Economics and Finance in Indonesia

Volume 67
Number 1 *June 2021*

Article 9

4-16-2021

Mobility Pattern Changes in Indonesia in Response to COVID-19

Setia Pramana
Politeknik Statistika STIS, Indonesia, setia.pramana@stis.ac.id

Yuniarti Yuniarti
Directorate of Statistical Analysis and Development, BPS-Statistics Indonesia, yuna@bps.go.id

Dede Yoga Paramartha
Directorate of Statistical Analysis and Development, BPS-Statistics Indonesia, paramartha.yoga@bps.go.id

Satria Bagus Panuntun
Directorate of Statistical Analysis and Development, BPS-Statistics Indonesia, satria.bagus@bps.go.id

Recommended Citation

Pramana, Setia; Yuniarti, Yuniarti; Paramartha, Dede Yoga; and Panuntun, Satria Bagus (2021) "Mobility Pattern Changes in Indonesia in Response to COVID-19," *Economics and Finance in Indonesia*: Vol. 67: No. 1, Article 9.
DOI: http://dx.doi.org/10.47291/efi.v67i1.924
Available at: https://scholarhub.ui.ac.id/efi/vol67/iss1/9

Economics and Finance in Indonesia
Vol. 67 No. 1, June 2021 : 75–96
p-ISSN 0126-155X; e-ISSN 2442-9260

Mobility Pattern Changes in Indonesia in Response to COVID-19

Setia Pramana[a,b,*], Yuniarti[b], Dede Yoga Paramartha[b], and Satria Bagus Panuntun[b]

[a] *Politeknik Statistika STIS, Indonesia*
[b] *Directorate of Statistical Analysis and Development, BPS-Statistics Indonesia*

Manuscript Received: 14 December 2020; Revised: 4 April 2021; Accepted: 16 April 2021

Abstract

All countries affected by the COVID-19 pandemic have established several policies to control the spread of the disease. The government of Indonesia has enforced a work-from-home policy and large-scale social restrictions in most regions that result in the changes in community mobility in various categories of places. This study aims to (1) investigate the impact of large-scale restrictions on provincial-level mobility in Indonesia, (2) categorize provinces based on mobility patterns, and (3) investigate regional socio-economic characteristics that may lead to different mobility patterns. This study utilized Provincial-level Google Mobility Index, Flight data scraped from daily web, and regional characteristics (e.g., poverty rate, percentages of informal workers). A Dynamic Time Warping method was employed to investigate the clusters of mobility. The study shows an intense trade-off of mobility pattern between residential areas and public areas. In general, during the first 2.5 months of the pandemic, people had reduced their activities in public areas and preferred to stay at home. Meanwhile, provinces have different mobility patterns from each other during the period of the large-scale restrictions. The differences in mobility are mainly led by the percentage of formal workers in each region.

Keywords: COVID-19; time series clustering; large-scale social restrictions; Google Mobility Index; community mobility; Indonesia

JEL classifications: A11; C38; J6; R11

1. Introduction

The declaration of the new outbreak of COVID-19 as a global pandemic by World Health Organization (WHO 2020) has affected the whole world, not only in terms of public health, but also economy and other aspects. Globally, as of 10:34 am CEST, July 29, 2020, there had been 16,523,815 confirmed cases including 655,112 deaths reported to WHO. COVID-19 affects 213 countries and territories around the world.

In Indonesia, the government announced the first case of the corona virus in early March 2020. According to the COVID-19 National Task Force of Indonesia, up to July 29, 2020, there were 4,975 people died, 62,138 people recovered, and 104,432 cases confirmed (the COVID-19 National Task Force, 2020). All 34 provinces have been affected and reporting confirmed cases and deaths. The province with the highest number of confirmed cases of COVID-19 is East Java (21,125 cases (20.7%)), followed by Jakarta (19,995 cases (19.6%)) and South Sulawesi (9,123 cases (8.9%)) (The COVID-19 National Task Force 2020).

The COVID-19 pandemic has led to the disruption to worldwide activities and forced the citizens to stay at home. All the affected countries have implemented several policies to contain the spread of the disease while maintaining their economic conditions. The most common policy is to reduce mobility in public places by imposing a full lockdown or semi lockdown policy. However, the lockdown policies to decrease the spread of COVID-19 have led to nearly no social and economic activities.

COVID-19 has changed the mobility of people around the world. By utilizing large-scale smart-

*Corresponding Address: Politeknik Statistika STIS, Jln. Otista 64C Jakarta 13330. Email: setia.pramana@stis.ac.id.

phone location-derived aggregated mobility data, Gao et al. (2020) report that human mobility changes across the United States during the first months of the pandemic. In addition, Linka et al. (2020) discuss travel restrictions in Europe in response to COVID-19. Saha, Barman & Chouhan (2020) show major changes in mobility trends of people over time prior to and subsequent to lockdown across different categories of places such as retail stores, groceries, parks, stations, workplaces, and residential areas. In Italy, a significant reduction in mobility is reported following the lockdown ordinance by -42% (Cartenì, Di Francesco, & Martino 2020).

The government of Indonesia had enforced a work-from-home policy for all government employees starting from March 17, 2020 (the Ministry of Administrative and Bureaucratic Reform 2020a). Starting from June 5, 2020, the government employees could may both from home and at the offices (the Ministry of Administrative and Bureaucratic Reform 2020b). However, Indonesia did not impose a full lockdown as other countries such as India. The local governments can enforce large-scale social restrictions (PSBB) based on the COVID-19 situation in the respective region. Most of the regions in Indonesia implemented this policy, even though the starting and duration of the restrictions were different across regions. The first COVID-19 Epicenter, namely Jakarta, started PSBB from April 10, 2020 until the end of July. All satellite districts around Jakarta then also implemented PSBB. South Tangerang have started PSBB from April 18, 2020, while Bogor, Depok, and Bekasi from April 15, 2020.

The restrictions results in changes in community mobility in various categories of places, including residential areas, workplaces, groceries, retail stores, parks, and transit stations in Indonesia. Furthermore, to prevent the disease transmission among regions, the government of Indonesia had closed the borders and suspended the bus, train, and flight services. The number of flights across Indonesia had been also reduced significantly to stop the spread of the disease.

People in several regions seem to respond to the large-scale social restrictions by the government differently. These differences may be caused by the number of positive cases and the socio-economic characteristics of the region.

This study aims to (1) investigate the impact of policies on work from home and large-scale restrictions on provincial-level mobility in Indonesia and the number of flights between regions, (2) categorize provinces based on mobility patterns, and (3) investigate regional socio-economic characteristics that may lead to different mobility patterns during work-from-home period and large-scale social restrictions period.

This study provides new insight and literature in terms of changes in population mobility during the COVID-19 pandemic in Indonesia and the factors driving the differences in mobility patterns. These findings will be significantly relevant to the current condition and become a reference material in the future. In addition, this study also provides insight from the use of existing data as well as the conditions of several regions during the pandemic in an effort to formulate policies.

2. Literature Review

People mobility analysis is usually related to urban planning programs, such as the development of green areas to improve wellbeing (Ferrara et al. 2018) and studies of travel demand to provide a better transportation system (Demissie et al. 2019). Human mobility also contributes to disease transmission, as mentioned by Findlater & Bogoch (2018) that greater human mobility will lead to the increase in the frequency of infection as well as the range of spread. During the COVID-19 pandemic, community mobility patterns become considerably important to be investigated accordingly. They will assist in informing national and regional authorities in promoting acceleration projects to stop the outbreak.

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

According to Jiang et al. (2017), mobility behavior can be captured simply using location-awareness devices, such as smartphones and GPS-enabled devices. These means of communication can provide geographical position and even social connection that will enable researchers to conduct comprehensive studies of the movement of the community in the targeted locations (Ebrahimpour et al. 2020). Google has utilized this advanced technology responsively to present reports on community mobility in response to the COVID-19 pandemic. People who have Google Account and activate their location history setting are selected as the objects of the studies of mobility.

Referring to a study by Moritz et al. (2020) regarding the effects of human mobility on controlling the COVID-19 pandemic in China, this study generates several basic assumptions. The ongoing spread of the pandemic can be controlled indirectly provided that mobility can be controlled. This is due to the characteristic of the COVID-19 virus that spreads rapidly through massive contact. In the areas outside of Wuhan where protocol tightening is still lacking, there remains an increase in the number of cases. This underlies the initial assumption about the effect of the pandemic on mobility in the affected areas. The change in mobility is none other than the result of the response to handling COVID-19.

Referring to a research on population mobility by MacPherson et al. (2009), it is concluded that limiting mobility and also the effects of globalization that facilitates mobility from time to time can control the existence of criminal acts or even the spread of disease. The limitation in this research refers to restricting population mobility to form resistance to drugs.

In fact, mobility is also affected by the characteristics of the area. Referring to a research by McGrath (2020), population mobility proxied through Google Mobility is one of the supplements to existing economic indicators. This supplement can be a support for data series or data for each region. Thus, this will lead to a different response regarding the mobility restriction policy implemented. The differences in regional characteristics will certainly result in the differences in the response to the pandemic.

Based on ASEAN policy brief (2020), the COVID-19 pandemic has disrupted economic activities and upended lives, reducing growth prospects worldwide. The AMS has launched various measures to counter the effects of the pandemic across the region, including stimulus measures such as tax breaks, subsidies including targeted support and cash assistance, and moratoriums on loan payments and pension contributions. Central banks have also lowered interest rates, reduced reserve requirements, and purchased government bonds. The pandemic may lead to long-term and considerable economic implications.

In a study by Pramana et al. (2020), there are also signs of a decrease in the level of mobility at several regional points in Indonesia. This decrease is based on a significant reduction in pollution levels at the beginning of March 2020. This is also based on the contribution of motorized vehicles to the air quality of an area. These signs are also an indirect response to the ongoing pandemic conditions.

3. Method

3.1. Data Source of the Study

The data in this study were collected from different sources. To study the mobility of people, Google Mobility Index was applied. The number of confirmed cases of COVID-19 was obtained from the COVID-19 National Task Force of Indonesia. Regarding regional characteristics, the study utilized the following variables obtained from Statistics Indonesia (BPS): poverty rate, unemployment rate of informal workers, Human Development Index, and regional GDP. The following section shall briefly describes these variables. Meanwhile, based on data availability the levels studied in the analysis are national and provincial levels.

3.1.1. Google Mobility Index

Google supplies users with a regularly updated global mobility dataset accessible at https://www.google.com/covid19/mobility/. In collecting data, Google Mobility Index uses tags given by mobile phone users. This report is generated with an anonymized and aggregated dataset from users who have the Location History setting turned on (it is off by default). This figure represents changes in percentage over time people visit (or time spent in) different categories of places compared to baseline days. This regularly updated dataset shows the changes in the movement of people during the pandemic.

Based on the similarities of characteristics adhering to the purpose of social distancing, Google has grouped the visited places into 6 categories as follows: (1) workplaces; (2) residential areas; (3) retail shops and recreational areas, including restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters; (4) grocery stores and pharmacies, including grocery markets, food warehouses, farmer's markets, specialty food stores, and drug stores; (5) parks, including national parks, public beaches, marinas, dog parks, plazas, and public gardens; and (6) transit stations, including public transport hubs such as subway, bus, and train stations.

Baseline days consist of 7 individual values representing normal mobility on every single day of the week. The baseline days are constructed using the median values of the mobility of people from January 3 to February 6, 2020, by eliminating seasonal effects. It should be taken into consideration that the same number of visits on two different days can result in different percentages. Therefore, comparing day-to-day changes should be avoided.

