MOBILITY-COVID-19 IMPACT QUADRANT : QUANTITATIVE APPROACH TO ANALYZE COMMUNITY RESPONSES TO COVID-19 PANDEMIC

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Abstract

There are two premises regarding the relationship between mobility and COVID-19, namely: (1) mobility affects the spread of COVID-19, or (2) the spread of COVID-19 affects mobility. This paper further explores both premises to analyze community responses to COVID-19 pandemic using Google Mobility Index (mobility) and the COVID-19 Spread Risk Index (risk) of Indonesia. Cross-correlogram of both indices is examined to determine optimum values called Risk Detection Time (Rdt). A scatter plot of Rdt and its correlation coefficient resulted Mobility-COVID-19 Impact Quadrant which maps the community responses into four zones based on quadrant ‘conscious–competence’ framework. The results confirmed both premises: (1) risk can be triggered by mobility in the previous few days, or (2) mobility can represent the community responses to risk information in the previous few days. Regarding the mobility restriction implemented in Indonesia, the analysis shows that the community responses leaped from Learning zone in PSBB period (15/03/2020 to 31/05/2020) to the Recovery zone in the New Normal and PPKM period (01/06/2020 to 02/07/2021). However, the policy was late responded so that the recovery target did not go as expected and brought the community into Fear and Uncertainty zone in the Emergency PPKM period (starting from 03/07/2021).

Abstrak

Ada dua premis mengenai hubungan mobilitas dengan COVID-19, yaitu: (1) mobilitas memengaruhi penyebaran COVID-19, atau (2) penyebaran COVID-19 memengaruhi mobilitas. Makalah ini mengeksplorasi lebih jauh kedua premis untuk menganalisis tanggapan masyarakat terhadap pandemi COVID-19 menggunakan *Google Mobility Index* (mobilitas) dan *COVID-19 Spread Risk Index* (risiko) Indonesia. *Cross-correlogram* dari kedua indeks diperiksa untuk menentukan nilai optimum yang disebut *Risk Detection Time* (Rdt). *Scatter plot* Rdt dan koefisien korelasinya menghasilkan *Mobility-COVID-19 Impact Quadrant* yang memetakan respons masyarakat ke dalam empat zona berdasarkan kerangka 'sadar-kompetensi' kuadran. Hasil mengkonfirmasi kedua premis: (1) risiko dapat dipicu oleh mobilitas dalam beberapa hari sebelumnya, atau (2) mobilitas dapat mewakili respons masyarakat terhadap informasi risiko beberapa hari sebelumnya. Terkait pembatasan mobilitas yang diterapkan di Indonesia, analisis menunjukkan bahwa respon masyarakat melonjak dari zona Belajar pada periode PSBB (15/03/2020 hingga 31/05/2020) ke zona Pemulihan pada periode *New Normal* dan PPKM (01/06 /2020 hingga 02/07/2021). Namun, kebijakan tersebut terlambat ditanggapi sehingga target pemulihan tidak berjalan sesuai harapan dan membawa masyarakat pada zona Takut dan Ketidakpastian pada masa PPKM Darurat (mulai 03/07/2021).

INTRODUCTION

Observing relationship between community mobility and the spread of COVID-19 is very interesting. In the early days of the pandemic, many researchers reviewed the impact of COVID-19 on people's mobility [1][2][3][4]. At that time, community mobility decreased because people instinctively avoided the transmission of COVID-19 which was triggered by the extraordinary spread in the city of Wuhan, China [5][6]. In addition, the policies taken by the government to prevent the spread of COVID-19 such as closing public facilities or entertainment venues that potentially cause crowds [7][3], appealing to stay at home [8], carrying out social distancing [9], and taking decision to lock down [1][10] became the premise of research on the effect of COVID-19 on community mobility. Over time, the government began to impose new normal rules to gradually spur economic activity with an appeal to maintain health protocols [11]. With the enactment of the new normal rules, the research premise began to change, namely community mobility should have an effect on the spread of COVID-19 [12][13][14][15][16].

Observing those two premises, this paper explores further the relationship between community mobility and the spread of COVID-19 to explain how community responds to the COVID-19 pandemic. Quantitatively—by mapping the correlation between mobility and the risk of spreading COVID-19 in the community into a quadrant matrix—the community's response to the pandemic can be categorized into four zones that describe the process of developing knowledge. The quantitative approach in this paper makes an important contribution that complements previous qualitative research [17]. Thus, this approach can be used as a tool for evaluating policies to prevent the spread of COVID-19.

To provide an overview of how this quantitative approach is carried out, this paper begins with an explanation of the data used. In particular, this research used the Google Mobility Index and the COVID-19 Spread Risk Index of Indonesian region which are processed using *Python* 3.0 programming language. Furthermore, several important things related to data processing are explained including the concept of *Risk Detection Time* (*Rdt*) which is an important key in this research. This paper ends with an explanation of the quadrant analysis technique to evaluate the mobility restriction policies implemented in Indonesia and concludes a summary of the analysis.

