“The Effects of Human Mobility Restriction During Covid-19 Pandemic on Indonesia’s Economy”
Ferdian Fadly

Abstract
In response to the coronavirus disease 2019 (COVID-19) pandemic, several national governments have implemented lockdown restrictions to reduce the risk of infection. However, this will have an impact on the economy of a country, including Indonesia. This study will analyze the effect of mobility restrictions on the economic growth in Indonesia during the pandemic in 2020. The data used are real-time data on community mobility report provided by Google. Data processing begins with factor analysis, followed by multiple linear regression. This study aims to model the changes in community mobility as exogenous factors affecting economic growth. As a result, restrictions on community mobility, particularly related to job factors, significantly affect the economic development of an area, particularly in the provinces of Java Island. The resulting model would explain 96.97 percent of Indonesia’s variations in regional economic growth in 2020. Besides, this study predicts that 25 provinces will experience a recession in the third quarter of 2020. This forecast is the result of economic growth estimated using the current condition. Learning the association between mobility and economy is essential to understand how much restrictions or relaxations needed that can be appropriate to our economy during the pandemic.
1. INTRODUCTION

The global population is currently facing one of the most life-threatening disasters since the last century, generally referred to as COVID-19 or 2019-nCoV (Backer et al., 2020). This infectious respiratory disease was first identified in Wuhan, the People’s Republic of China (Setiati & Azwar, 2020). Globally, as of August 25, 2020, there have been 23,518,343 confirmed cases of COVID-19, including 810,492 deaths (WHO, 2020). The COVID-19 has different characteristics of rapid spreading because of the viral properties (e.g., long incubation period, asymptomatic effects for the super spreader, droplet carriers) as well as current socio-demographic globalization and urbanization (Rahman et al., 2020). Thus, COVID-19 spreading is still unclear and could easily infect people (Liu et al., 2020). For this reason, the World Health Organization (WHO) declared the virus as a pandemic on March 11 (Nicola, Sohrabi, et al., 2020).

To tackle the coronavirus disease 2019 (COVID-19) pandemic, several national governments have implemented lockdown restrictions to reduce the risk of infection (Feroze, 2020). For example, China, where the pandemic originated, was the first country to enforce the quarantine and lockdown of cities and later whole provinces, starting at the end of January (Fang et al., 2020). On March 22, 2020, the Government of India decided to completely lockdown 82 districts in 22 states and Union Territories of the country where confirmed cases have been reported till March 31 (Sahu et al., 2020). On April 10, 2020, Jakarta, which stated to be the epicenter of the COVID-19 in Indonesia, finally introduced a stay-at-home order, called the PSBB (Pembatasan Sosial Berskala Besar, or Large-scale Social Restrictions), followed by many other provinces and cities in Indonesia (Aldila et al., 2020). The rationale for implementing the restriction on community mobility policy is that the virus has already infected a part of the population with an accurate infectious proportion (hidden and asymptotic cases) being completely unknown (Lu et al., 2020). This measure has seen the success of such countries as China where the curves for reported cases and deaths have started flattening (Shen, 2020).

However, COVID-19 and the implementation of community mobility restriction will have impacts on the economy and society (Prawoto et al., 2020). As a policy to deal with the pandemic, mobility restriction policy harms production because it reduces the amount of work and employment (Zhou et al., 2020). Economic conditions during COVID-19 and the implementation of community mobility restriction were under pressure (O’Connor et al., 2020). China, the first infected nation, dropped 6.8 % in the first quarter, which was lower than the previous year at 6.2 %. US economic growth remained positive at 0.3 % compared to 2.0 % in the last year. In the second quarter, the US, Singapore and Europe’s growth declined at 9.5 %, 12.6 % and 14.4 %. The development of these countries was so low compared to China, at 3.2 %. In the meantime, Indonesia has also had to struggle in dealing with this situation. Indonesia’s growth in the first quarter was 3.0 %. Although it remained positive, the increase was much lower than 5.1 % in the same quarter in 2019. Also, the economic growth in the second quarter was minus 5.3 %, which has been the country’s lowest growth since 1999 (Trading Economics, 2020).

Therefore, in this study, we want to learn the impact of community mobility on Indonesia’s economic growth. Studying the relationship between mobility in pandemic and economy is essential to better view the current situation. Fortunately, Google provides real-time data as some indicators representing human mobility during COVID-19 (Google, 2020). Using Google mobility big data, we try to construct a model that can reflect the economic-mobility relationship. Then, this study also wants to use a selected model to forecast economic growth of each province in Indonesia in the third quarter. This forecast could be an early warning to some provinces and Indonesia, which predicted a recession in the next quarter. It would be a new challenge for the government to pursue policies that minimize the economic impact while also dealing with COVID-19 spreading. Studying the relationship between mobility and economy will be the key to understanding how much restriction or relaxation required during the pandemic that could be acceptable for Indonesia’s economy.
2. LITERATURE REVIEW

2.1. Economic Growth

The indicator of economic growth is the development of Gross Domestic Products (GDP) for national or Gross Regional Domestic Products (GRDP) for Provincial level. This figure represents the increase or decrease in the production of goods and services in an economic area within a specific time (BPS, 2020). The formula for calculating economic growth is as equation 1:

\[ Growth = \frac{y_t - y_{t-1}}{y_{t-1}} \times 100 \]  

(1)

Where:

- Growth = Economic Growth (%)
- \( y_t \) = Gross Domestic Products (GDP)/Gross Regional Domestic Products (GRDP) (Rp)

The formula uses GDP/GRDP at the constant prices (2010=100) to represent the real development of a region. It may measure economic development in 3 types of growth that depends on the comparison of the time. They are quarter to quarter (q-to-q), year on year (y-on-y), and cumulative to cumulative (c-to-c).