This study utilized Google Mobility Index of all 34 provinces in Indonesia from February 15 to June 30, 2020. It is available in the public domain (https://www.google.com/covid19/mobility/).

3.1.2. Flight Data

Flight data were collected using the web scraping method from the Flight status site. The web scraping (Mahto & Singh 2016) was employed using the Scrapy library (Kouzis-Loukas 2016) in the Python programming language. The data were collected daily by collecting flight data on the previous day as the site stores a history of flight data for the previous three days. The data of the previous day were collected to ensure that the status of the captured flight data remains the final status of the flight, for example arriving or canceled (Panuntun & Pramana 2021).

3.1.3. Poverty

Head Count Index (HCI-P0) is the percentage of the population below the Poverty Line. Poverty Line is the sum of the Food Poverty Line (FPL) and Non-Food Poverty Line (NFPL). Residents who have an average per capita expenditure per month below the Poverty Line are categorized as poor people. The poverty level used in this study was the latest poverty level of March 2020.

3.1.4. Unemployment Rate

The unemployment rate is the percentage of unemployment in the total labor force. The unemployed consist of: those who do not have a job and are looking for a job, those who do not have a job and are preparing for a business, those who do not have a job and are not looking for a job because they feel it is impossible to obtain a job, or those who already have a job but have not started working. The unemployment rate used in the study was the unemployment rate of February 2020.

3.1.5. Regional GDP

Gross Regional Domestic Product at market price is the total gross value added arising from all economic sectors in a region. Value added is a combination of factors of production and raw materials in

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

the production process. The value added is calculated by subtracting the intermediate costs from the value of production (output). Gross value added in this regard includes factors of income (wages and salaries, interest, land rent and profits), depreciation, and net indirect taxes. Thus, by adding up the gross value added of each sector and adding up the gross value added of all these sectors, a Gross Regional Domestic Product will be obtained at the market price. This study used the Q1 Regional GDP.

3.1.6. Human Development Index (HDI)

HDI explains how residents can access the results of development in obtaining income, health, education, and others. The index was introduced by the United Nations Development Program (UNDP) in 1990 and is published regularly in the annual Human Development Report (HDR). HDI is formed by three basic dimensions: Long and healthy life, Knowledge, and Decent standard of living. The analysis was based on the 2019 HDI.

3.1.7. Formal Worker Rate

Formal workers include those conducting business with the assistance of permanent workers and laborers/employees, while the rest are included as informal workers. Currently, BPS determines the population working in the formal/informal sector based on the status of their main occupation. The formal worker rate is the percentage of the number of formal workers to total workers. This study used the formal worker rate of September 2019.

3.2. Data Analysis

An exploratory data analysis was used to obtain an insight into the movement of the people of Indonesia before, during, and after work-from-home period and large-scale social restrictions. The work-from-home (WFH) policy for all government employees started from March 17 to May 31, 2020. Meanwhile, study-from-home policy for all students started from March 17 to an unspecified time.

Even though the WFH policy for public services is defined by the central government, local governments can regulate their policies on social restrictions. Moreover, as provinces in Indonesia are quite diverse in terms of area and socio-economic situations, the response of the people to pandemic may be different, leading to different mobility patterns.

3.2.1. The Differences in Residential Areas

To observe how people tend to stay at home, we calculated the difference between the average Google Mobility Index during WFH period (March 17–June 31, 2020) and before WFH period (February 15–March 16, 2020).

3.2.2. Average Positive Cases of COVID-19 per Day

Changes in the number of confirmed cases of COVID-19 are the average number of positive cases added per day from a region i in the span of time n:

$$\mathrm{avg.positive.perday_i} = \sum_{\mathrm{j=1}}^{\mathrm{n}} \frac{\mathrm{positive_{i,j+1}} - \mathrm{positive_{i,j}}}{\mathrm{n}}. \tag{1}$$

3.2.3. Dynamic Time Warping Clustering

To investigate these differences, a time series clustering was implemented. Dynamic time warping (DTW) is one of the algorithms in time series analysis to measure the similarity between two temporal sequences. For example, the similarity in the driving pattern can be detected by using DTW, even if one person drives faster than another, or if there is acceleration and deceleration during observation. In general, DTW is a method that calculates an optimal match between two given sequences (ex: time series) with the following restrictions and rules:

- Each index of the first sequence must be matched with one or more indices from the other sequence, and vice versa

- The first index of the first sequence must be matched with the first index from the other sequence (but not necessarily the only match)
- The last index of the first sequence must be matched with the last index from the other sequence (but not necessarily the only match)
- The mapping of the indices from the first sequence to the indices from the other sequence must increase monotonically, and vice versa, i.e., if $\mathbf{j} > \mathbf{i}$ is the index of the first sequence, then there should not be two indices $\mathbf{l} > \mathbf{k}$ in another sequence, thus index $\mathbf{i}$ is matched with index $\mathbf{l}$ and index $\mathbf{j}$ is matched with index $\mathbf{k}$, and vice versa.

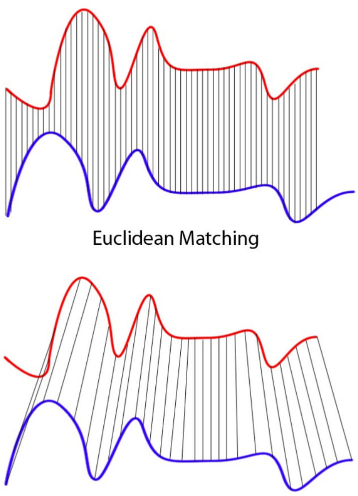

Figure 1. Euclidean Matching and Dynamic Time Warping Matching

Figure 1 illustrates the difference between Euclidian matching and Dynamic Time Warping (DTW) matching. It is evident that these two series follow the same pattern, but the blue curve is longer than the red. The Euclidian matching (one-to-one matching) is not perfectly synced and the tail of the blue curve is being left out. Meanwhile, DTW overcomes the issue by developing a one-to-many match, allowing the troughs and peaks with the same pattern to be perfectly matched, and there is no left out for both curves.

When determining the DTW distance between two-time series, first an $(\mathrm{n} \times \mathrm{m})$ local cost matrix (LCM) is calculated, where the elements (i, j) contain the distance between $\mathrm{x_i}$ and $\mathrm{y_j}$. This distance is usually defined as the quadratic difference: $\mathrm{d}(\mathrm{x_i}, \mathrm{y_j}) = (\mathrm{x_i} - \mathrm{y_j})^2$. Next, a warping path $\mathrm{W} = \mathrm{w_1}, \mathrm{w_2}, \dots, \mathrm{w_k}$ is determined, where $\max(\mathrm{n}, \mathrm{m}) \leq \mathrm{K} \leq \mathrm{m}+\mathrm{n}-1$. This path traverses the LCM under three constraints:

- Boundary condition: The path must start and end at the diagonal corners of the $\mathrm{LCM} : \mathrm{w_1} = (1, 1)$ and $\mathrm{w_k} = (\mathrm{n}, \mathrm{m})$
- Continuity: Only adjacent elements in the matrix are allowed for steps in the path. This includes adjacent diagonal elements. Therefore, supposing $\mathrm{w_q} = (\mathrm{i}, \mathrm{j})$, then $\mathrm{w_{q+1}}$ is either of the elements $(\mathrm{i}+1, \mathrm{j}), (\mathrm{i}, \mathrm{j}+1)$ or $(\mathrm{i}+1, \mathrm{j}+1)$ for $\mathrm{q} = 1, ..., \mathrm{K}-1$ and $\mathrm{i} = 1, ..., \mathrm{n}-1$ and $\mathrm{j} = 1, ..., \mathrm{m}-1$.
- Monotonicity: Subsequent steps in the path must have a monotonic time interval. In the example in constraint 2, this can be observed by the fact that indices i and j must not decrease in the subsequent steps.

The total distance for path W is obtained by summing the individual elements (distances) of the LCM that the path traverses. To obtain the DTW distance, the path with minimum total distance is required. This path can be obtained by an O(nm) algorithm based on dynamic programming (DP). The following DP recurrence can be used to find the path with minimum cumulative distance:

$$\begin{aligned}\mathrm{d_{cum}}(\mathrm{i}, \mathrm{j}) \quad = \quad & \mathrm{d}(\mathrm{x_i}, \mathrm{y_j}) + \min\{\mathrm{d_cum}(\mathrm{i}-1, \mathrm{j}-1), \\ & \mathrm{d_{cum}}(\mathrm{i}-1, \mathrm{j}), \mathrm{d_{cum}}(\mathrm{i}, \mathrm{j}-1)\}. \end{aligned} \tag{2}$$

We obtained the DTW distance by summing the elements of the path with minimum cumulative distance. In the literature, different scales of this sum are taken to be the DTW distance. We used the definition from Górecki (2018) and thus took the root of the sum:

$$\mathrm{d_{DTW}}(\mathrm{x}, \mathrm{y}) = \min \sqrt{\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{w_k}}), \tag{3}$$

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

where $\mathrm{w_k}$ is the distance that corresponds to the kth element of the warping path W. Note that this distance is equal to the Euclidean distance for the case where $\mathrm{n} = \mathrm{m}$ and only the diagonal of the LCM is traversed. Furthermore, the DTW distance does not satisfy the triangle inequality, even when the local distance measure is a metric (Micó & Oncina 1998).

To find the most optimal number of clusters, we first used a dendrogram. Then, we calculated dissimilarities using minimal Euclidean distance between clusters. Supposing the distance between the clusters is more than 2.5 standard deviation, the clusters are considered well divided.

The R software (R Core Team 2014; Pramana et al. 2017) and Power BI were employed for data analysis and visualization.

4. Result

4.1. Mobility of People

The first confirmed case of COVID-19 was announced on March 2, 2020, officially marking the outbreak in Indonesia. As a result, the government enforced a new policy starting from March 17, 2020, in which people should work from home (WFH) instead of work at offices (WO) to control the spread of the disease in a wider range. This policy has shifted the mobility behavior of the people substantially. This policy was firstly adopted by the Jakarta Metropolitan Area (Jabodetabek) as the epicenter of the pandemic. Later, as the disease spread, more local governments implemented the WFH policy based on the situation of their respective region.

As pointed in Figure 2, there is a significant trade-off between the mobility in workplaces and the mobility at residential areas following the enforcement of WFH policy. People tended to spend most of their time at home, as indicated by positive change in mobility compared to baseline. Meanwhile, working activities at the offices have reduced significantly. The magnitude of the trade-off between both places is not necessarily equal, in which changes in residential mobility are relatively smaller, as people already spent most of their day at home even during working days prior to COVID-19 pandemic.

Nearly all provinces in Indonesia experienced the same change in mobility pattern as shown by the national level. Since working from home becomes a public requirement, people started conducting most businesses from home, including remote works and educational training, to stay safe. Residential mobility has been more intense (Figure 3) while offices have become significantly quiet (Figure 4) during holidays, such as *Nyepi*, Good Friday, and *Waisak*. *Nyepi* has a considerable contribution to the increasing trend of residential mobility in Bali by 37% and decreasing mobility in workplaces by 89% compared to baseline. Particularly for the Balinese people, this celebration was continued the next day.

The official date for the implementation of large-scale social restrictions (PSBB) in Jakarta is April 10, 2020. As it coincided with the Good Friday holiday, it created a double impetus for the escalation of residential mobility that reached 15% compared to baseline. PSBB also influenced human mobility in the surrounding provinces, namely Banten and West Java.