THE DATA SOURCE

To find out the relationship between mobility and the spread of COVID-19, this paper used big data sourced from the internet. Mobility data is taken from Google which is updated regularly and is available on https://www.google.com/covid19/mobility/. The data is in the form of a Mobility Index. The mobility information obtained by Google from individuals who consciously choose to enable Location History of their Google account. Mobility changes are aggregated and anonymized to form an index. The index represents the percentage change in total visitors to a number of places (shops and pharmacies, parks, workplaces, retail and recreation, and transit stations) or the change in duration of stay at the places of residence compared to the baseline measurement [18][19]. The baseline measurement represents "normal conditions", which is the median value for each day of the week, from January 3 to February 6, 2020. This paper used the daily Google Mobility Index (denoted by *M*) by Province of Indonesia from 15th February 2020 to 17th August 2021.

Data on the risk of spreading COVID-19 cases were obtained from the report of the Indonesian COVID-19 Handling Task Force. The data is in the form of index numbers published weekly on the https://covid19.go.id/peta-risiko. The index is calculated based on public health indicators using scoring and weighting. The indicators consist of Epidemiological Indicators (ten variables), Public Health

Surveillance Indicators (two variables), and Health Service Indicators (two variables). Observing these indicators, the index is a representation of the cumulative public health condition over the past week. The use of this index has the advantage because variables related to the spread of COVID-19 are already represented implicitly. The index is a continuous scale from 0 (highest risk) to 3 (no risk). This paper used the weekly COVID-19 Spread Risk Index (denoted by *R*) by province of Indonesia from 1st March 2020 to 15th August 2021.

In M an increase in the number indicates an increase in people's mobility, while in R an increase in the number indicates a decrease in risk. Defining the value of *R* like this is sometimes confusing. Therefore, in this paper, the R value is rescaled so that the higher the R' (the R value after the rescaling process), the higher the risk of spreading COVID-19 in the community. The rescaling process using formula (1) makes R' become a percentage value. In addition, the rescaling process will make the correlation between the two variables easy to interpret. A positive correlation indicates the higher the mobility the higher the risk of spreading COVID-19, and vice versa.

$$R' = \left(1 - \frac{R}{3}\right) \times 100 \tag{1}$$

RISK DETECTION TIME

Several studies on the relationship between community mobility and the spread of COVID-19 have shown that the number of new confirmed cases of COVID-19 in a day is directly related to the mobility in the previous days [20][21]. This time lag provides the largest correlation between the two variables and is termed Positivity Detection Time (*Pdt*) [21][22]. The procedure for determining the *Pdt* is basically similar to the popular Cross Correlation Function (*Ccf*) method in statistics and signal processing [23] and is used to explain the relationship between mobility and the spread of new confirmed COVID-19 cases [24][25]. In this paper, the *Pdt* concept is adopted and a new term Risk Detection Time (*Rdt*) is used as the research focus is to explain the relationship between community mobility and the risk of spreading COVID-19.

Rdt can be determined by tracing the similarity of the M and R' patterns. However, tracing can only be performed if both variables have the same time reference. The easiest process to equalize the time reference between the two variables is to aggregate *M* into weekly data according to the time reference of *R'*. After that, to adopt the concept of *Pdt* or *Ccf*, this paper determined *Rdt* using the framework as shown in Figure 1.

The Google mobility index consists of several types according to the place of reference, namely: (1) grocery and pharmacy, (2) parks, (3) workplaces, (4) retail and recreation, (5) transit stations, and (6) residential. For further discussion, mobility type 1 through 5 is referred to as *outward mobility*. The algorithm in Figure 1 is used to determine *Rdt* for each type of mobility. The algorithm is different from the algorithms carried out in previous studies which used categorized correlations frequency for all types of mobility [21], or used the median of *Pdt* for all areas studied [24].

The moving average of *M* was chosen as the aggregation method so that *Pdt* or *Ccf* concept that requires time lag variables can be adopted. In addition, the risk of spreading COVID-19 may be due to cumulative community mobility in the previous days (i.e R' is associated with cumulative moving average of a negative time lag of *M*). On the other hand, the

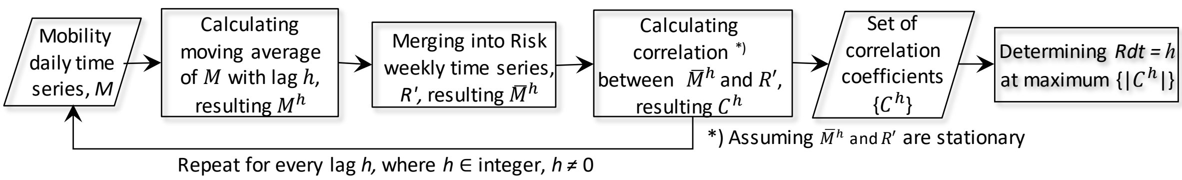

Figure 1. *Rdt* Determination Algorithm

cumulative mobility can also represent the community's response to information a few days earlier about the risk of spreading COVID-19 (i.e R' is associated with cumulative moving average of a positive time lag of *M*). This paper sets the time lag of *M*, denoted by h, in a range that depends on the time span of the variable under study. If the variable has a long time span, assuming the maximum *Pdt* is 21 days [20] and considering the Risk index is updated weekly, the maximum lag of *M* is set to 150 days. It is important to note that from this stage *M* has become a cumulative moving average denoted by M^h.