Quarter to quarter (q-to-q) economic growth is a measuring technique that calculates the change between one quarter (t) and the previous quarter (t-1). The term is similar to the year-on-year (y-on-y) measure, which compares the quarter of one year (such as the first quarter of 2020) with the same quarter of the previous year (the first quarter of 2019). Also, C-to-C economic growth compares year-on-year cumulative economic growth (such as year-on-year cumulative data up to the third quarter of 2020) to the same quarter of the previous year (such as year-on-year cumulative data up to the third quarter of 2019).

Every type of economic growth has a different objective. In this study, we use y-on-y economic growth to show the progress of an economy compared to the situation in the previous year. Y-on-Y comparison is standard when evaluating the output of a country as it helps to minimize seasonality, a factor that can affect most business in a region (Box et al., 2013; Ghysels et al., 2006).

2.2. Human Mobility

To handle the Coronavirus pandemic, countries around the world have implemented some policies, including stay-at-home 'lockdowns'; closures of school and workplace; cancellation of events and public gatherings; and restrictions on public transport (Rahman et al., 2020). The mobility restriction in Indonesia, beginning in Jakarta, is called Large-Scale Social Restriction (Muhammad Rosyidi et al., 2020).

It is not easy to monitor human mobility. Fortunately, Google provides data called mobility reports (https://www.google.com/covid19/mobility/) to track people’s mobility during a pandemic (Google, 2020). It uses aggregated, anonymized data from Google users who have turned the location history setting on their devices to display changes in people’s movements in locations like supermarkets, grocery stores, parks, mass transit stations, offices, and residential areas.

These reports show how the visits and duration of stay at various locations change relative to the baseline. Google measures these changes using the same form of aggregated and anonymized data used to show popular times for places on Google Maps. Changes for each day are compared to the average value for that day of the week on baseline day (January 3 - February 6 2020).

Google provides a variety of useful categories for social distancing activities and access to vital services (Google, 2020).
• Retail & recreation
  Mobility trends for places like restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres.
• Grocery & Pharmacy
  Mobility trends for places like grocery markets, food warehouses, farmers markets, speciality food shops, drug stores, and pharmacies.
• Parks
  Mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens.
• Transit stations
  Mobility trends for places like public transport hubs such as subway, bus, and train stations.
• Workplaces
  Mobility trends for places of work.
• Residential
  Mobility trends for places of residence

2.3. Previous Study

Several studies have reported on the economic effects of Covid-19. In the case of COVID-19, policy initiatives to prevent the spread and mortality of this disease have dramatically decreased jobs and economic activity worldwide (Abu-Rayash & Dincer, 2020). Governments have faced a problematic trade-off issue; namely how much reduction in employment and economic activity to accept as a result of allowing more liberal opportunities for social interaction. This type of choice involves an opportunity cost and a trade-off problem, and conceptually can be subjected to economic analysis (Tisdell, 2020).

One of the economic sectors most impacted by the outbreak of COVID-19 is the tourism industry, which affects both travel supply and demand (Sigala, 2020). As a direct consequence of COVID-19, the World Travel and Tourism Council warned that 50 million jobs in the global travel and tourism sector might be at risk. In Europe, the European Tourism Manifesto Coalition, which comprises more than 50 European public and private organizations from the travel and tourism industries, highlighted the need for immediate action. The travel industry is dealing with an unprecedented wave of cancellations and a significant drop in demand amid strict governmental instructions to implement social distancing and the restriction of unnecessary travel (Nicola, Sohrabi, et al., 2020). The situation has affected travel-dependent industries, such as hotels, educational institutions and public transport, while the sectors that are mandatory for human life, such as offices, residential areas, restaurants and shopping malls, are recovering rapidly (Tan et al., 2020).

COVID-19 is a disease which has affected most, if not all, countries in the world. The magnitude of the effect of Covid-19 has varied across countries. There are many reasons why some countries might have been harder affected than others. The differences in government policy responses may explain some of the differences. In Australia, as many state jurisdictions have begun to slowly ease restrictions, travel activity has started to slowly return, in particular by private car, and in particular for shopping and social or recreational activities. There is still concern about the use of public transport, although it has declined dramatically since the first wave of data collection. We see that working from home continues to be an effective strategy for reducing travel and burden on limited transport networks, and a policy intervention that, if moved to a post-pandemic environment, would be a significant step towards more sustainable transport in the future (Beck & Hensher, 2020).

China, the causal impact of human mobility restrictions, particularly the lockdown of the city of Wuhan on January 23, 2020, delays of the spread of the Novel Coronavirus (2019-nCoV) (FANG et al., 2020). They employ a set of difference-in-differences (DID) estimations to disentangle the lockdown
effect on reducing human mobility. The study found that the Wuhan lockdown reduced Wuhan inflows by 76.64\%, Wuhan outflows by 56.35\%, and within-Wuhan movements by 54.15\% (FANG et al., 2020). Indeed, the reduction has affected the economy. However, analysis at the provincial level showed that the self-sufficient and self-sustainable economic regions, with internal supplies, production, and consumption, have recovered faster than those regions relying on global supply chains (Tan et al., 2020).