Furthermore, Figure 2 shows the change in mobility for home visits that is completely low compared to baseline on the first day of Eid al-Fitr (May 24, 2020). It reveals that people spent most of their time outdoors. They might carry out “halal-bi-halal”, a cultural habit of visiting relatives to ask for forgiveness from each other. Prior to this occasion, people usually buy a large number of various groceries. During the COVID-19 pandemic, the risk of disease transmission could not seem to reduce the passion for shopping as the community mobility unexpectedly exhibited positive change precisely 5 days prior to the Eid al-Fitr Holiday (Figure 5). Days prior to the celebration, the community behaved as if everything was normal. Hazardous things might happen during their shopping that they should consider health protocol guidelines.

Economics and Finance in Indonesia, Vol. 67 [2021], No. 1, Art. 9

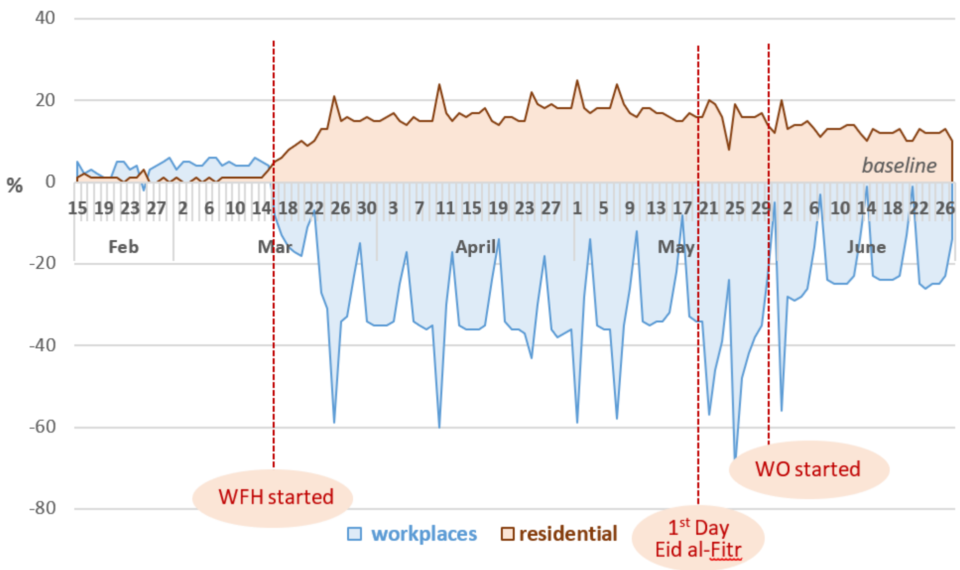

Figure 2. Mobility Change in Workplaces and Residential Areas

Outdoor activities have been greatly restricted since the outbreak of the pandemic. The places that potentially have a large number of people gathering are forcefully closed by the authorities, such as shopping centers, restaurants, cafes, cinemas, and libraries. It leads to a significant reduction in mobility to retail shops and recreational areas compared to baseline (Figure 6). Immediately following the Eid al-Fitr, the chance to visit these spots has been opened wider, particularly when the government has allowed several shopping centers to operate their businesses as of June 5, 2020. The continuous increasing trend offers a prediction that the intensity of mobility will soon reach the normal condition.

Public transportation is accessible by people at any time even during pandemic outbreaks. Following the social distancing and health protocol guidelines, the number of passengers for every means of transportation is limited consequently. For example, an online taxi can carry a maximum of 2 passengers only, and a bus can only carry 50% of its capacity. These rules, in addition to public concern for the contagious virus, have prompted a great number of people to use their own vehicles. Not surprisingly, the trend of community mobility in transit stations has turned into a big negative (nearly -70%) compared to baseline in the last April to early May 2020 (Figure 7). However, people have been perpetually dependent on public transport afterward, mainly following the reorganization by the government to work at the offices (WO) since June 5, 2020.

Parks are usually comfortable green areas for physical exercise and stress relief. In addition to restrictions on social activities, the interest of the public to visit these places has declined along with the decision to close several parks. Human mobility in terms of park visits drops seasonally to a significantly low percentage each weekend (Figure 8). It indicates that people tended to choose weekdays when they should visit parks for particular purposes during the COVID-19 pandemic. They might assume that a few people come to the parks during weekdays, thus parks are safer in weekdays rather than weekends. Since the end of April 2020, this mobility pattern has shown a quite optimistic sign to reach the normal state soon.

The COVID-19 outbreak has brought notable changes in community mobility behavior, particularly in the public areas. Contrary to baseline, community mobility has shifted (on average) to -15% in grocery stores and pharmacies, -36% in retail

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

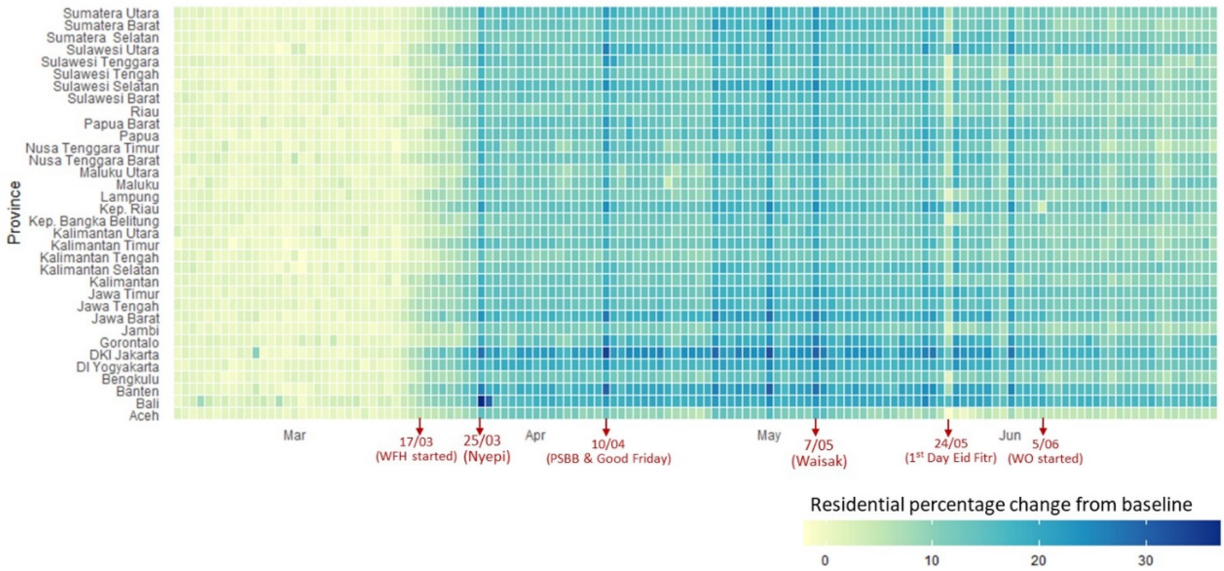

Figure 3. Mobility Changes in the Residential Areas by Provinces

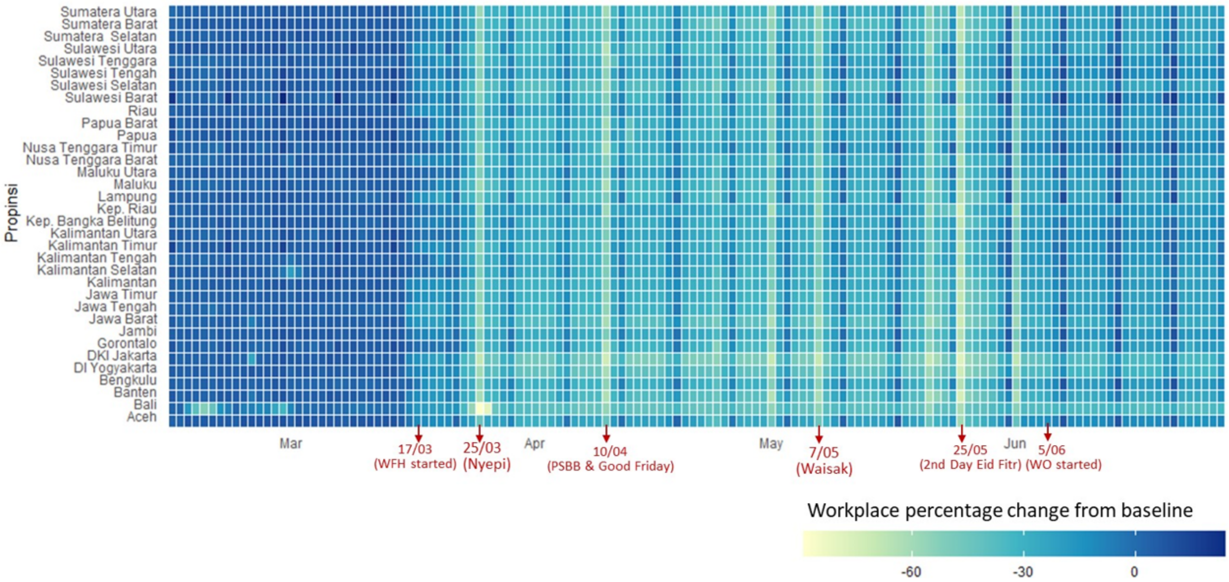

Figure 4. Mobility Changes in the Workplaces by Provinces

shops and recreational areas, -34% in parks, and -52% in transit stations during the WFH period. As people do nearly everything from home, the mobility at the residential areas has increased by 16% and while the mobility in workplaces has decreased by 32% compared to baseline.

June is considered as the beginning of the transition period in which community mobility tended to be less restricted. Entering this moment, community mobility pattern has turned (on average) to -7% in grocery stores and pharmacies, -25% in retail shops and recreational areas, -23% in parks, and -43% in transit stations compared to baseline. Activities at offices are permitted but the number of workers are limited. It has caused a decline in

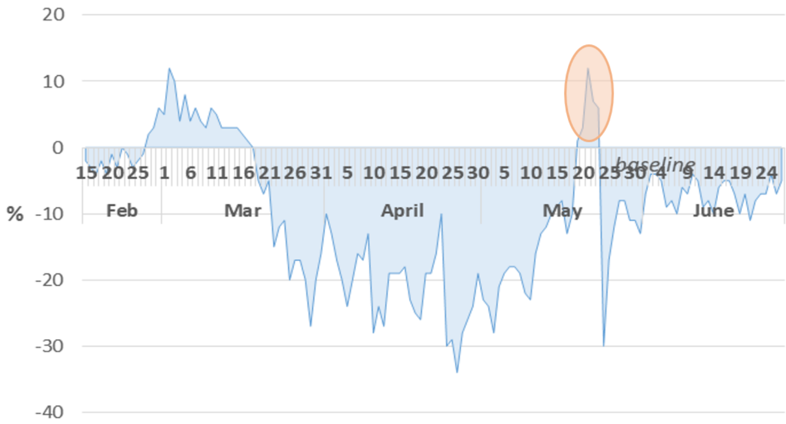

Figure 5. Mobility Changes in Grocery Stores and Pharmacies

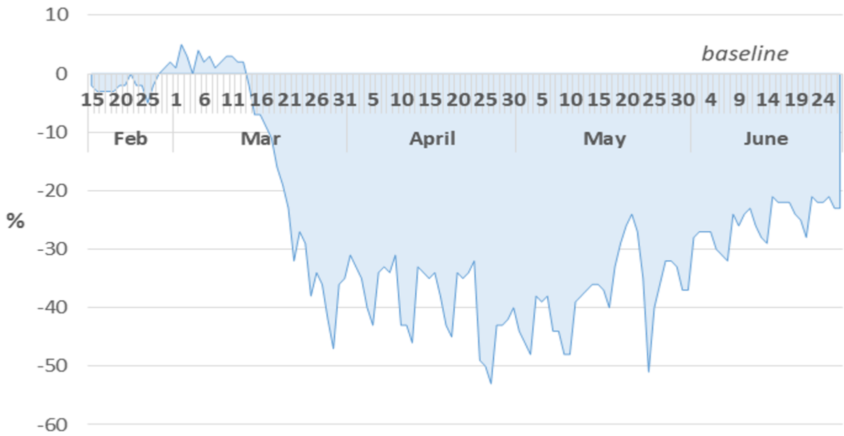

Figure 6. Mobility Changes in Retail Shops and Recreational Areas

mobility in workplaces by 21% and an increase in residential mobility by 13% compared to baseline.