Furthermore, M^h is merged with R' to get new data with the same (weekly) time references denoted by $\bar{M}^h$. This kind of merging process can explain the relationship between M and R' more broadly. Although the data is a weekly series, the premise or hypothesis regarding the relationship between *M* and R' can be expressed on a daily basis according to the value of *h*. The merging process is a necessary condition to calculate correlation coefficient between $\bar{M}^h$ and R' denoted by C^h.

Because the pandemic is a non-normal condition, this paper calculated the correlation coefficient using the Spearman correlation which is distribution free and relatively robust against outlier [26]. The coefficient can range from -1 (uncorrelated) to +1 (perfectly correlated). The correlation is said to be strong if the absolute value of the correlation coefficient is at least 0.5 [27] or 0.7 [26].

The set of correlations $\{C^h\}$ and their significance were calculated using *Python's* module *scipy.stats.spearmanr* for each h value, so that for each type of mobility there were as many correlation coefficients as the h elements used. After that the largest correlation was identified from the absolute value of the significant correlation coefficients (at the 5% level). According to the *Pdt* or *Ccf* concept, at the time lag h where the maximum of $\{|C^h|\}$ is obtained, $\bar{M}^h$ and R' have the best similarity or the largest correlation. The *h* value which gives the maximum correlation was defined as *Rdt*.

QUADRANT ANALYSIS FRAMEWORK

The *Rdt* shows the time lag (in days) of *M* that has the highest correlation with *R'*. If the concept of a causal relationship between two events is closely related to the time of occurrence of the two events, then *Rdt* can be used to know the causal relationship between M and R'. A negative *Rdt* indicates a backward relationship and means that M is the cause of the emergence of R'. The backward relationship can be expressed as a function:

$$R'_t = f(\bar{M}^h) = f(\bar{M}_{t-h}). \quad (2)$$

On the other hand, a positive *Rdt* indicates a forward relationship, i.e. M occur as a community's response to information of R' and can be expressed as a function:

$$\bar{M}_t = f(R'_{t-h}) \text{ or } \bar{M}^h = \bar{M}_{t+h} = f(R'_t). \quad (3)$$

The subscript *t* in equation (2) or (3) indicates the release date of R', and the subscript *h* refers to *Rdt*. In equation (2) $\bar{M}^h$ can be called the lead variable for R' because $\bar{M}^h$ appears before R', while in equation (3) $\bar{M}^h$ is the lag variable for R' because $\bar{M}^h$ occurs after R' [22].

Exploration is then carried out visually using a scatter plot between *Rdt* and its corresponding absolute correlation coefficient to form a quadrant analysis. Several previous studies used quadrant analysis to analyze the impact of COVID-19 on the economy [28], public health [29] [30], and the development of human knowledge about the COVID-19 pandemic [17]. The quadrant analysis approach in this paper can be regarded as a new contribution that discusses the relationship between community mobility and the spread of COVID-19. This approach can be used as a more careful policy evaluation tool to complement the information on COVID-19 Risk Zone Map that has been carried out by the Indonesian COVID-19 Handling Task Force.

Before the pandemic, people's mobility should not be associated with the spread of COVID-19. Therefore, during the pandemic, a weak correlation between $\bar{M}^h$ and R' may be an indication of recovery condition. On the other hand, a strong correlation is an indication that the condition of the community is still not recovering. Based on this logical thinking, this paper took the absolute value of the correlation coefficient and used a value of 0.5 as the boundary between weak and strong correlations. The possible positions of *Rdt* for each mobility type and their corresponding absolute correlation coefficients on the scatter plot form four quadrants as shown in Figure 2.

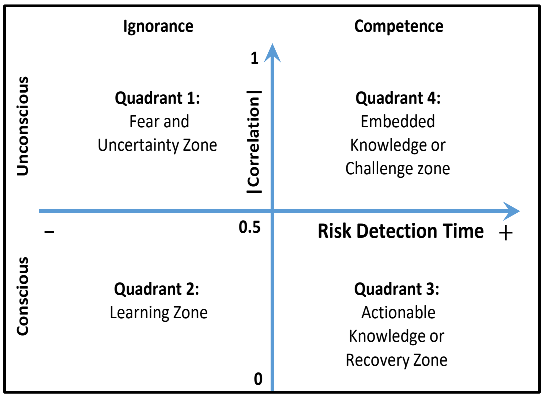

Figure 2. Mobility-COVID-19 Impact Quadrant

The quadrants generated in this paper are relevant to the "conscious-competence" quadrant matrix framework. Previous research used the same framework to qualitatively describe the process of developing public knowledge about COVID-19 [17]. This paper complements the research with a quantitative approach to analyze the dynamics of community's response to the COVID-19 pandemic.