In Italia, human mobility restrictions under COVID-19 also have an impact on Economic and social. Using real-time Italian mobility data provided by Facebook, Bonaccorsi (Bonaccorsi et al., 2020) investigated how lockdown policies impact the economic conditions of individuals and local governments. The study modelled mobility as an exogenous shock equivalent to a natural disaster affecting the economy. They found that the impact of lockdown is more substantial in municipalities with higher fiscal capacity (Bonaccorsi et al., 2020).

In Indonesia, previous research shows that there are significant differences in retail, grocery and pharmacy, and residential mobility before and during the COVID-19 pandemic in Indonesia. It also shows that during the COVID-19, there are severe economic losses, industry, companies, and real disruptions are painful for all levels of life due to large-scale restrictions (Caraka et al., 2020). Unfortunately, none of the papers seeks to link economic growth quarterly and mobility during the pandemic, especially in Indonesia. Therefore, this study hopes to fill the gap in this research.

2.4. Theoretical Framework

The proposed model assesses mobility using six indicators reported by Google for economic growth. Mobility is a variable constructed using factor analysis. It is a score factor that may reflect the movement of people in a variety of locations, such as stores, restaurants, supermarkets, parks, stations, offices, and residential areas. Mobility is believed as one of the variables that affects economic growth. The theoretical framework is:

![Figure 1. Theoretical Framework](http://dx.doi.org/10.31685/kek.V5.1.678)
3. METHODOLOGY

3.1. Data Source

The data used in this study comprises of daily observations of community mobility reports provided by Google Big data in an integrated application dashboard. It can be accessed in real-time on mobility reports (https://www.google.com/covid19/mobility/). The period of collected data is from February 15, 2020, to August 17, 2020, with a total of 6,476 observations covering 34 provinces in Indonesia. The data shows how our community is moving around differently due to COVID-19. Also, the quarterly data of economic growth obtained from Official Statistics News released on August 5, 2020. The data source is on the website of Badan Pusat Statistik (https://bps.go.id/).

3.2. Analysis Method

In this study, we analyzed the effects of community mobility on quarterly economic growth. Therefore, the first step that we have to do is to measure the average changes in the community mobility report for every quarter. This study estimates the changes in every specific place such as retail and restaurants, groceries, parks, transit stations, offices, and residential areas for every quarter. The full step by step analysis is as follows:

1. Data Preparation
   This study transforms daily community mobility report into quarterly data using a simple average method.

2. Factor Analysis
   The research uses Factor analysis to reduce the dimension of mobility indicators (Hair et al., 2018). As we know, the mobility report provided by Google includes six variables correlated with each other. For example, mobility in the workplace probably has a significant positive correlation with the mobility in the transit station. The correlation among these independent variables called multicollinearity is a problematic issue for the regression model. Factor analysis should compact the dimension of mobility to ensure that there is no further correlation in the independent variables (Hair et al., 2018). Therefore, this study resolves the issue in the next step. Also, we will produce the mobility score factor used in the regression model.

3. Regression Analysis
   This research uses the Multiple Linear Regression Model to demonstrate the effects of human mobility on quarterly economic development. Also, we use some dummy variables to describe the various situations that have arisen in each group of islands in Indonesia. The specification for the model is as follows:

   \[ Y_{it} = \beta_0 + \beta_1X_{it} + D_1Sumatera_{it} + D_2Kalimantan_{it} + D_3Sulawesi_{it} + D_4Papua_{it} + \epsilon_{it} \]

   Where:
   - \( Y \) = Economic Growth y-on-y (%)
   - \( X \) = Mobility (Score factor measured from the second step)
   - \( Sumatera \) = a dummy variable (Sumatera=1, for provinces in Sumatera island)
   - \( Kalimantan \) = a dummy variable (Kalimantan=1, for provinces in Kalimantan island)
   - \( Sulawesi \) = a dummy variable (Sulawesi=1, for provinces in Sulawesi island)
   - \( Papua \) = a dummy variable (Papua=1, for provinces in Papua and Maluku Island)
   - \( i \) = Province (Aceh, North Sumatera, ..., Papua)
   - \( t \) = Time (1st Quarter of 2020, 2nd Quarter of 2020)
4. The goodness of Fit and Assumption Model Checking
   The selected model then tested using several indicators before used to the interpretation and forecasting step. The goodness of fit indicators used is Adjusted R-Squares. This indicator represents the amount of variation of economic growth explained by the selected model. Also, the chosen model has tested using assumption Model Checkings, such as Normality, Non-autocorrelation, and Homoscedasticity. In terms of normality, this study uses Jarque-Berra Test using Eviews Application. For the assumption of Non-autocorrelation, we use Durbin-Watson statistics shown in the output of model estimation. Also, the homoscedasticity is detected using the Breusch Pagan Godfrey Heteroscedasticity Test.

5. Interpretation and Forecasting
   Using the chosen model that there is no longer a problem, the study interprets the model and uses it to predict economic growth situation in the third quarter. For the mobility score factor in the third quarter, we measure the simple average of daily community mobility report as the independent variable from July 1, 2020, to August 17, 2020. This study assumes that there are no significant changes in mobility at the half-end of the third quarter.

4. RESULTS OF ANALYSIS AND DISCUSSION

4.1. Community Mobility Report in Indonesia

   The Google Community Mobility Report (Google, 2020) uses location data from mobile phones to show the percent change in visits to places like grocery stores and parks within a geographic area compared to the baseline (Jan 3, 2020 – Feb 6, 2020). As shown in Figure 2, which summarizes this information for Indonesia as a whole, the amount of time spent at home has increased. In contrast, the amount of time spent at workplaces, retail and recreation, and transit locations has decreased dramatically since mid-March. The trend is relatively similar to that of Australia (Beck & Hensher, 2020).