4.1.1. The Factors Related to Mobility Changes in Residential Areas during the Work-from-Home Period

Even though in general people in Indonesia tended to reduce mobility in workplaces and stayed at home during the work-from-home period and large-scale restrictions, Figure 2 shows that different provinces have different mobility pattern changes in residential areas. These difference may be driven by the number of daily cases and socio-economic characteristics of the provinces.

Figure 9 shows the average number of daily new confirmed cases and the differences in mobility in residential areas between during and before the WFH period. The highest difference in mobility is found in Jakarta, followed by Banten, West Java, and Bali. People in Jakarta, the epicenter of the pandemic, and the surrounding provinces tend to stay at home much longer compared to the baseline period. The highest average number of daily new confirmed cases is found in East Java, followed by Jakarta. Despite the highest number of new cases (160 positive cases), mobility differences are low. It seems that the people in East Java tend not to stay at home during the WFH period, even though the pandemic is worsening.

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

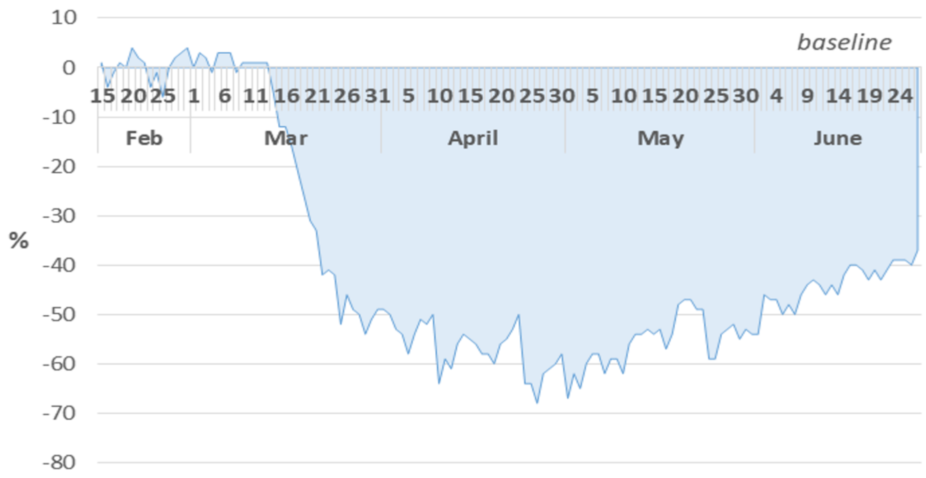

Figure 7. Mobility Changes in Transit Stations

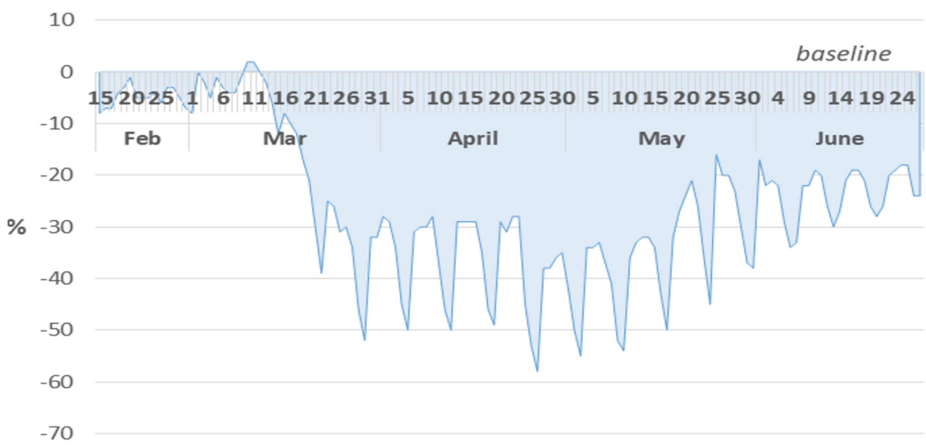

Figure 8. Mobility Changes in Parks

Figure 10 shows that people from provinces with more formal workers (such as Jakarta and Banten) tended to stay at home during the WFH period. Furthermore, people in the provinces with lower GRDP and higher poverty rate seemed not to stay at home during the WFH period. Formal sector workers can easily work remotely from home, yet it is not the case for informal workers. Informal workers typically do not have secure employment contracts, thus during the pandemic, many lost their jobs and discovered other options. It will be more difficult for people in the regions with more informal workers and a large poverty rate to stay at home for a long period.

4.1.2. Time Series Cluster Analysis

Based on the inspection on the dendrogram and the distance between clusters, five clusters are the most optimal number. Figure 1 shows that during the mid-March to June, all provinces in Indonesia began to experience declining mobility in recreational and retail areas. The decline is due to several areas that have closed down large malls as well as recreational areas to reduce contact with residents to control the spread of COVID-19. The regions experiencing a larger drop were Jakarta and Bali. The decline in Jakarta is associated with the national first case of COVID-19 identified in the area. In addition, Jakarta is an area with high

Economics and Finance in Indonesia, Vol. 67 [2021], No. 1, Art. 9

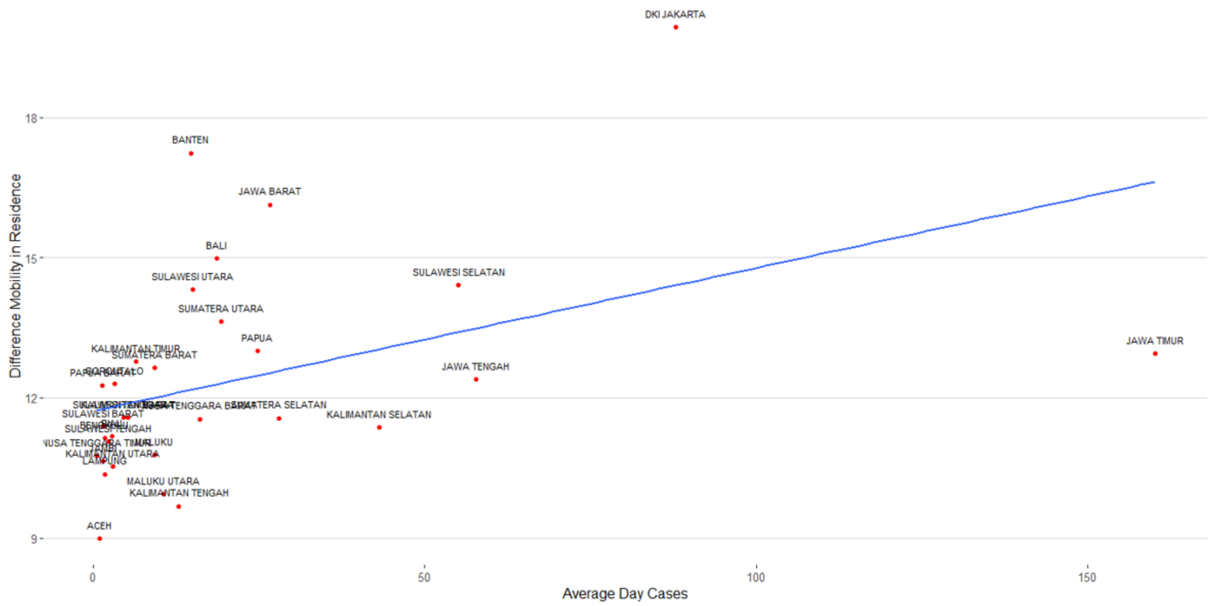

Figure 9. The Scatter Plot of Average Daily New Confirmed Cases and the Differences in Residential Mobility During and Before the WFH Period

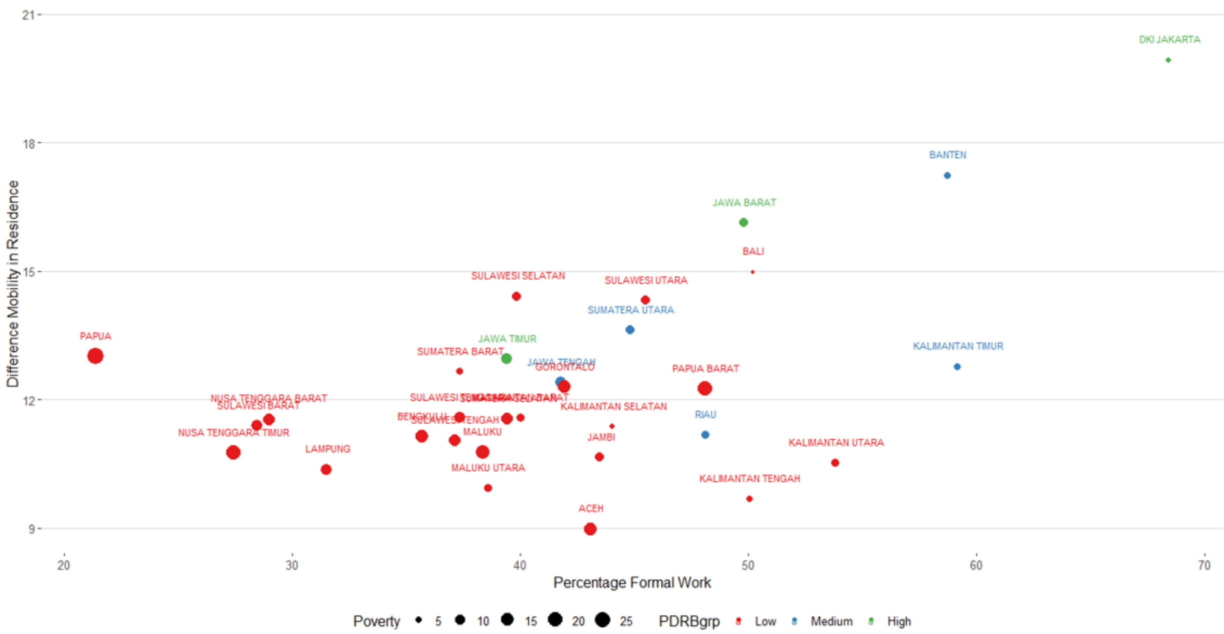

Figure 10. The Plot of the Percentage of Formal Workers, Differences in Residential Mobility, Poverty Rate, and GRDP

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

mobility and density, causing a high increase in the number of cases.

The line in Figure 11 shows patterns from all 34 provinces, and the colors show the category of cluster based on a similar pattern across the time span. The clusters seem to have a similar pattern, though the magnitude is quite different. In terms of mobility in retail areas, Jakarta forms a single-member cluster (cluster 3). Jakarta significantly shows low mobility during April and May 2020. It peaks in May 2020, a week prior to the celebration of Eid al-Fitr in Indonesia. Several provinces show a rapid increase during this week in relation to the preparation for the celebration. However, people in Jakarta were not interested in visiting retail and recreational areas.