Referring to the framework, the horizontal axis shows the level of community's competence regarding the risk of spreading COVID-19 which is divided into two categories, namely *Ignorance* and *Competence*. This axis is relevant to *Rdt*. Quadrant 1 or 2, which has negative *Rdt*, inform the dynamics of community mobility which have implications for the risk of spreading COVID-19. This condition occurs due to people's ignorance that their mobility can cause the spread of COVID-19 to be more widespread [13] [22]. These two quadrants are visualizations of equation (2) which informs that the risk of spreading COVID-19 at time *t* is the cumulative impact of mobility over the previous *Rdt* days. On the other hand, Quadrant 3 or 4, which has positive *Rdt*, describes the public's response to information on the risk of spreading COVID-19. These two quadrants are visualizations of equation (3) where information on the risk of spreading COVID-19 published on day *t* is responded in the form of accumulation of mobility from day *t* up to *Rdt* days later. If community mobility describes the state of the economy [31][32][33], then in this situation the smaller the *Rdt* value, the faster the economy changes.

Meanwhile, the vertical axis shows the level of public awareness of the risk of spreading COVID-19 which is divided into two categories: *Conscious* and *Unconscious*. This axis is relevant to the correlation coefficient between $\bar{M}^h$ and R' where unconscious and conscious states are associated with strong and weak correlations, respectively. Furthermore, the characteristics of each quadrant can be explained as follows:

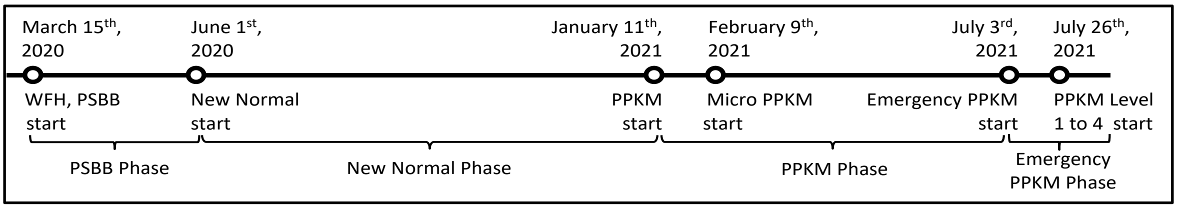

Figure 3. Policy phases for handling the COVID-19 pandemic in Indonesia

1. Quadrant 1: Fear and Uncertainty Zone

This quadrant shows the condition of people's ignorance about the risk of spreading COVID-19 and not yet realizing that their mobility will have an impact on the risk of spreading COVID-19. This condition is relevant to the early days of the pandemic where the community and stakeholders do not have much knowledge about COVID-19 [17].

2. Quadrant 2: The Learning Zone

In this quadrant, people begin to learn about the spread of COVID-19 and are aware that a COVID-19 pandemic has happened. Public and stakeholder knowledge about the risk of spreading COVID-19 has begun to develop—shown by the large number of studies related to the impact of the spread of COVID-19 [17]. The government has begun to increase public awareness through various programs to control the spread of COVID-19 [11].

3. Quadrant 3: Actionable Knowledge or Recovery Zone

This quadrant shows the condition of the community who already have sufficient knowledge and concern about the risk of spreading COVID-19. In this zone, it is hoped that mobility control by the government will be effective because the community has the competence to respond to information related to the risk of spreading COVID-19. Therefore, this zone may represent a signal of recovery from the COVID-19 pandemic.

4. Quadrant 4: Embedded Knowledge or Challenge Zone

Conditions in this zone are opposite to quadrant 2. The community already has the competence but it is not accompanied by sufficient awareness to prevent the spread of COVID-19. So that the existing competencies do not guarantee the achievement of recovery conditions due to lack of public awareness of the risk of spreading COVID-19. A competent government must continue to make efforts to raise public awareness so that recovery conditions can be achieved.

POLICIES FOR HANDLING THE COVID-19 PANDEMIC IN INDONESIA

The policies to reduce the spread of COVID-19 in Indonesia can be divided into four phases as shown in Figure 3, namely:

1. PSBB Phase: 15th March – 31st May 2020

At the beginning of the pandemic, the President of the Republic of Indonesia through a press release delivered on 15th March 2020 appealed to start doing work, study and worship activities from home [34]. The appeal was followed up with regulations regarding work from home [35][36], distance learning [37][38], and the implementation of restrictions on community mobility in general through the Large-Scale Social Restriction (PSBB) policy [39][40][41].