![Figure 2. The Changes In Community Mobility Compared To Baseline (%)](http://dx.doi.org/10.31685/kek.V5.i1.678)
The mobility restriction policy implemented by the Government has undoubtedly had an impact on trends in mobility in socio-economic activities. As shown in Figure 2, the movement of activity mobility trends, including retail and recreation sectors, grocery and pharmacy, parks, transit stations, workplaces, and residential sectors in Indonesia from March to August.

| Categories           | Q1 (Up to Aug 17, 2020) | Q2 (Up to Aug 17, 2020) | Q3 (Up to Aug 17, 2020) |
|----------------------|--------------------------|--------------------------|--------------------------|
| Retail and Recreation| -9.67                    | -33.79                   | -16.58                   |
| Grocery and Pharmacy | -2.72                    | -13.37                   | -1.67                    |
| Parks                | -12.22                   | -31.54                   | -12.52                   |
| Transit Stations     | -13.33                   | -51.92                   | -34.00                   |
| Workplaces           | -5.76                    | -29.65                   | -20.10                   |
| Residential          | 4.85                     | 15.44                    | 10.88                    |

Table 1 measures the average of changes in the community mobility report for each category since the first quarter to the third quarter (up to August 17, 2020). The mean of the retail and recreation sector in the second quarter was -33.79% compared to baseline. It reflects the reduction in human mobility in restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theatres. This figure is relatively improved at -16.58% in the third quarter, although it remained a long way from normal baseline condition.

For the second category, the mean of the grocery and pharmacy in the second quarter was -13.37% compared to baseline. It represents the decline in mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies. Nowadays, this number is almost back to its normal baseline state. In the third quarter, the condition is just 1.67 percent lower than the baseline. It is because mobility in Groceries and pharmacy places is relatively more crucial to our lives than other categories to satisfy our everyday needs, particularly food and products from farmers’ markets (Google, 2020).

The other category that has significant improvement in community mobility is the parks category. It represents the mobility trends for places like national parks, public beaches, marinas, dog parks, plazas, and public gardens. In the second quarter, parks mobility was 31.54% compared to baseline. In terms of changes in the transit station sector, the trend in Figure 2 indicates a reasonably high decline compared to other industries. Indeed, it is due to restrictions of human mobility, causing the industry to collapse (Prawoto et al., 2020). It is in line with the condition in Italy (Nicola, Sohrabi, et al., 2020).

At first, the mobility pattern in the workplace sector remained optimistic until mid-March. At the beginning of April, there was a relatively significant fall. The condition was 29.65 percent lower than the usual baseline condition in the second quarter. The reason for this is the implementation of the work-shift mechanism at the workplace, such as civil servants and other business sectors (Savić, 2020).

Besides, the residential mobility trend, which has increased since the COVID-19 emerged in Indonesia, is too contrasting compared to the other categories. It demonstrates that the rules of residence at home enable high-level mobility in settlements. There are a lot of people who do their jobs and work at home. Residents obey the Government’s order to stay at home, particularly in Jakarta (Aldila et al., 2020). However, it is undeniably evident that certain people remain to do activities outside. Moreover, the development of COVID-19 is rapidly spreading across the world, even across the Indonesian islands (Prawoto et al., 2020).
4.2. Spatial data for Community Mobility Report in The Second Quarter 2020

The Google Community Mobility Report also provides provincial-level data (Google, 2020). As shown in Table 2 and Figure 3, which summarizes this information for each province in Indonesia, the amount of time spent at home has increased. In contrast, the amount of time spent at workplaces, retail and recreation, and transit locations has decreased dramatically in the second quarter. The explanation is in line with the community mobility report for Indonesia, as mentioned before.

Table 2. The mean of changes in community mobility in 2nd quarter for each province compared to baseline (%)

| Categories            | Minor Province | % change to baseline | Major Province | % change to baseline |
|-----------------------|----------------|----------------------|----------------|---------------------|
| Retail And Recreation | Aceh           | -16.20               | DKI Jakarta    | -50.13              |
| Grocery and Pharmacy  | Lampung Central| -2.77                | Bali           | -33.56              |
| Parks                 | Sulawesi Central| -7.36                | DKI Jakarta    | -75.88              |
| Transit Station       | Lampung Nusa Tenggara| -42.22  | Bali           | -75.31              |
| Workplaces            | Timur Nusa Tenggara| -16.64              | DKI Jakarta    | -41.85              |
| Residential           | Aceh           | 7.95                 | DKI Jakarta    | 20.52               |

Figure 3. The changes of community mobility for each province in the 2nd Quarter (%)

http://dx.doi.org/10.31685/kek.V5.i1.678
On the one hand, DKI Jakarta has the most significant changes in community mobility for several categories, such as declining at retail and recreation (-50.13%), Parks (-75.88%), and Workplaces category (-41.85%). People in this province also have the highest rise in the mobility community in residential area class due to the implementation of Large Scale Social Restriction (PSBB) and 'stay at home' order by the Government. Bali has the highest decline in grocery and pharmacy category (-33.56%) and Transit Stations such as airport, terminals, and other hub stations (-75.31%). Indeed, this condition affected the economic growth of these provinces, especially in Bali, which decreased in the first and second quarters of 2020. The situation caused Bali to experience a recession in 2020 due to contraction occurred in 2 or more quarters in a row.