The regions with the highest decrease in mobility are clusters 3 (Jakarta) and 5 (e.g. West Java and Bali). Observed from their characteristics, the regions in cluster 3 have the highest human development index, the highest percentage of formal workers, and high GRDP, but they also have high unemployment. This is associated with trade centers in Jakarta that are classified as high in addition to the quality of the population dominated by formal workers. Therefore, these regions tend to avoid hazardous areas such as malls and recreational areas.

Similar to mobility in retail and recreational areas, mobility in grocery stores and pharmacies starts to decline in mid-March, as shown in Figure 12. However, due to the basic needs required during Ramadan in May, several provinces experience an increase in mobility and the peak occurs during the Eid al-Fitr week. Provinces with a majority Muslim population experience this, however provinces with a majority of Hinduism and Christianity, such as Bali and Papua, experience an insignificant impact (cluster 3). Bali becomes a spotlight since, in June, nearly all regions have started to return to normal. It may be caused by the regional pattern that have started to return to normal, and Ramadan and Eid al-Fitr lead to an insignificant decrease in mobility than in March. In other words, they are accustomed to high intensity, and thus the decrease is not as significant as the previous decrease. However, Bali also experiences a slowdown towards normality due to the decline in tourism sector.

Population mobility in parks, as presented in Figure 13, generally declines from mid-March to April and starts to increase in May 2020. However, in several provinces included in cluster 3 (Jakarta, Bali, and Yogyakarta), the decline is quite significant and it remains considerably low until June. The decline in Jakarta is due to the large-scale social restrictions. Meanwhile, Bali and Yogyakarta are tourist areas, thus the decline is caused by the massive decline in the number of tourists.

Following the recommendation of the government regarding the large-scale restrictions, there is certainly a significant decrease in mobility in the workplaces, as shown in Figure 14, in all provinces in mid-March. The enforcement of this social restrictions does not appear to be implemented simultaneously. The most responsive provinces are those in cluster 3 (Jakarta, Yogyakarta, and Bali), while the provinces that tend to response slowly are those in clusters 1 (e.g., Aceh and North Sumatera) and 4 (e.g., Riau and Jambi). The area with the highest decrease in mobility is cluster 3, in which the fast response is given due to the urgent conditions. The area in cluster 3 with the lowest mobility is Jakarta. In June, there has been an increase in mobility in the workplaces on average. This is marked by the "new normal era" initiated by the government. However, the area that tends to remain low and even begins to decline is Bali. This is quite alarming, considering that tourism in Bali has not been able to be active.

Figure 15 shows a radar plot of the socioeconomic characteristics of clusters. The provinces in cluster 3 have a high human development index, a high percentage of formal workers, and a high GRDP. Therefore, people in this cluster can choose not to actively engage in mobility in workplaces and work from home instead. The readiness to work from home does require good human resources, hence the ability of cluster 3 to quickly adapt.