2. New Normal Phase: 1st June 2020 – 10th January 2021

After observing the development of public health conditions and the declining economy, the Indonesian government prepared a health protocol to accelerate the handling of COVID-19 in health and socio-economic aspects [42][43]. The health protocol is prepared to enter a phase called the Adaptation of New Habits (New Normal) starting on 1st June 2020 [42][44]. In this phase, activity restrictions have begun to be relaxed, several public facilities have been opened [45] and office activities have been activated up to a maximum of 100% according to the risk zone of the office area [46][47].

3. PPKM Phase: 11th January – 8th February 2021

About six months after the implementation of the New Normal policy, public health conditions have not shown any improvement, even the curve of the daily number of positive COVID-19 cases until January 2021 continues to increase rapidly (https://covid19.go.id/peta-sebarancovid19). Therefore, the government has again implemented more stringent restrictions on community mobility, known as the Enforcement of Community Activity Restrictions (PPKM) [48]. The PPKM policy has been in effect since 11th January 2021 in the Java-Bali region [49] whose condition still have not improved [50][51]. The PPKM policy was then continued on a smaller regional scale named Micro PPKM in all regions of Indonesia from 9 February 2021 [52].

4. Emergency PPKM Phase: Starting 3rd July 2021

To suppress a surge of cases Covid-19, the Indonesian government has once again imposed restrictions on the mobility of people that are more stringent than the previous policy. The mobility restrictions are named: Emergency PPKM in Java and Bali (enacted 3-25 July 2021), and PPKM Level 1 to 4 throughout Indonesia (enacted from 26 July) [53][54][52].

THE ANALYSIS RESULTS

The above policy phases form the basis of the analysis in this paper. Based on the available series span used, the number of weeks according to PSBB, New Normal, PPKM, and Emergency PPKM Phases are 12, 31, 24, and 7 respectively—not statistically sufficient to explain the relationship between variables at the Indonesian national level. Therefore, for each phase this paper used the merged weekly series data of $\bar{M}^h$ and R' from 34 provinces in Indonesia as a pooled cross-sectional data [55] [56] to determine *Rdt*. The analysis aims to explore the community's response to the pandemic conditions related to the above policy phases.

1. Overview of Community Mobility During the COVID-19 Pandemic

Figure 4 explains the attitude of the Indonesian people in dealing with the COVID-19 pandemic.

At the beginning of each phase of mobility restriction, *outward mobility* decreases drastically, but over time the mobility began to move up to baseline measurements (normal conditions). Although during the pandemic the average *outward mobility* is still below the normal conditions level, the mobility tends to increase. At the end of the New Normal and PPKM phases, mobility to several places was even above normal conditions.

The opposite condition occurs in *residential mobility*. At the beginning of the pandemic, people tended to stay at home longer than the duration of staying at home

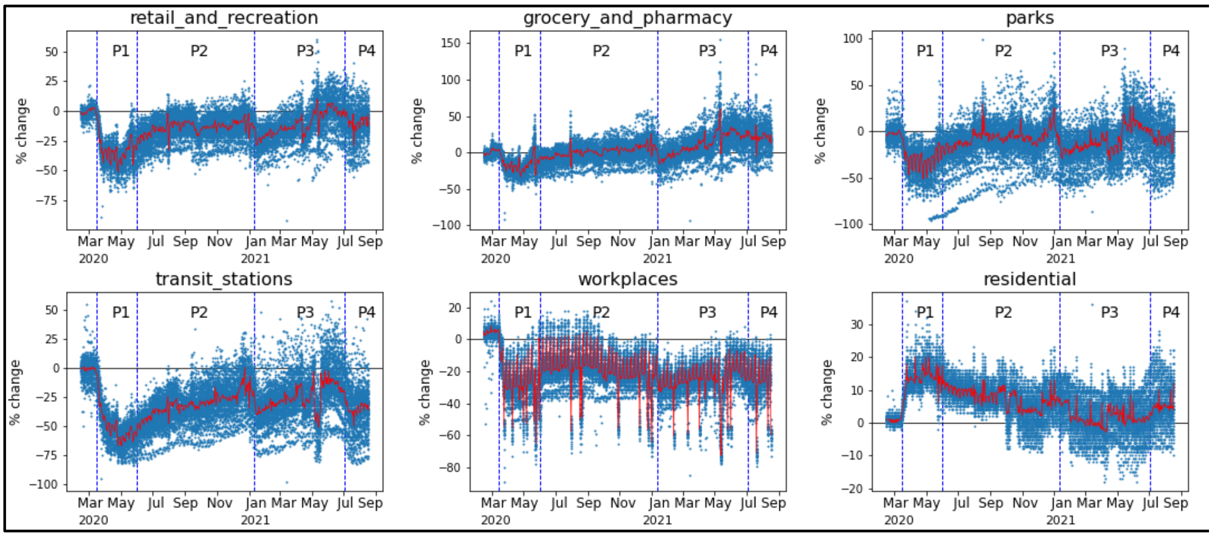

Figure 4. Google Mobility Index

Note: The red graph shows the median value. The vertical dotted lines indicate the start of the mobility restriction phases, i.e. P1 = PSBB phase, P2 = New Normal phase, P3 = PPKM phase, P4 = Emergency PPKM phase.

under normal conditions. Over time the duration of staying at home tends to decrease, even in the last period the duration in some provinces is lower than normal conditions. However, the average *residential mobility* during the pandemic is still above normal conditions.

