Quality & Quantity
https://doi.org/10.1007/s11135-022-01497-4

Considering the temporal interdependence of human mobility and COVID-19 concerning Indonesia's large-scale social distancing policies

Atina Ahdika[1] · **Arum Handini Primandari**[1] · **Falah Novayanda Adlin**[1]

Accepted: 23 June 2022

Abstract
The year 2020 has marked the beginning of a new life in which humans must struggle and adapt to coexist with a new coronavirus, known as COVID-19. Population density is one of the most significant factors affecting the speed of COVID-19's spread, and it is closely related to human activity and movement. Therefore, many countries have implemented policies that restrict human movement to reduce the risk of transmission. This study aims to identify the temporal dependence between human mobility and virus transmission, indicated by the number of active cases, in the context of large-scale social restriction policies implemented by the Indonesian government. This analysis helps identify which government policies can significantly reduce the number of active COVID-19 cases in Indonesia. We conducted a temporal interdependency analysis using a time-varying Gaussian copula, where the parameter fluctuates throughout the observation. We use the percentage change in human mobility data and the number of active COVID-19 cases in Indonesia from March 28, 2020, to July 9, 2021. The results show that human mobility in public areas significantly influenced the number of active COVID-19 cases. Moreover, the temporal interdependencies between the two variables behaved differently according to the implementation period of large-scale social distancing policies. Among the five types of policies implemented in Indonesia, the policy that had the most significant influence on the number of active COVID-19 cases was several restrictions during the Implementation of Restrictions on Community Activities (Pelaksanaan Pembatasan Kegiatan Masyarakat/PPKM) period. We conclude that the strictness of rules restricting social activities generally affected the number of active COVID-19 cases, especially in the early days of the pandemic. Finally, the government can implement policies that are at least equivalent to the rules in PPKM if, in the future, cases of COVID-19 spike again.

Keywords COVID-19 · Human mobility · Large-scale social distancing · Temporal interdependence · Time-varying copula

✉ Atina Ahdika
atina.a@uii.ac.id

Extended author information available on the last page of the article

Published online: 09 August 2022

1 Introduction

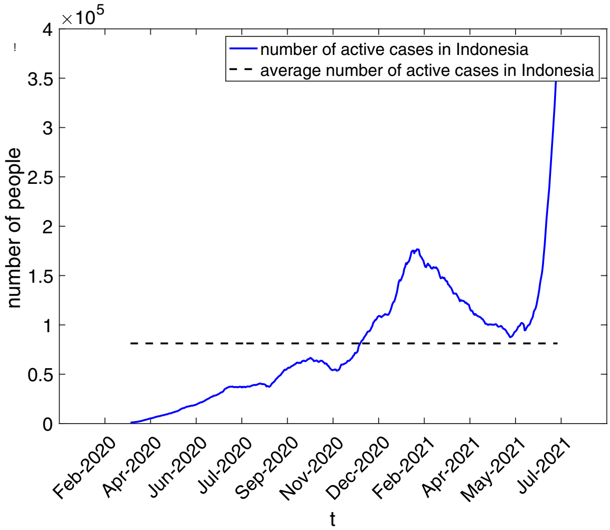
The year 2020 has marked the beginning of a new life in which humans must struggle and adapt to coexist with a new coronavirus, known as COVID-19, that has caused an acute respiratory syndrome epidemic in humans (Zhou et al. 2020). This epidemic was declared a pandemic on March 11, 2020 by the World Health Organization (WHO), as it was actively spreading in many countries (CDC 2020). The pandemic has changed all forms of normal human activity, including dietary patterns, consumption, and physical activities (Sánchez-Sánchez et al. 2020; Di Renzo et al. 2020). Limiting physical activity is one of the main measures that must be taken to contain COVID-19 because the virus has a fairly high infection rate and can be transmitted through the air. Several studies show that social parameters like population density (Hassan et al. 2021; Abedi et al. 2021; Bhadra et al. 2021; Bontempi and Coccia 2021; Sharif and Dey 2021; Sun et al. 2021), demographic diversity (Abedi et al. 2021; Sun et al. 2021), poverty level (Hassan et al. 2021), and the availability of highways (Nakada and Urban 2021) significantly affect COVID-19's rate of spread. Other parameters, including environmental and meteorological factors such as air pollution (Hassan et al. 2021; Bontempi and Coccia 2021; Aabed and Lashin 2021; Coccia 2021), climate and weather (Hassan et al. 2021; Bontempi and Coccia 2021; Aabed and Lashin 2021; Coccia 2021; Sharif and Dey 2021; Sun et al. 2021)also have significant effects in increasing the infection rate of COVID-19. To control the spread of COVID-19, humans must act at both the individual and policy levels. Among the previously mentioned parameters, social parameters can be controlled through human intervention.