Economics and Finance in Indonesia, Vol. 67 [2021], No. 1, Art. 9

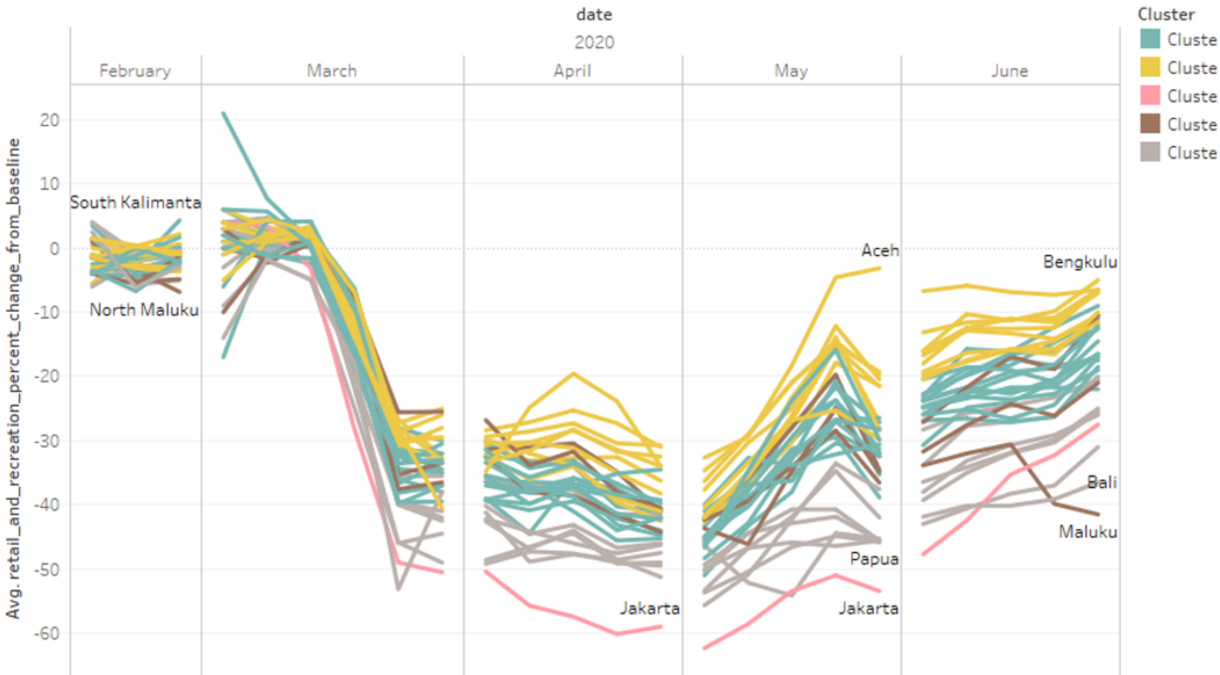

Figure 11. The Mobility Patterns of Provinces in Retail and Recreational Areas

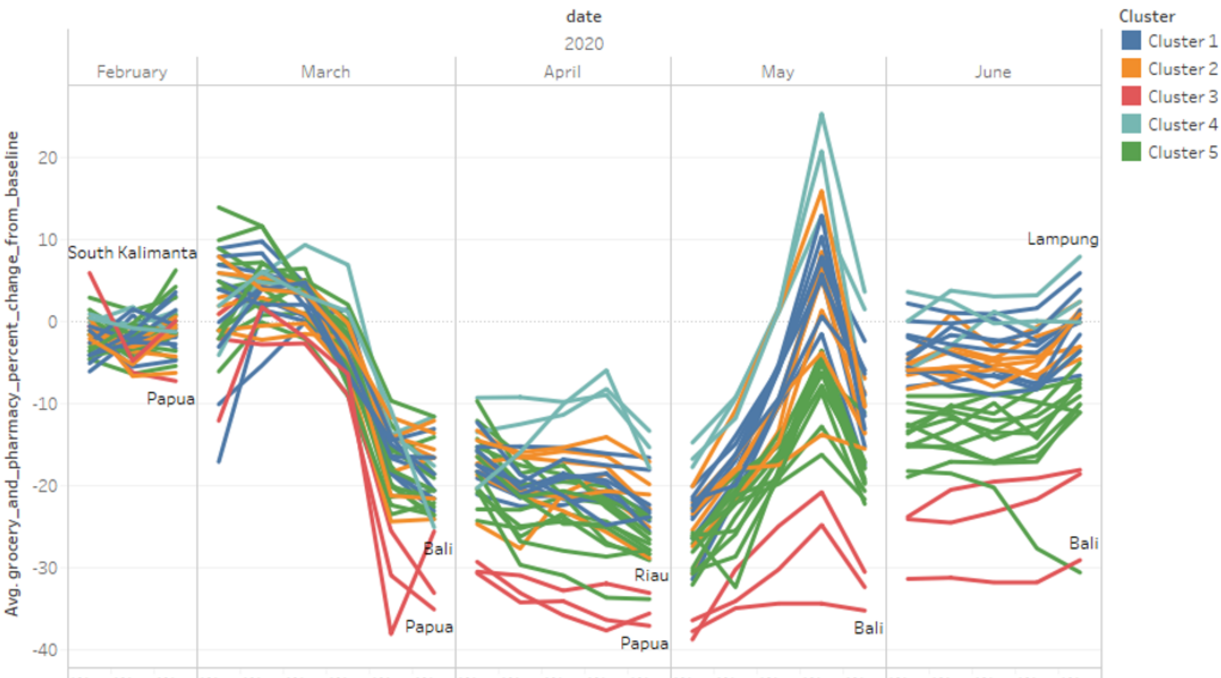

Figure 12. The Mobility Patterns of Provinces in Grocery Stores and Pharmacies

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

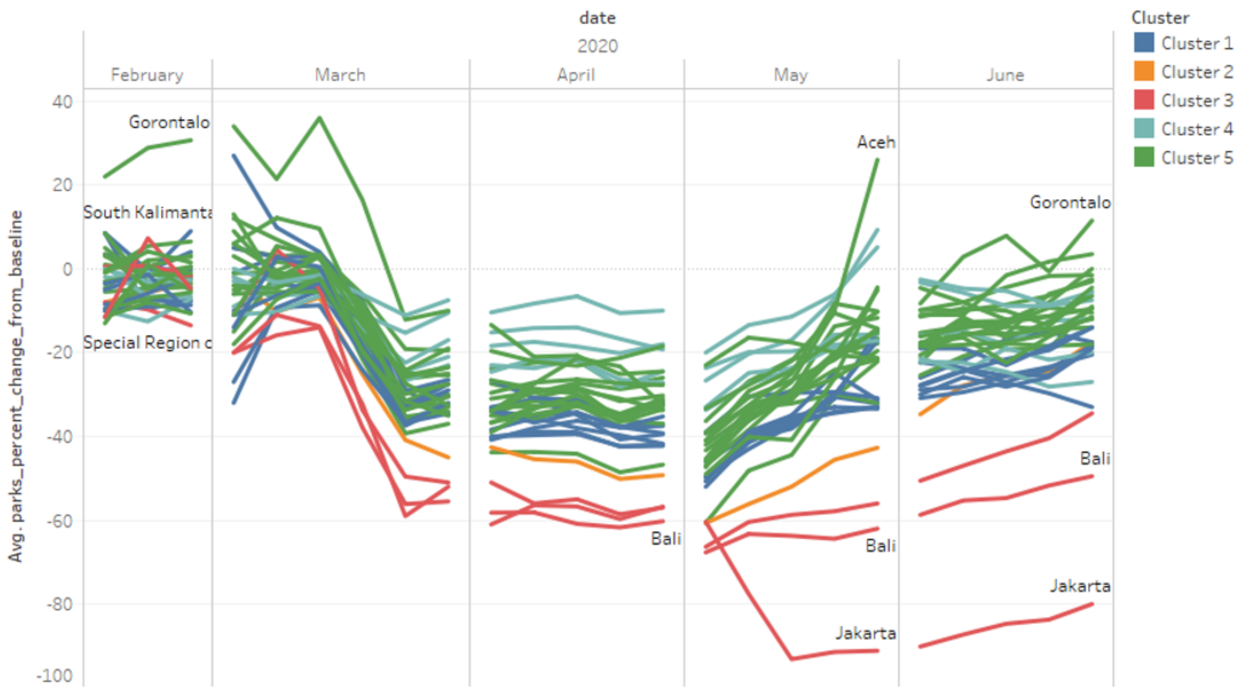

Figure 13. The Mobility Patterns of Provinces in Parks

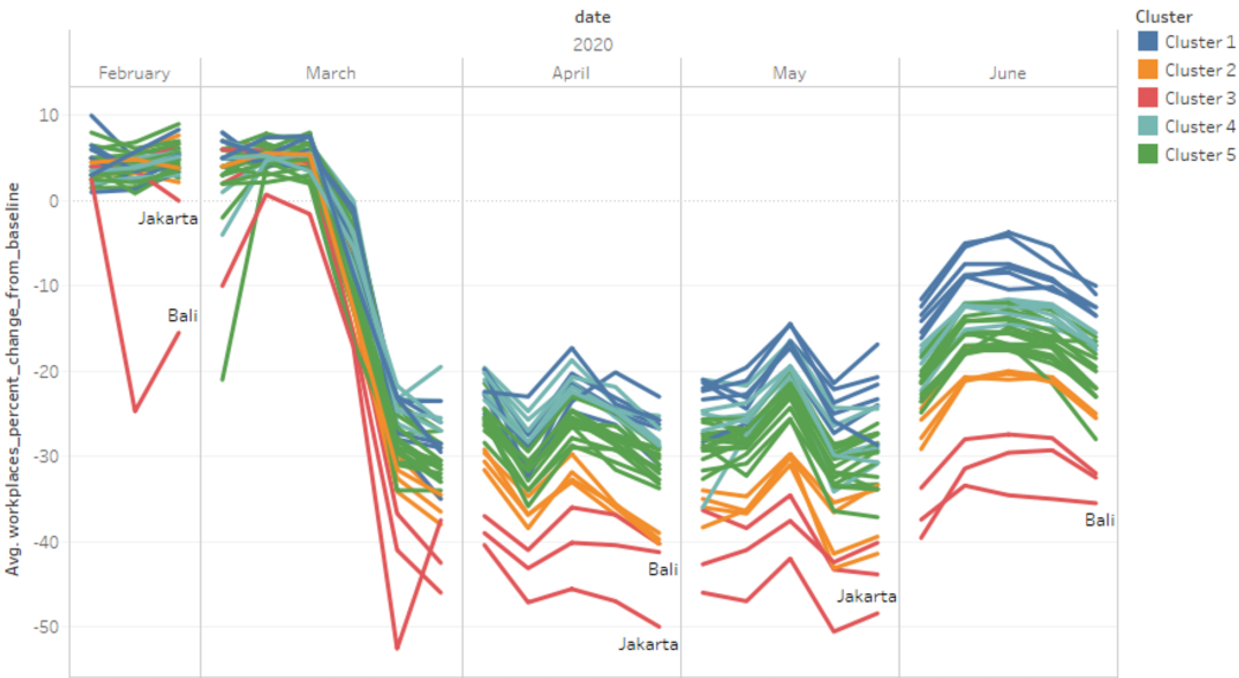

Figure 14. The Mobility Patterns of People in Workplaces

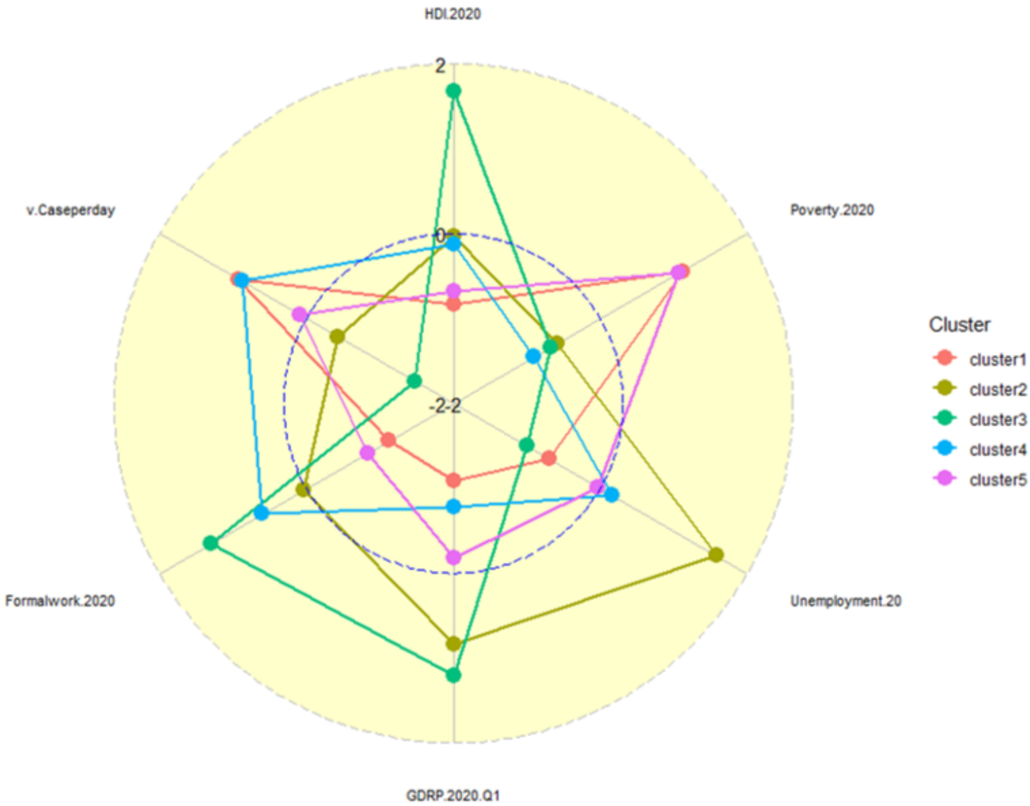

Figure 15. Radar Plot for Clusters Based on Mobility in Workplaces

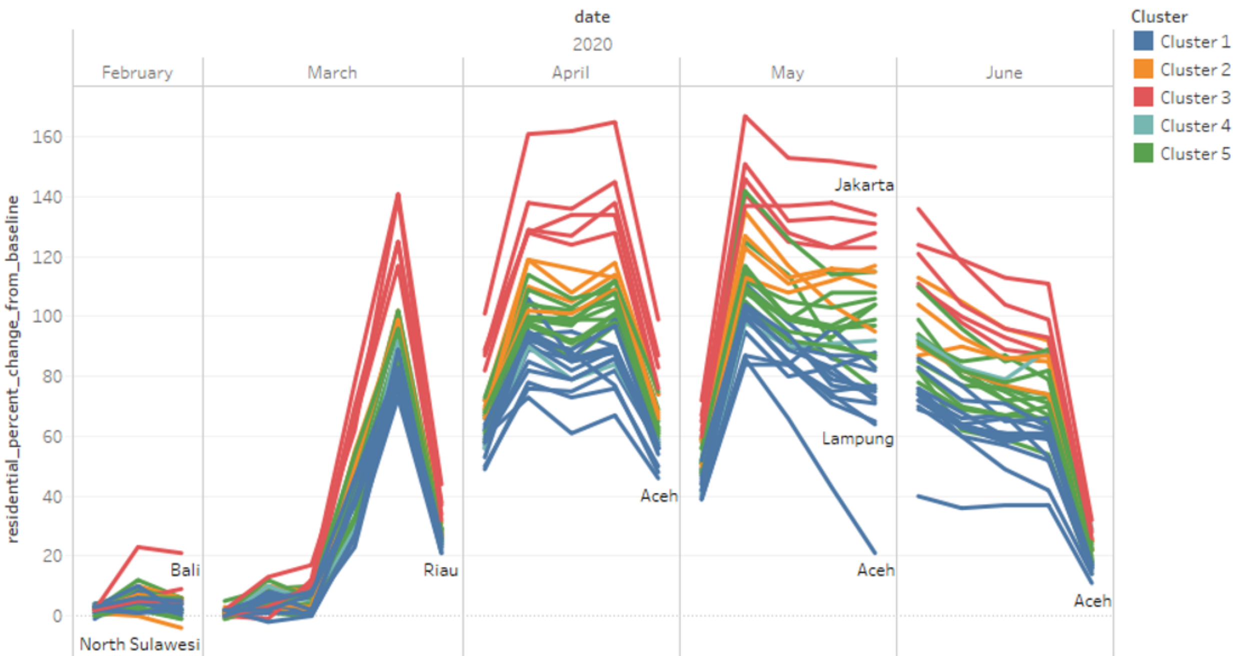

Figure 16. The Mobility Patterns of Provinces in Residential Areas

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

The decline in population mobility in outdoor areas will certainly lead to increased mobility in residential areas in nearly all provinces, as can be observed in Figure 16. This is inseparable from the policy of the government on working and studying from home. However, uniquely there is always a decrease in mobility in residential areas at the end of the month. The cluster with the lowest increase in mobility in the residential areas is cluster 1 (e.g., Aceh, Riau, and Jambi), while the one with the highest increase is cluster 3 (Jakarta, Banten, West Java, and Bali).

Figure 17 shows that cluster 1 is an area with low socioeconomic indicators, while cluster 3 is the opposite. This shows that cluster 1 is a reflection of areas with high informal workers and high poverty rate. This forces the area to exercise high mobility in workplaces.

4.2. Mobility between Regions

4.2.1. Domestic Flight

The conditions of domestic flight for the 15 busiest airports in Indonesia are divided into two types of flights, namely domestic departures from 15 airports and domestic arrivals to 15 airports. Figure 18 presents a graph of the number of daily departures from 15 airports for the period of March 15, 2020–June 30, 2020, with important cut-off dates related to the COVID-19 pandemic in Indonesia.

Figure 18 shows that the number of domestic departures from 15 airports tends to decrease from mid-March until Large Scale Social Restrictions (PSBB) in several regions in Indonesia. The three airports with the most decrease in the number of departures are Soekarno Hatta International Airport in Jakarta, Juanda International Airport in Surabaya, and Sultan Hasanuddin International Airport in Makassar, with a decrease of 71.4%, 61%, and 70.8% respectively.

The most significant decrease in the number of flights from all 15 airports occurs after April 24, 2020, namely the date of the issuance of the Regulation of the Minister of Transportation No. 25 of 2020 concerning Transportation Control during the Eid al-Fitr to prevent the distribution of COVID-19. The regulation prohibits mass transportation from carrying passengers, including air transportation whose operational activities were restricted until May 31, 2020. The average number of daily domestic departures from 15 airports in the period of the issuance of the regulation is 24 flights per day, a drastic decline from average daily departures of 345 flights prior to the regulation.

Referring to Figure 18, it is evident that following the end of the regulation on May 31, 2020, the number of daily flights starts to increase. The average number of daily domestic departures from 15 airports in June 2020 is 178 flights per day, or an increase of 741% from the period when the regulation came into effect. Table 1 shows the average number of domestic departures from the five airports with the highest share in each period.

Similar to the conditions of departure flights, arrival flights to the 15 busiest airports in Indonesia have also tended to decline since mid-March 2020. The decreasing and increasing trend of daily arrivals are also similar to that of the departure flights as presented in Figure 19.

The number of daily domestic arrivals starts to decrease since mid-March 2020. Until April 23, 2020 (prior to the implementation of the regulation of transportation restrictions), the biggest decrease occurs at Soekarno Hatta International Airport in Jakarta, Juanda International Airport in Surabaya, and Sultan Hasanuddin International Airport in Makassar by 72.5%, 60.9%, and 71.2%, respectively. The most significant decrease also occurs when the regulation on transportation restrictions was issued on April 24, 2020. During that period, the average number of daily arrivals to 15 airports is 25 flights per day, decreasing from 362 flights per day prior to the issuance of the regulation. Then, after June 1, 2020, the number of daily arrivals stars to rise again with an average number of daily arrivals of 186 flights per day, increasing 744% from the period of the regulation.