Overall, it can be concluded that during the pandemic, *outward mobility* tends to increase and *residential mobility* tends to decrease.

2. Overview of Public Health Conditions During the COVID-19 Pandemic

Figure 5 depicts the dynamic of public health conditions which from the beginning of the pandemic until the end of the New Normal Phase were overshadowed by the increasing risk of spreading COVID-19. The mobility restrictions imposed by the Indonesian government in the PPKM Phase appear to be an anticipatory measure to reduce the increased risk. Looking at Figure 5, the policies taken by the government appear to be successful in the early stages of the PPKM Phase where the risk chart shows a downward trend. However, after two months running, the risk chart begins to show an increasing trend towards the end of the period under study.

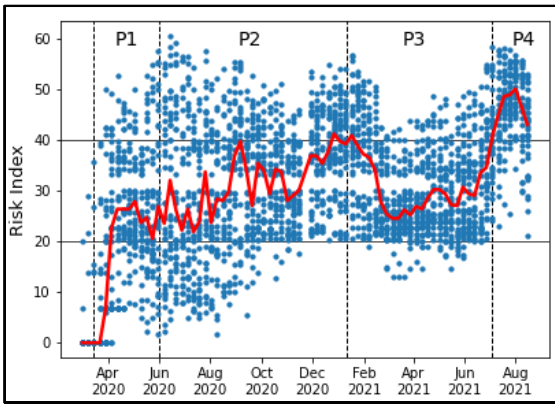

Figure 5. Risk Index for the Spread of COVID-19 in Indonesia

Note: The red graph shows the median value. The vertical dotted line indicates the start of the phase of the implementation of the restriction on community mobility. P1 = PSBB phase, P2 = New Normal phase, P3 = PPKM phase, P4 = Emergency PPKM phase

Overall, public health conditions during the pandemic are very diverse, where there are areas with low, medium, and high risk. Although the overall picture shows a trend of increased risk and some areas are at high risk, on average the public health condition is at medium risk.

3. The Association Between Community Mobility and the Risk of Spreading COVID-19

Relating mobility to the risk of spreading COVID-19, the previous subsections implicitly show that *outward mobility* is in line with the risk, while *residential mobility* is opposite to the risk. In other words, high *outward mobility* leads to high risk, and conversely the risk is reduced by staying at residential longer. However, this information is still not sufficient to be used as a basis for decision making, especially regarding restrictions on mobility. Further information—described in the following subsections—such as how strong the relationship is, how quickly the impact of the relationship will be, whether mobility impacts on risk or otherwise is mobility affected by risk, will be more useful to decision makers.

4. Determination of Rdt

Rdt determination is the most important step in this paper. The value of *Rdt* depends on the time lag of *M*, while the number of lag (h) depends on the number of data studied. To maintain the validity of the calculation results, the value of h should not exceed the time span of the variable under study. Therefore, for each policy phase this paper used different interval of h, namely: ($-29 \leq h \leq 150$) for PSBB phase, ($-107 \leq h \leq 150$) for New Normal phase, ($-150 \leq h \leq 150$) for PPKM phase, and ($-150 \leq h \leq 45$) for Emergency PPKM phase. Using the algorithm described in Figure 1, for each value of h in all phases, the weekly series of risk and cumulative moving average of mobility are first differenced to meet the stationarity assumption. The resulted correlation coefficients are depicted in a cross-correlogram in Figure 6.

The *Rdt* for each type of mobility, i.e. the optimum value of the correlation coefficient, lies in the blue shaded regions of Figure 6. The *Rdt* figures show interesting results where *outward mobility* has a negative correlation, while *residential mobility* is positively correlated with *risk*. The results logically explain how the community has responded to the COVID-19 pandemic. The increased risk is overcome by reducing *outward mobility* and diverting it with more residential activities so that *residential mobility* increases (hereinafter referred to as *Condition 1*). On the other hand, the increase *outward mobility* occurred because people feel that conditions outside their residential are of low risk, so that