On the other hand, provinces such as Aceh, Lampung, Central Sulawesi, and Nusa Tenggara Timur have relatively minor changes in community mobility compared to baseline. Figure 3 provides a complete picture of the changes in community mobility in the second quarter for each province. The darker colour in the image reflects the more significant mobility changes in the region in the 2nd quarter.

4.3. Dimension Reduction Using Factor Analysis

To tackle the potential multicollinearity issue among the mobility changes provided by Google, we employ factor analysis. Using this analysis tool, we eliminate the correlation of the independent variables mentioned before, such as retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential areas. As a result, this study produces several factors that no longer align with each other. Moreover, the analysis reduces the dimension of the components.

Before using the factor score, we evaluated the data in a variety of statistical measures to assess the fitness of the model. The first indicator used is KMO and Bartlett’s test. Classification for KMO Sampling adequacy scores can be divided into six groups (Hair, Anderson, Tatham and Black, 1995). They are unacceptable (<0.5), miserable (0.5 - 0.6), mediocre (0.6 - 0.7), middling (0.7 - 0.8), meritorious (0.8 - 0.9), and marvelous (>0.9). Since the KMO test is 0.875, the study using analysis factor is on excellent rating. It means that our measurement is sufficient for the data (Table 3).

The other indicator is the performance of anti-image matrices, which shows that the study of the factor can explain well the mobility changes in Indonesia. In Table 4, we can see that the main diagonal for anti-image correlation is more than 0.8. It ensures that the data is reasonably reliable and meets the standards for factor analysis.

Table 3. The output of KMO and Bartlett’s Test

| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | .875 |
| Approx. Chi-Square | 908.429 |
| Bartlett’s Test of Sphericity | df |
| | 15 |
| Sig. | .000 |

Although the dimension reduces to 2, the built factors will describe the initial data well. Using table 5, we can explain the more than 90 percent of the variation in retail and recreation (x1), transit station (x4), workplace (x5), and residential area (x6) data described using the constructed factor. At least 83 percent of the variation of parks data (x3) and grocery and pharmacy, expressed using the same elements. Generally, the two constructed factors can explain 92.53 % variation of the initial data of the community mobility Google Report (Table 6).
Table 4. The output of Anti-image Matrices

|      | x1  | x2  | x3  | x4  | x5  | x6  |
|------|-----|-----|-----|-----|-----|-----|
| x1   | .091| -.090| -.043| -.002| .004| .021|
| x2   | -.090| .267| -.068| -.024| .010| -.018|
| x3   | -.043| .068| .324| .023| .037| -.018|
| x4   | -.002| -.024| .023| .095| .018| .024|
| x5   | -.004| .010| -.037| -.018| .048| .030|
| x6   | .021| -.018| -.018| .024| .030| .043|

Anti-image Covariance

|      | x1  | x2  | x3  | x4  | x5  | x6  |
|------|-----|-----|-----|-----|-----|-----|
| x1   | .878| -.580| -.253| -.026| .055| .332|
| x2   | -.580| .852| .914| .130| .299| .153|
| x3   | -.253| -.233| .636| .013| .262| .373|
| x4   | -.055| .084| -.299| -.262| .858| .658|
| x5   | .332| -.170| -.153| .373| .658| .830|

Table 5. The output of Cummunalities

|      | Initial Extraction |
|------|--------------------|
| x1   | 1.000 .934 |
| x2   | 1.000 .889 |
| x3   | 1.000 .833 |
| x4   | 1.000 .949 |
| x5   | 1.000 .969 |
| x6   | 1.000 .978 |

Table 6. The output of Constructed Factors

| Component | Initial Eigenvalues | Rotation Sums of Squared Loadings |
|-----------|--------------------|-----------------------------------|
| Total     | % of Variance      | Cumulative %                     | Total     | % of Variance | Cumulative %                     |
| 1         | 5.021 | 83.692 | 83.692 | 3.194 | 53.228 | 53.228                     |
| 2         | .530  | 8.839  | 92.530 | 2.358 | 39.303 | 92.530                     |
| 3         | .280  | 4.673  | 97.204 |       |        |                            |
| 4         | .084  | 1.400  | 98.604 |       |        |                            |
| 5         | .057  | .950   | 99.554 |       |        |                            |
| 6         | .027  | .446   | 100.000 |       |        |                            |

Using the matrix in Table 7, we were constructing the score variables. The rotated parameter matrix attempts to transform the variable into a particular factor/parameter. On the one side, the variable transit station (x4) and the workplace (x5) have a more significant association with the 1st element. Also, the residential area has a significantly negative correlation at -0.905 to the 1st factor. On the other hand, the variable grocery and pharmacy (x2) and parks (x3) have a more significant correlation to the 2nd factor or component.

Using this classification, we can define the name of each element. The name for the first factor is the jobs factor due to its correlation with the workplace (x4), transit station (x5), and the decrease in length in the residential area (x6). Moreover, the second factor is shopping and leisure factors. It is because the factor has a more significant correlation to the groceries and pharmacy (x2) and parks (x3).
Table 7. The Rotated Component Matrix

| Component | 1 | 2 |
|-----------|---|---|
| x1        | .708 | .658 |
| x2        | .351 | .875 |
| x3        | .417 | .812 |
| x4        | .891 | .394 |
| x5        | .885 | .432 |
| x6        | -.905 | -.399 |

4.4. Estimation and Evaluation of Model

To analyze the relationship between economy and mobility, we estimate the coefficient using a multiple linear regression model. Using this analysis tool, we regress the score factor 1/ F1 (jobs) and the score factor 2/ F2 (non-jobs/ shopping and leisure) to economic growth in the first and second quarter of 2020.