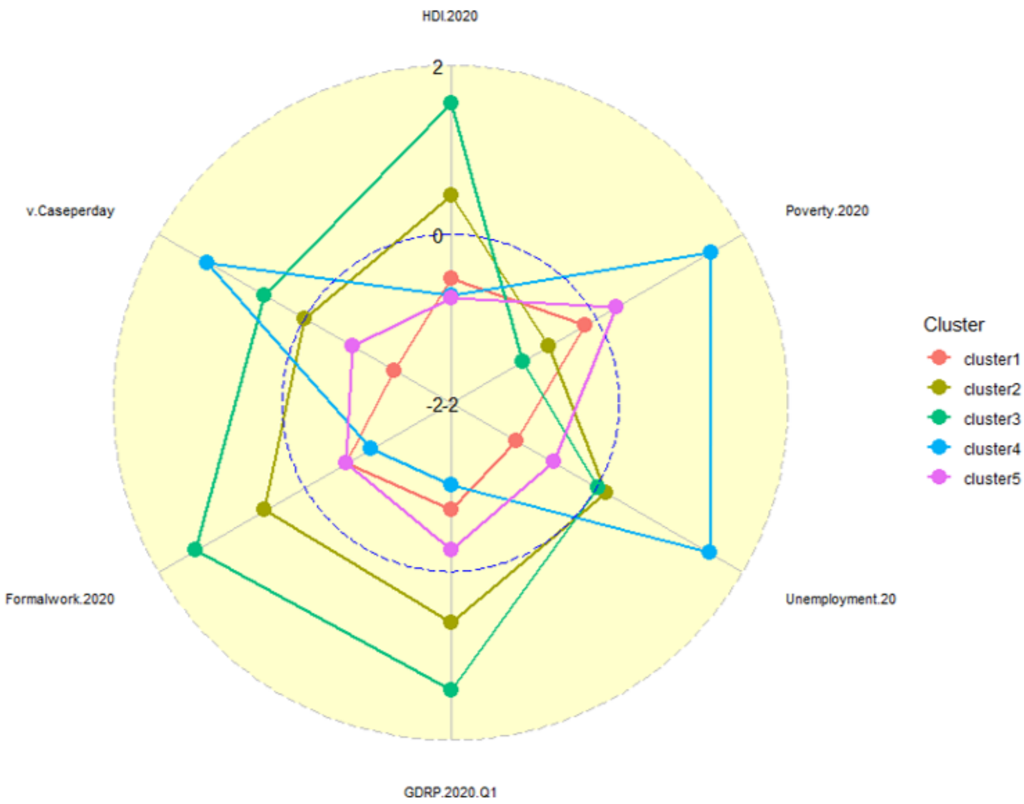

Figure 17. Radar Plot for Clusters Based on Mobility in Residential Areas

Table 1. The Average of Daily Domestic Departures from 5 Airports (March 15–June 30, 2020)

AVERAGE NUMBER OF DAILY DEPARTURE FLIGHTS				
AIRPORT	BEFORE PSBB	PSBB	ON REGULATION	AFTER REGULATION
Juanda International Airport	111	60	2	25
Sultan Hasanuddin International Airport	80	37	3	23
Ngurah Rai International Airport	67	26	1	7
Kuala Namu International Airport	40	23	1	10
Soekarno-Hatta International Airport	258	102	13	67
TOTAL	556	248	20	131

Table 2 shows the average number of daily arrivals to all airports in each period.

There are also differences between the origin and destination flight behavior of the five busiest airports in Indonesia for each period as presented in Figure 20. Observed from the Figure, it can be concluded that there are no significant differences in flight behavior of the five airports before and after the implementation of the regulation of transportation restrictions on April 24, 2020.

4.2.2. International Flights

Figure 21 shows daily international departures from the 15 busiest airports during the period of March 15, 2020–June 30, 2020, with important cut-off dates related to the COVID-19 pandemic in Indonesia. It demonstrates that international departure flights from 15 airports in Indonesia have decreased sharply from mid-March to early April 2020. The two airports that become the main gate of international flights in Indonesia, namely Soekarno Hatta

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

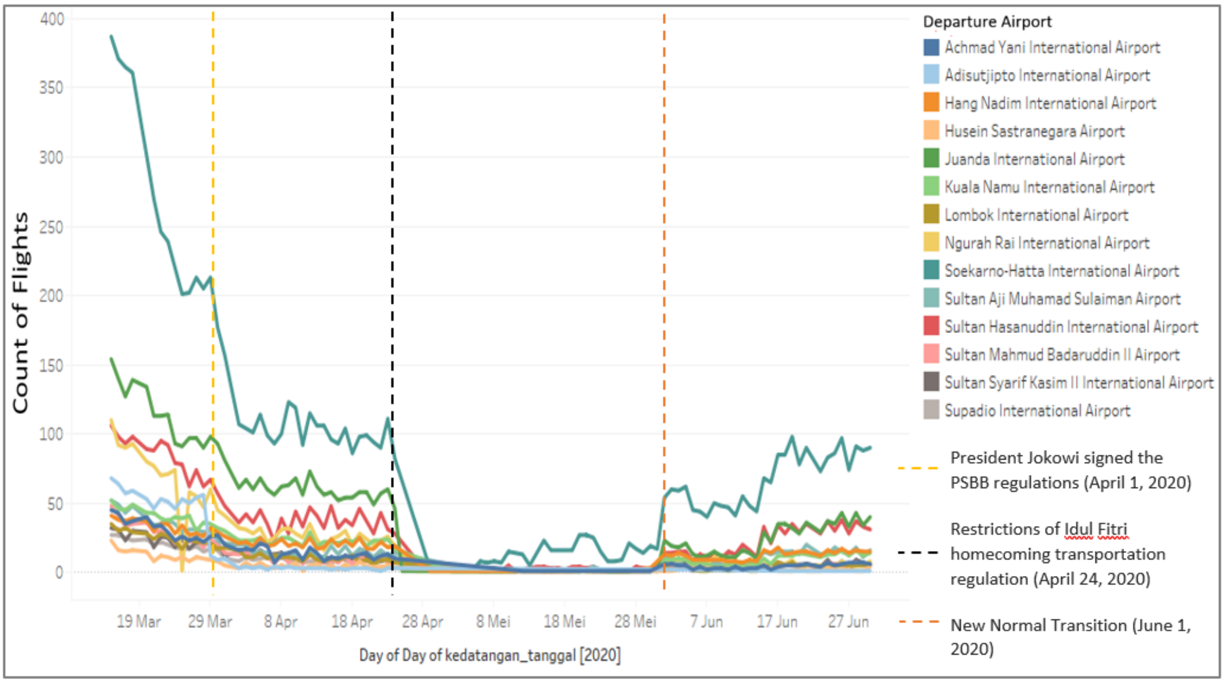

Figure 18. The Number of Domestic Departures from 15 Airports in Indonesia (March–June 2020)

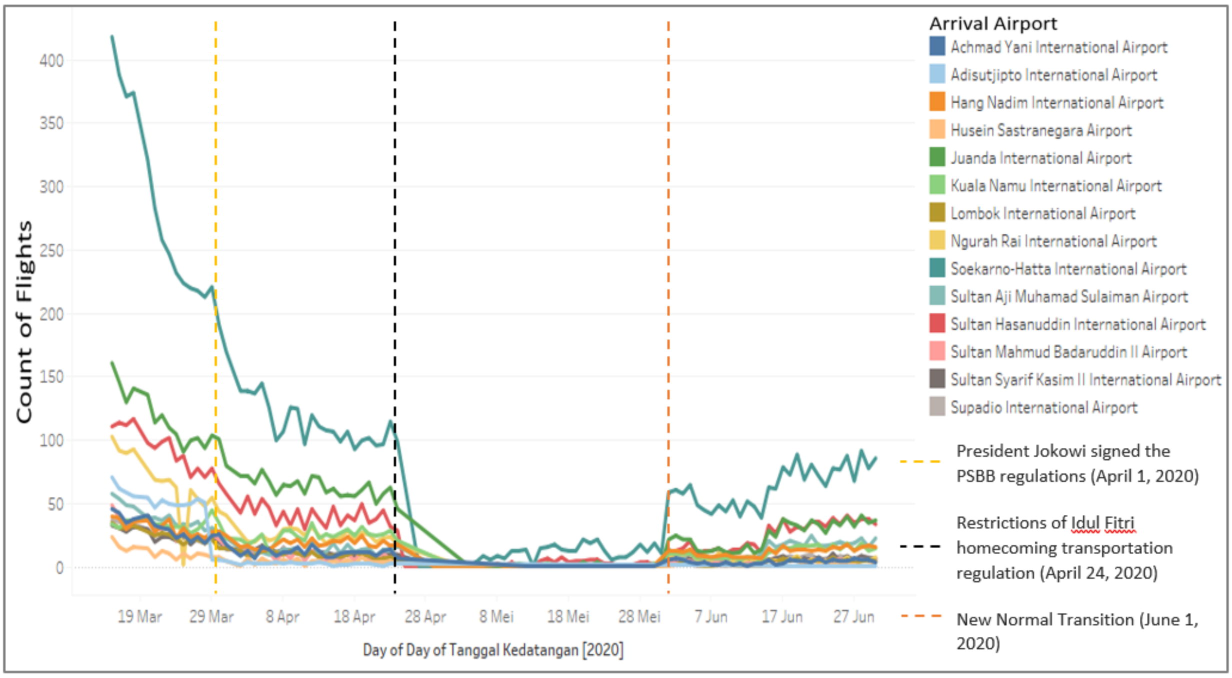

Figure 19. The Number of Domestic Arrivals to 15 Airports in Indonesia (March - June 2020)

Table 2. The Average of Daily Domestic Arrivals to 5 Airports (March 15–June 30, 2020))

AVERAGE NUMBER OF DAILY ARRIVAL FLIGHTS				
AIRPORT	BEFORE PSBB	PSBB	ON REGULATION	AFTER REGULATION
Juanda International Airport	115	64	2	25
Sultan Hasanuddin International Airport	90	41	3	25
Ngurah Rai International Airport	64	25	1	7
Kuala Namu International Airport	34	25	2	12
Soekarno-Hatta International Airport	272	113	12	64
Total	**575**	**268**	**20**	**133**