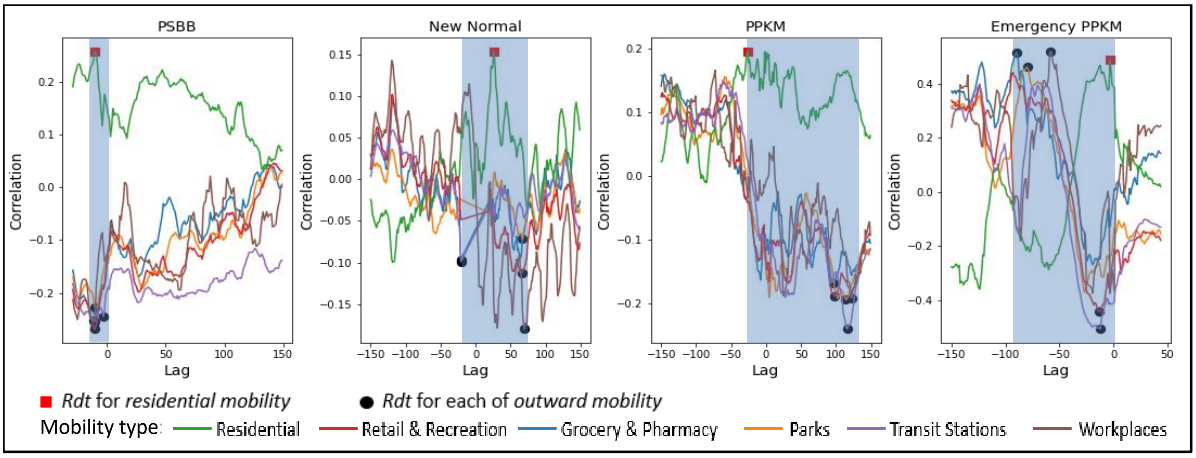

Figure 6. Cross-correlogram of Mobility versus Risk by Mobility Restriction Phase

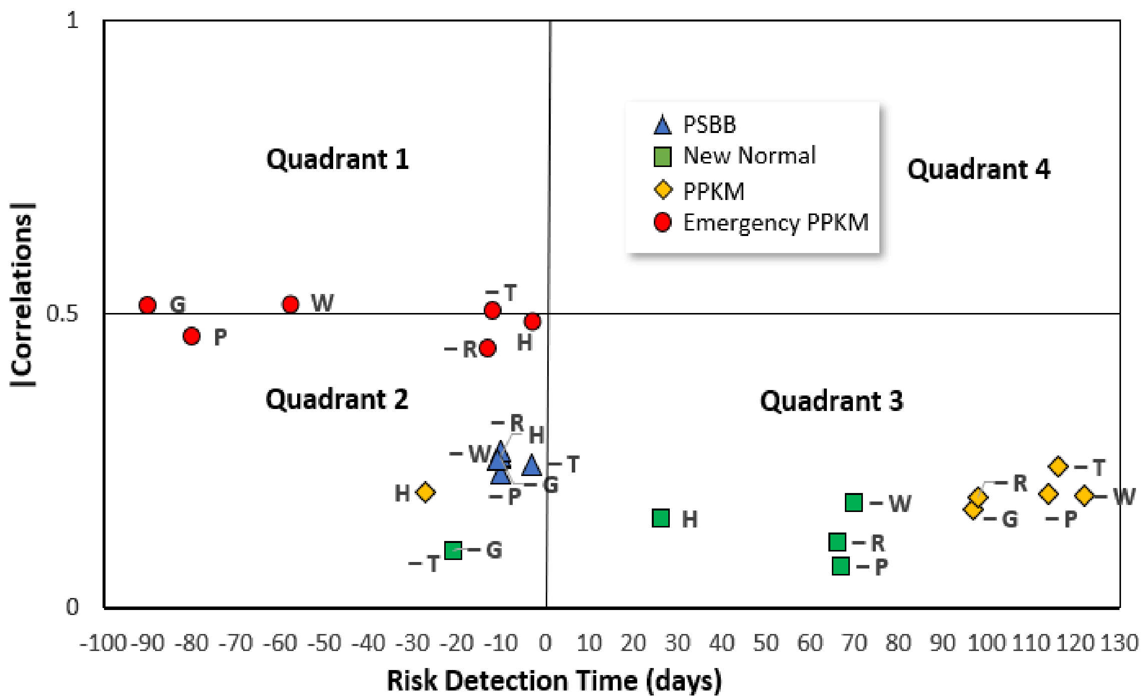

Figure 7. Mobility-COVID-19 Impact Quadrant

Note:

The data labels indicating the initial of mobility type, i.e.:

H = residential, P = parks, G = grocery and pharmacy,

R = retail and recreation, T = transit stations, W = workplaces.

A negative sign in front of the initial represents a negative correlation.

residential mobility decreases (hereinafter referred to as *Condition 2*).

