuel**
An individual is said to be deprived when they do not use electricity or gas for cooking, but rather they use kerosene, charcoal, briquettes, or firewood.

3) **Indicator of Roof, Floor and Wall Conditions**
An individual is said to be deprived if their roof, floor, and walls are not in a very good condition. An individual who is deprived in this indicator cannot meet the conditions that are described as adequate for the three sub-indicators (roofs, floors, and walls).

   a. Roofs
   A house roof is said to be in an inadequate condition when the roof is made of materials other than concrete, tile, zinc, or asbestos, such as bamboo, wood/shingles, straw/fibers /leaves and others.

   b. Floors
   A house floor is said to be in an inadequate condition if the floor is made of materials other than marble, ceramics, granite, tiles, titeraso, cement, or wood, such as bamboo, low quality wood/boards, soil, and other materials.

   c. Walls
   A house wall is said to be in an inadequate condition if the wall is made of materials other than bricks or wood, such as woven bamboo, sticks, bamboo, and other materials.

Appendix 2

Table 4 shows that households 2 and 4 experience multidimensional poverty, while households 1 and 3 do not experience it. This conclusion is indicated by the multidimensional poverty deprivation scores. If the score is below the limit of 0.333, then the individuals do not experience multidimensional poverty and vice versa.

Table 4. An Example of the Indonesian MPI Calculation

Indicators	Households				Weight
	1	2	3	4	
Number of individuals	4	7	5	4	
Health Dimension					
Sanitation	0	1	0	1	1/9=0.111
Drinking water	0	1	0	0	1/9=0.111
Nutritional intake for toddlers	1	1	1	1	1/9=0.111
Education Dimension					
Access to PAUD	0	1	0	1	1/6=0.167
School Sustainability	0	0	1	1	1/6=0.167
Living Standards Dimension					
Cooking fuel	0	1	0	1	1/9=0.111
Lighting source	0	0	0	0	1/9=0.111
Conditionof roof, floors, and walls	0	1	0	1	1/9=0.111
Score (the amount of each deprivation multiplied by the weight)	0.111	0.722	0.278	0.778	
Are these households included in the category of multidimensionally poor population? (≥ 1/3=0.333)	No	Yes	No	Yes	

Appendix 3

Table 5. Population Summary of the Multidimensionally Poor At High Risk Groups

Provinces	Populations (people)	Multidimensionally Poor (people)	Multidimensionally Poor At High Risk (people)	Multidimensionally Poor At High Risk (percent)
Aceh	5.258.214	383.746	21.597	0,41
Sumatera Utara	14.376.960	1.360.855	101.119	0,70
Sumatera Barat	5.366.879	654.995	43.822	0,82
Riau	6.775.315	584.216	27.624	0,41
Jambi	3.556.500	374.978	21.543	0,61
Sumatera Selatan	8.344.293	631.575	19.863	0,24
Bengkulu	1.956.011	150.577	8.429	0,43
Lampung	8.350.053	812.768	53.013	0,63
Kep. Bangka Belitung	1.452.303	94.491	6.162	0,42
Kepulauan Riau	2.122.826	168.219	12.910	0,61
DKI Jakarta	10.445.556	227.524	3.706	0,04
Jawa Barat	48.520.564	2.655.914	72.772	0,15
Jawa Tengah	34.432.052	1.286.762	53.331	0,15
DI Yogyakarta	3.793.710	84.223	3.057	0,08
Jawa Timur	39.449.708	2.045.947	54.189	0,14
Banten	12.627.282	906.037	32.812	0,26
Bali	4.281.709	176.898	8.108	0,19
Nusa Tenggara Barat	4.998.090	401.799	33.891	0,68
Nusa Tenggara Timur	5.351.292	1.960.193	159.286	2,98
Kalimantan Barat	4.983.233	621.747	29.921	0,60
Kalimantan Tengah	2.385.608	1.171.763	92.241	3,87
Kalimantan Selatan	2.832.044	439.674	21.510	0,76
Kalimantan Timur	3.046.491	233.554	12.174	0,40
Kalimantan Utara	1.572.735	126.281	1.668	0,11
Sulawesi Utara	3.511.156	213.493	18.041	0,51
Sulawesi Tengah	2.239.308	201.547	9.534	0,43
Sulawesi Selatan	7.858.803	689.959	45.145	0,57
Sulawesi Tenggara	4.007.881	314.275	25.440	0,63
Gorontalo	1.029.719	134.927	10.367	1,01
Sulawesi Barat	1.492.151	172.726	19.036	1,28
Maluku	2.149.579	312.379	21.294	0,99
Maluku Utara	1.534.564	312.174	35.546	2,32
Papua Barat	1.151.140	342.079	36.789	3,20
Papua	2.977.030	1.332.078	156.128	5,24
National	**264.230.759**	**21.580.370**	**1.272.069**	**0,48**