Before interpreting, we evaluated the model using a variety of statistical measures to assess the fitness of the model. The first indicator used is Prob F statistics. This figure estimates the overall test of a model. Using these statistics, we can conclude that at least one of the independent variables is significant to impact economic growth. The second indicator used is an adjusted R-Square. The figure in this model is 0.9697. It means that 96.97% of the variance of the economic growth described using this model. It shows that the constructed model is excellent for use in the forecasting the situation in the third quarter.

The other indicators used are the assumption checking such as normality, non-autocorrelation, non-multicollinearity, and homoscedasticity. In terms of normality performance, the Jarque Berra (Probability) in Figure 4 is at 0.100 (greater than 0.05). The decision of the test due to the statistics is to accept the null hypothesis that the model is to follow the normality criterion. In terms of non-autocorrelation, Durbin Watson’s statistics are evaluated around two, reflecting no autocorrelation in this model. In the case of non-multicollinearity, we use the VIF measure, which indicates no scores higher than 5. It implies that there is no collinearity between these independent variables.

Table 8. Estimation and Evaluation of The Selected Model

| Variable          | Coefficient | Std. Error | t-Statistic | Prob. | VIF  |
|-------------------|-------------|------------|-------------|-------|------|
| C                 | -1.264188   | 0.267289   | -4.729664   | 0.0000| 1.286|
| F1                | 2.750363    | 0.087690   | 31.36474    | 0.0000| 1.355|
| F2                | 1.039278    | 0.172041   | 6.040863    | 0.0000| 1.575|
| DSUMATERA         | 0.403837    | 0.300656   | 1.343184    | 0.1842| 1.340|
| DKALIMANTAN       | 0.443932    | 0.317831   | 1.396669    | 0.1676| 1.395|
| DSULAWESI        | 2.006627    | 0.311740   | 6.436864    | 0.0000| 1.285|
| DPAPUA            | 2.672167    | 0.579438   | 4.61657     | 0.0000| 1.286|
| R-squared         | 0.972428    | Prob(F-statistic) | 0.00000 | 1.719941 |
| Adjusted R-squared| 0.969716    | Durbin-Watson stat | 0.00000 | 1.719941 |

Also, we use generalized least squares (GLS) to tackle the heteroscedasticity issue. Based on the Breusch Pagan GoodFrey-test, the initial model should be estimated using GLS to ensure that the model generates the Best Linear Unbiased Estimator (BLUE).
4.5. Model Interpretation and Forecasting The 3rd quarter

The lockdown, one of the social isolation restrictions, has been observed to prevent the COVID-19 pandemic and showed that the spread of the virus could be significantly reduced by this preventive restriction (Atalan, 2020). However, the limitation in mobility will affect the economy as equation (2)

\[ Y_{it} = -1.26 + 2.75xF1_{it} + 1.04xF2_{it} + 0.40x\text{Sumatera}_{it} + 0.44x\text{Kalimantan}_{it} + 2.01x\text{Sulawesi}_{it} + 2.67x\text{Papua}_{it} + \epsilon_{it} \]  

Where:

- \( Y \) = Economic Growth y-on-y (%)
- \( F1 \) = Score for jobs Factor
- \( F2 \) = Score for non-jobs/ Shopping and Leisure Factor
- \( \text{Sumatera} \) = a dummy variable (Sumatera=1, for provinces in Sumatera island)
- \( \text{Kalimantan} \) = a dummy variable (Kalimantan=1, for provinces in Kalimantan island)
- \( \text{Sulawesi} \) = a dummy variable (Sulawesi=1, for provinces in Sulawesi island)
- \( \text{Papua} \) = a dummy variable (Papua=1, for provinces in Papua and Maluku Island)
- \( i \) = Province (Aceh, North Sumatera, ..., Papua)
- \( t \) = Time (1st Quarter of 2020, 2nd Quarter of 2020)

The jobs factor is more dominant in the economic growth in the model. We can see the coefficient of this component at 2.75 is significantly positive, affecting economic growth. On the one hand, the improvement of the mobility in job factors at 1 unit could affect the economic growth at 2.75 %. On the other hand, the stay-at-home order can reduce the mobility score factor for jobs. Indeed, the situation affects economic growth.

Moreover, the shopping and leisure factor is a less dominant factor affecting the economic growth in the model compared to the jobs factor. However, we can also see that this component’s coefficient at 1.04 is significantly positive, affecting economic growth. On the one hand, the improvement of mobility in shopping and leisure factor at 1 unit could affect the economic growth at 1.04 %. On the other hand, a large-scale restriction can reduce the mobility score factor for shopping and leisure. Indeed, the situation also affects economic growth.

Our model shows the effects of various types and magnitudes of mobility changes on controlling COVID-19 outbreaks in Indonesia affect different economic growth. The economic growth province in Java island is relatively lower than the economic development of the provinces in Sulawesi and Papua Island. As an average, we can see that Provinces in Sulawesi have higher economic growth by 2.01 % than the provinces in Java Island. In the meantime, the provinces in Papua have the highest economic growth by 2.67% (cateris paribus).