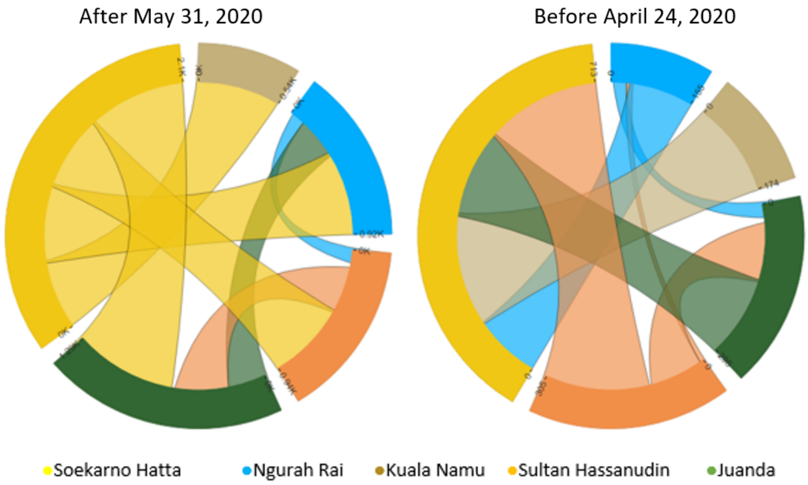

Figure 20. Circos Plot of the Five Busiest Airports in Indonesia

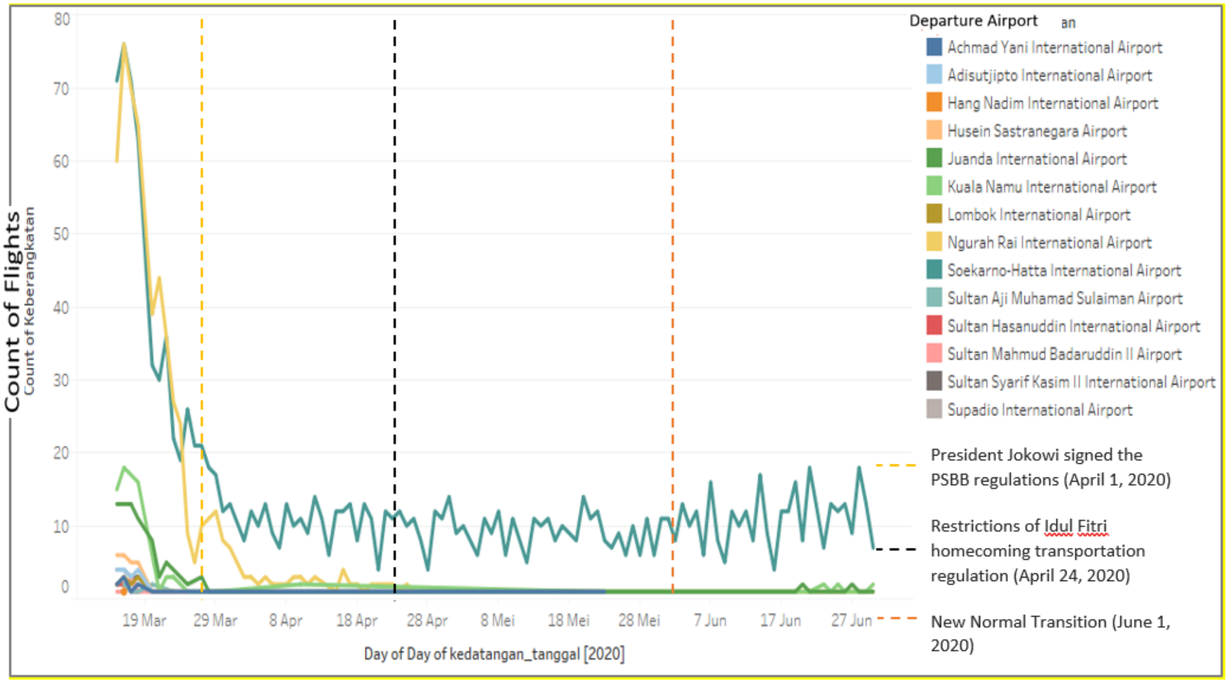

Figure 21. The Number of International Departures from 15 Airports in Indonesia (March–June 2020)

https://scholarhub.ui.ac.id/efi/vol67/iss1/9
DOI: http://dx.doi.org/10.47291/efi.v67i1.924

International Airport in Jakarta and I Gusti Ngurah Rai International Airport in Bali, have international departures decreased by 71.1% and 64.5%, respectively. In contrast to domestic flights, international flights are not affected by the Regulation of the Minister of Transportation No. 25 of 2020 concerning Transportation Control, thus observed from the graph, there are no significant changes either before, during, or after the issuance of the regulation. The average international departures from Soekarno Hatta International Airport in Jakarta and I Gusti Ngurah Rai International Airport in Bali from the beginning of April 2020 to the end of June is 9 flights per day.

The top five international destinations from Indonesia are Singapore, Kuala Lumpur, Tokyo, Hong Kong, and Doha. Departure flights to Singapore and Kuala Lumpur experiences the largest decline in the number of flights until early April 2020 by 77.8% and 84.4%, respectively. Then, from the beginning of April to the end of June 2020, the average flights to the two cities are stable at 2 or 3 flights per day.

5. Conclusion

The study shows extensive changes in community mobility in all provinces of Indonesia during the COVID-19 pandemic. In general, during the first 2.5 months of the pandemic, people reduced their activities in public areas and preferred to stay at home. In June, the activities tended to be in the new normal situations. Provinces have different mobility patterns during the period of large-scale restrictions. The provinces that are and close to the epicenter of the pandemic tend to have similar mobility patterns. Furthermore, the socio-economic characteristics of the provinces force these differences. Provinces with a high percentage of formal workers, Human Development Index, and GDP tend to follow the instruction to reduce activities outside the home and work from home. It is also supported by reducing mobility between provinces through travel restrictions such as closing access between provinces and limiting number of flights.

In addition, the study shows that by utilizing the new big data source (e.g. Google Mobility and flight tracker), it is easier to analyze population mobility from several locations. Furthermore, the relationship between mobility and the socio-economic characteristics of a region in Indonesia also has quite a variety of patterns, accommodated by the time series clustering analysis to observe the diversity of patterns more concise and easily.

References

[1] ASEAN 2020, 'Economic impact of COVID-19 outbreak on ASEAN', *ASEAN Policy Brief April 2020*. Association of Southeast Asian Nations (ASEAN). viewed 28 March 2021, <https://asean.org/storage/2020/04/ASEAN-Policy-Brief-April-2020_FINAL.pdf>.

[2] Cartenì, A, Di Francesco, L, & Martino, M 2020, 'How mobility habits influenced the spread of the COVID-19 pandemic: Results from the Italian case study', *Science of the Total Environment*, vol. 741, p. 140489. doi: https://doi.org/10.1016/j.scitotenv.2020.140489.

[3] Demissie, MG, Phithakkitnukoon, S, Kattan, L, & Farhan, A 2019, 'Understanding human mobility patterns in a developing country using mobile phone data', *Data Science Journal*, vol. 18, no. 1, pp. 1-13. doi: https://doi.org/10.5334/dsj-2019-001.

[4] Ebrahimpour, Z, Wan, W, Velázquez García, JL, Cervantes, O, & Hou, L 2020, 'Analyzing social-geographic human mobility patterns using large-scale social media data', *ISPRS International Journal of Geo-Information*, vol. 9, no. 2, p. 125. doi: https://doi.org/10.3390/ijgi9020125.

[5] Ferrara, E, Liotta, A, Ndubuaku, M, Erhan, L, Giusto, D, Richardson, M, Sheffield, D, & McEwan, K 2018, 'A demographic analysis of urban nature utilization', *2018 10th Computer Science and Electronic Engineering (CEEC)*, pp. 136-141. doi: https://doi.org/10.1109/CEEC.2018.8674206.

[6] Findlater, A & Bogoch, II 2018, 'Human mobility and the global spread of infectious diseases: A focus on air travel', *Trends in Parasitology*, vol. 34, no. 9, pp. 772-783. doi: https://doi.org/10.1016/j.pt.2018.07.004.

[7] Gao, S, Rao, J, Kang, Y, Liang, Y, & Kruse, J 2020, 'Mapping county-level mobility pattern changes in the United States in response to COVID-19', *SIGSPATIAL Special*, vol. 12, no. 1, pp 16-26 doi: https://doi.org/10.1145/3404820.3404824.

[8] Górecki, T 2018, 'Classification of time series using combination of DTW and LCSS dissimilarity measures', *Communications in Statistics-Simulation and Computation*, vol. 47, no. 1, pp.263-276. doi: https://doi.org/10.1080/03610918.2017.1280829.

[9] Jiang, H, Li, Q, Zhou, X, Chen, Y, Yi, S, Wang, H,

& Lu, Z 2017, 'A collective human mobility analysis method based on data usage detail records', *International Journal of Geographical Information Science*, vol. 31, no. 12, pp. 2359-2381. doi: https://doi.org/10.1080/13658816.2017.1370715.

[10] Kouzis-Loukas, D 2016, *Learning scrapy*, Packt Publishing Ltd.

[11] Linka, K, Peirlinck, M, Sahli Costabal, F, & Kuhl, E 2020, 'Outbreak dynamics of COVID-19 in Europe and the effect of travel restrictions', *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 23, no. 11, pp. 710-717. doi: https://doi.org/10.1080/10255842.2020.1759560.

[12] MacPherson, DW, Gushulak, BD, Baine, WB, Bala, S, Gubbins, PO, Holtom, P, & Segarra-Newnham, M 2009, 'Population mobility, globalization, and antimicrobial drug resistance', *Emerging Infectious Diseases*, vol. 15, no. 11, pp. 1727-1732. doi: https://dx.doi.org/10.3201/eid1511.090419.

[13] Mahto, DK & Singh, L 2016, 'A dive into web scraper world', *2016 3rd International Conference on Computing for Sustainable Global Development (INDIACom)*, pp. 689-693.

[14] McGrath, L 2020, *Google mobility trends for the western region: A supplement to the timely economic indicators series*, Western Development Commission. viewed 28 March 2021, <https://westerndevelopment.ie/publications/google-mobility-trends-for-the-western-region-a-supplement-to-the-timely-economic-indicators/>.

[15] Micó, L & Oncina, J 1998, 'Comparison of fast nearest neighbour classifiers for handwritten character recognition', *Pattern Recognition Letters*, vol. 19, no. 3-4, pp. 351-356. doi: https://doi.org/10.1016/S0167-8655(98)00007-5.

[16] Panuntun, SB & Pramana, S 2021, 'Development of automated flight data collection system for air transportation statistics', *Journal of Physics: Conference Series*, vol. 1863, no. 1, p. 012020. doi: 10.1088/1742-6596/1863/1/012020.

[17] Pramana, S, Yordani, R, Kurniawan, R, & Yuniarto, B 2017, *Dasar-dasar statistika dengan software R: Konsep dan aplikasi* (Edisi Kedua), In Media.

[18] Pramana, S, Paramartha, DY, Adhinugroho, Y, & Nurmalasari, M 2020, 'Air pollution changes of Jakarta, Banten, and West Java, Indonesia during the first month of COVID-19 pandemic', *The Journal of Business Economics and Environmental Studies*, vol. 10, no. 4, pp. 15-19. doi: https://doi.org/10.13106/jbees.2020.vol10.no4.15.

[19] R Core Team 2014, *R: A language and environment for statistical computing*, R Foundation for Statistical Computing. viewed 1 December 2014, <http://www.R-project.org/>.

[20] Saha, J, Barman, B, & Chouhan, P 2020, 'Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports, 2020', *Children and Youth Services Review*, vol. 116, p. 105160. doi: https://doi.org/10.1016/j.childyouth.2020.105160.

[21] The COVID-19 National Task Force 2020, 29 July, *Infografis COVID-19 (29 Juli 2020)*. viewed 9 November 2020 from <https://covid19.go.id/p/berita/infografis-covid-19-29-juli-2020>.

[22] The Ministry of Administrative and Bureaucratic Reform 2020a, *Circular Letter of the Minister of Administrative and Bureaucratic Reform No. 19 of 2020 on Adjustment of the Civil Servant Work System in Preventing the Spread of COVID-19 in Government Agencies*.

[23] The Ministry of Administrative and Bureaucratic Reform 2020b, *Circular Letter of the Minister of Administrative and Bureaucratic Reform No. 58 of 2020 on the Civil Servant Work System in New Normal Period.*

[24] WHO 2020, *WHO characterizes COVID-19 as a pandemic*. viewed 1 May 2020 from <https://www3.paho.org/hq/index.php?option=com_content&view=article&id=15756:who-characterizes-covid-19-as-a-pandemic&Itemid=1926&lang=en>.