The *Rdt* figures also indicate the different attitudes taken by the community in each phase. Referring to equation (2) and (3), the negative *Rdt* in PSBB and Emergency PPKM phases confirmed the first premise that mobility has an impact on the spread of COVID-19, while the positive *Rdt* in New Normal and PPKM phases confirmed the second premise that mobility is affected by the spread of COVID-19. Plot of *Rdt* in Figure 7 explains further both premises regarding the association between mobility and risk of spreading COVID-19.

5. Mobility-COVID-19 Impact Quadrant

Figure 7 describes the dynamics of the community's response to Covid-19 during pandemic. In the first phase of mobility restriction (PSBB), people experienced how to survive by learning by doing due to lack of information about COVID-19 while the government tried to increase knowledge about the nature of COVID-19 and invited stakeholders to jointly overcome the spread of Covid-19 [34] [35] [37]. The *Rdt* value which ranges from -3 (at transit stations) to -11 (at workplaces) means the risk in this phase is triggered by mobility in the previous three to eleven days.

Except for mobility at transit stations and grocery and pharmacies which are still in Quadrant 2, the community's response has developed to Quadrant 3 in the New Normal phase. The government decision to start the New Normal Phase shows a leap towards a recovery condition that forces the public to be aware and concerned about the pandemic situations and conditions [11]. The implementation of the New Habit Adaptation program determined by the government corroborates the community's decision to remain in *Condition 2*, especially at transit stations or grocery stores and pharmacies where people fulfill their daily needs. The positive *Rdt* value indicates the success of the program, but community responses tend to be late when compared to the lag time of the impact of mobility on risk. The *Rdt* values which range from 66 to 70 means that only after about two months from the establishment of the recovery program, *outward mobility* started to slow down (around July or August 2020 as shown in Figure 4). However, the slowdown in *outward mobility* has not been accompanied by an increase in *residential mobility* (instead Figure 4 shows the downward trend in *residential mobility* from July to December 2020). In addition, various violations of health protocols also occurred in this phase [57]. So, it can be said that the implementation of the mobility restriction in the New Normal Phase has not reached the recovery target as expected.

Furthermore, taking into account the risks that continued to increase during the New Normal Phase, the government began to reimpose mobility restrictions in the PPKM Phase. In this phase, the *Rdt* values of *outward mobility* still in Quadrant 3. The implementation of the mobility restrictions resulted in a temporary drastic reduction in *outward mobility*, namely at the beginning of the PPKM Phase and when the homecoming ban was imposed in May [58]. Shortly after that *outward mobility* increased again. Therefore, this situation needs special attention from policy makers because the community tended to choose to remain in *Condition 2* where *outward mobility* tends to increase and is accompanied by a decrease in *residential mobility*. Although at the beginning of the PPKM Phase there was a reduction in risk, changes in mobility tended to be difficult to control. The *Rdt* value ranging from 97 to 122 indicates that the PPKM policy only received a significant response after 3 to 4 months since it was implemented. Based on the timeline, the PPKM effect appears around April or May which is the fasting month.

After that, the *Rdt* values in Emergency PPKM phase reflects an atmosphere of “fear and uncertainty” due to the lack of information and knowledge of the community and stakeholders regarding the nature of COVID-19 [59][60][61]. This reflection can be seen from mobility at Grocery and Pharmacy, Workplaces, and

Transit Stations which are located in Quadrant 1. The *Rdt* values of *outward mobility* which range from -58 (at workplaces) to -90 (at grocery and pharmacy) mean the risk in this phase is triggered by mobility in the previous two weeks up to three months before. Based on the timeline, the increased risk is triggered by mobility in grocery and pharmacies (about 2 months earlier) and workplaces (about 3 months earlier) i.e., in April-May 2021, after the fasting month.

CONCLUSION

Two research premises regarding whether mobility is affected by the spread of COVID-19 or instead mobility impacts on the spread of COVID-19 have been answered in this paper by analyzing community's response to the COVID-19 pandemic. The analysis results concluded that both premises are valid. Using the optimal correlation between mobility and the risk of spreading COVID-19, called *Risk Determination Time* (*Rdt*), it is known that the risk of spreading COVID-19 can be triggered by mobility in the previous few days (first premise), or mobility can represent the community’s responses to information about the risk in the previous few days (second premise). The analysis also found that community responded to the pandemic under two conditions: (1) high risk is overcome by reducing *outward mobility* and shifting it to more residential activities, and (2) high *outward mobility* occurs because people perceive outward conditions as low risk, resulting in reduced *residential mobility*.

Further exploration using quadrant analysis framework, referred to as Mobility-COVID-19 Impact Quadrant, shows that the community responded the pandemic as learning phase in the PSBB period (15 March to 31 May 2020). After that, the government's policy in the New Normal period (1 June 2020 to 10 January 2021) and PPKM period (11 January to 2 July 2021) showed a leap towards recovering from the pandemic. However, the community was late to respond to the recovery program and the situation was exacerbated by the emergence of health protocol violations. This situation brings the community in the next period (Emergency PPKM phase, starting from 2 July 2021) to a worse condition.

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