However, there is no evidence that the economic growth of the provinces in Sumatera and Kalimantan were higher than the province in Java Island. It is indicated by the positive coefficient at the dummy variable for Sumatera and Kalimantan that not significant. Using the selected model, we also predict economic growth in the third quarter for each province, as shown in Table 9.
Based on Table 9, there are 25 provinces predicted to be a recession in the third quarter. A recession is a condition that economic growth is negative in two or more quarters in a row (Nicola, Alsafi, et al., 2020). This study also predicts that Indonesia's economic growth will be a recession in the third quarter since the decline in the second quarter (5.32%) and the prediction in the third quarter (2.25%). Bali and DI Yogyakarta even have experienced a recession in the second quarter. It is because negative growth occurred in these provinces in the first and second quarter.

* predicted to be a recession in the third quarter
** experienced a recession in the second quarter
Figure 5. The Economic Growth In Indonesia In 2020 (%)
To complete this analysis, we provide the development of economic growth in 3-period maps. In the first quarter, we can see that there are only two provinces (Bali and DI Yogyakarta) declining. The effect of mobility is relatively smaller to economic growth since there is no implementation of large-scale restriction. In contrast, we can see that only two provinces had a positive change in the second quarter.

Moreover, the situation in the third quarter prediction is relatively better than the second quarter, but there is a long way to go to get back to the normal condition. The prediction conducted is based on the average of the community mobility report up to August 17, 2020. Thus, it can be updated using the newest data provided almost real-time by Google. Understanding the relationship between mobility and economy could be the key to solve this problem. Using the updated data, we can monitor the impact of COVID-19 and simulate it with the selected model.

5. CONCLUSIONS AND RECOMMENDATIONS

Indonesia has introduced a large-scale social restriction (PSBB) to deal with the spread of COVID-19. This policy, however, has a side effect. The Covid-19 and its system have an impact on the economy. Changes in community mobility for the jobs factor (workplace, transit station, residential area) have a more significant effect on economic development relative to mobility for shopping and leisure. Thus, instead of increasing mobility at parks and recreation places, it should be better for economic growth if the mobility at jobs factor rises. However, the worker must follow strict preventive measures or health protocols such as wearing a face mask, physical distancing, and frequently washing hands.

To further research, we need to develop the relationship between mobility and the infected COVID-19 cases in Indonesia. Combining this research with this current paper can be a wonderful thing to do. The fascinating part of this is that the data generated by Google is almost real-time data. Thus, we can simulate and monitor the effect of the changes in mobility not only for social (infected cases) but also for economic growth simultaneously. Moreover, it could be fantastic if there is an application or dashboard software that can facilitate this combined research fast. Therefore, we can know the amount of restriction or relaxation needed that can minimize the impact of COVID-19 in the social aspect as well as economic development quickly and easily.

6. ACKNOWLEDGEMENT

The authors would like to thank Badan Pusat Statistik BPS - Statistics of Riau Province and Google that provides big data. Furthermore, the authors would like to thank Erika Sari, a statistician at Statistics of Riau Province and Dr Arisman Adnan from the Statistics Department Faculty of Mathematics and Sciences of Riau University.

7. REFERENCES

Abu-Rayash, A., & Dincer, I. (2020). Analysis of mobility trends during the COVID-19 coronavirus pandemic: Exploring the impacts on global aviation and travel in selected cities. In Energy Research and Social Science. https://doi.org/10.1016/j.erss.2020.101693

Aldila, D., Khoshnaw, S. H. A., Safitri, E., Anwar, Y. R., Bakry, A. R. Q., Samiadiji, B. M., Anugerah, D. A., GH, M. F. A., Ayulani, I. D., & Salim, S. N. (2020). A mathematical study on the spread of COVID-19 considering social distancing and rapid assessment: The case of Jakarta, Indonesia. Chaos, Solitons and Fractals. https://doi.org/10.1016/j.chaos.2020.110042

Atalan, A. (2020). Is the lockdown important to prevent the COVID-9 pandemic? Effects on psychology, environment and economy perspective. Annals of Medicine and Surgery. https://doi.org/10.1016/j.amsu.2020.06.010

Backer, J. A., Klinkenberg, D., & Wallinga, J. (2020). Incubation period of 2019 novel coronavirus (2019-nCoV) infections among travellers from Wuhan, China, 20 28 January 2020. In Eurosurveillance. https://doi.org/10.2807/1560-7917.ES.2020.25.5.2000062

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia - The early days under restrictions. Transport Policy. https://doi.org/10.1016/j.tranpol.2020.07.001

http://dx.doi.org/10.31685/kek.V4.3.678
Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Schmidt, A. L., Valensise, C. M., Scala, A., Quattrociocchi, W., & Pammolli, F. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences of the United States of America*. https://doi.org/10.1073/pnas.2007658117

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (2013). *Time series analysis: Forecasting and control: Fourth edition*. In *Time Series Analysis: Forecasting and Control: Fourth Edition*. https://doi.org/10.1002/9781118619193

BPS. (2020). *Sistem Rujukan Statistik*. Badan Pusat Statistik. https://www.sirusa.bps.go.id/

Caraka, R. E., Lee, Y., Kurniawan, R., Herliansyah, R., Kaban, P. A., Nasution, B. I., Gho, P. U., Chen, R. C., Toharudin, T., & Pardamean, B. (2020). Global Journal of Environmental Science and Management Impact of COVID-19 large scale restriction on environment and economy in Indonesia. *Global J. Environ. Sci. Manage*. https://doi.org/10.22034/GJESM.2019.06.S1.07

FANG, H., WANG, L., & YANG, Y. (2020). Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China. *SSRN Electronic Journal*. https://doi.org/10.1101/2020.03.24.20042424

Feroze, N. (2020). Forecasting the patterns of COVID-19 and Causal Impacts of Lockdown in Top Ten Affected Countries using Bayesian Structural Time Series Models. *Chaos, Solitons & Fractals*. https://doi.org/https://doi.org/10.1016/j.chaos.2020.110196

Ghysels, E., Osborn, D. R., & Rodrigues, P. M. M. (2006). Chapter 13 Forecasting Seasonal Time Series. In *Handbook of Economic Forecasting*. https://doi.org/10.1016/S1574-0706(05)01013-X

Google. (2020). *Community Mobility Report*. Google. https://www.google.com/covid19/mobility/

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2018). *Multivariate Data Analysis*, Multivariate Data Analysis. In *Multivariate Data Analysis, Multivariate Data Analysis* B2 - Multivariate Data Analysis.

Liu, J., Wang, L., Zhang, Q., & Yau, S. T. (2020). The dynamical model for COVID-19 with asymptotic analysis and numerical implementations. *Applied Mathematical Modelling*. https://doi.org/10.1016/j.apm.2020.07.037

Lu, H., Stratton, C. W., & Tang, Y. W. (2020). Outbreak of pneumonia of unknown etiology in Wuhan, China: The mystery and the miracle. In *Journal of Medical Virology*. https://doi.org/10.1002/jmv.25678

Muhammad Rosyidi, R., Priyanto, B., Putu Wisnu Wardhana, D., Tsaniadi Prihastomo, K., & Kamil, M. (2020). COVID-19 and its impact on neurosurgery: our early experience in Lombok Island Indonesia. *Interdisciplinary Neurosurgery*. https://doi.org/10.1016/j.inat.2020.100868

Nicola, M., Alsafi, Z., Sohrabi, C., Kerwan, A., Al-Jabar, A., Iosifidis, C., Agha, M., & Agha, R. (2020). The socio-economic implications of the coronavirus pandemic (COVID-19): A review. In *International Journal of Surgery*. https://doi.org/10.1016/j.ijsu.2020.04.018

Nicola, M., Sohrabi, C., Mathew, G., Kerwan, A., Al-Jabar, A., Griffin, M., Agha, M., & Agha, R. (2020). Health Policy and Leadership Models During the COVID-19 Pandemic- Review Article. *International Journal of Surgery*. https://doi.org/10.1016/j.ijsu.2020.07.026

O’Connor, C. M., Anoushiravani, A. A., DiCaprio, M. R., Healy, W. L., & Iorio, R. (2020). Economic Recovery After the COVID-19 Pandemic: Resuming Elective Orthopedic Surgery and Total Joint Arthroplasty. *Journal of Arthroplasty*. https://doi.org/10.1016/j.arth.2020.04.038

Prawoto, N., Purnomo, E. P., & Zahra, A. A. (2020). The impacts of Covid-19 pandemic on socio-economic mobility in Indonesia. *International Journal of Economics and Business Administration*. https://doi.org/10.35808/ijeba/486

Rahman, M. A., Zaman, N., Asyhari, A. T., Al-Turjman, F., Alam Bhuiyan, M. Z., & Zolkipi, M. F. (2020). Data-driven dynamic clustering framework for mitigating the adverse economic impact of Covid-19 lockdown practices. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2020.102372

Sahu, D., Agrawal, T., Rathod, V., & Bagaria, V. (2020). Impact of COVID 19 lockdown on orthopaedic surgeons in India: A survey. *Journal of Clinical Orthopaedics and Trauma*. https://doi.org/10.1016/j.jcot.2020.05.007

Savić, D. (2020). COVID-19 and work from home: Digital transformation of the workforce. *Grey Journal*. https://dx.doi.org/10.31685/kek.V5.I1.678
Setiati, S., & Azwar, M. K. (2020). COVID-19 and Indonesia. *Acta Medica Indonesiana*.

Shen, C. Y. (2020). A logistic growth model for COVID-19 proliferation: experiences from China and international implications in infectious diseases. *International Journal of Infectious Diseases: IJID: Official Publication of the International Society for Infectious Diseases*. https://doi.org/10.1016/j.ijid.2020.04.085

Sigala, M. (2020). Tourism and COVID-19: Impacts and implications for advancing and resetting industry and research. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2020.06.015

Tan, J., Xiong, Y., Zhao, S., Liu, C., Huang, S., Lu, X., Thabane, L., Xie, F., Sun, X., & Li, W. (2020). Quantifying the impacts of human mobility restriction on the spread of COVID-19: an empirical analysis from 344 cities of China. *MedRxiv*. https://doi.org/10.1101/2020.07.13.20148668

Tisdell, C. A. (2020). Economic, social and political issues raised by the COVID-19 pandemic. *Economic Analysis and Policy*. https://doi.org/10.1016/j.eap.2020.08.002

Trading Economics. (2020). *Indonesia GDP Annual Growth Rate*. TradingEconomics.Com. https://tradingeconomics.com/indonesia/gdp-growth-annual

WHO. (2020). *WHO Coronavirus Disease (COVID-19) Dashboard*. World Health Organization. https://covid19.who.int/

Zhou, Y., Xu, R., Hu, D., Yue, Y., Li, Q., & Xia, J. (2020). Effects of human mobility restrictions on the spread of COVID-19 in Shenzhen, China: a modelling study using mobile phone data. *The Lancet Digital Health*. https://doi.org/10.1016/S2589-7500(20)30165-5