Population density is one of the most significant factors affecting the speed of the spread of COVID-19. It is closely related to human activity and movement; the denser the population, the more movement occurs. Moreover, more movement corresponds to more interaction between people. This can further increase the spread of COVID-19. A study in Italy showed that before the country entered lockdown on March 9, 2020, people's mobility caused transmission in all regions in the country almost homogeneously and resulted in an increasing number of cases and deaths in some areas more than others (Cartenì et al. 2020). The data showed that transmission gradually decreased after Phase 2 of the COVID-19 situation, when fewer mobility limitations were applied. Oztig and Askin (2020) found that Schengen countries, countries with higher population density, and countries with a higher percentage of the elderly population had more positive COVID-19 cases than other countries. Specifically, they observed that a higher volume of airline passenger traffic in a country and a higher number of airports are positively associated with the number of COVID-19 patients (Oztig and Askin 2020). Many countries implemented lockdown policies and other government measures to reduce people's movement after COVID-19 was declared a pandemic, as well as Indonesia.

In Indonesia, the first case of COVID-19 was confirmed on March 2, 2020. At the beginning of this pandemic, the number of cases experienced a continuous increase until October 2020 and then decreased until November 2020 (see Fig. 1). Then it was increased again until it reached a second peak in February 2021 and decreased until May 2021. After that, the number of active cases experienced a very drastic increase until early July 2021. With this relatively significant increase, government policies are needed to reduce the number of active COVID-19 cases in Indonesia.

In order to provide recommendations to policy makers regarding the best strategy to reduce the spread of COVID-19, we conducted a study to identify the dependencies between percentage change in human mobility-as a result of the implementation of social

Fig. 1 Active COVID-19 cases in Indonesia



restriction policies-and the number of active COVID-19 cases in Indonesia. Unlike other studies which mostly identify factors that influence COVID-19 cases through a cross-sectional approach (Jamshidi et al. 2021; Lin and He 2021; D'Urso et al. 2022), this research focuses on a temporal approach to identify the dependencies between percentage change in human mobility and the number of active COVID-19 cases because both variables are dynamic. Therefore, the temporal approach is very suitable to model this issue. Moreover, we relate this temporal interdependency analysis to the social distancing policies implemented in Indonesia. In Indonesia, the government has imposed several social restrictions to reduce the spread of COVID-19. Our study explores the temporal interdependencies between the percentage change of human mobility in public areas and the number of active COVID-19 cases during these policies' enactment periods. Moreover, we study the behavioral changes in the relationship between the two variables. We identify how each social restriction policy affects the relationship between human mobility and the number of active COVID-19 cases. As it is known that social restriction policies can reduce human mobility, through this research we obtain an overview of the effect of changes in human mobility in each period of policy implementation on the number of active COVID-19 cases. In this way, we can determine which policies suppresses COVID-19 most effectively.

To do this, we identify the temporal interdependencies between human mobility and active COVID-19 cases using time-varying copula models, first introduced by Patton (2006). There have many developments in the time-varying copula model. In this paper, we use the approach developed by Ahdika et al. (2021), who extend the dynamic parameter function of the time-varying copula model introduced by Patton (2006) to obtain a more general form. We use the ARIMA time-series for marginal modeling of human mobility and active COVID-19 cases. Furthermore, the time-varying copula used to model the temporal dependencies between the two marginal variables is the time-varying Gaussian copula.

The paper is organized as follows. Section 2 provides the literature review for both the research related to lockdown-like policies in reducing COVID-19 cases and the analysis of copula. Section 3 briefly explains the methods, which consist of ARIMA for marginal modeling and time-varying Gaussian copula models with extended dynamic parameters for temporal dependency modeling. Section 4 presents and discusses the main results. The conclusions are reported in Sect. 5.

2 Literature review

2.1 Lockdown-like policies to reduce COVID-19 cases

One of the efforts made by many countries in the world to overcome the surge in the number of active cases of COVID-19 is to enforce social distancing policies. Studies examining this policy have noted that such policies provide quite effective results in reducing the number of active COVID-19 cases. Rahman et al. (2020) investigated the interplay between mobility changes in some public areas and the severity of the COVID-19 pandemic. They reported that lockdowns have a substantial impact on encouraging people to maintain social distance to limit infection risk (Rahman et al. 2020). Pan et al. (2020) found that government orders and policies significantly influenced the social distancing behavior of the community. In the UK, the Foreign Office advised against all non-essential travel, prohibited gathering in crowded places, closed all schools except those for the children of key workers and vulnerable children, suspended driving tests for up to 3 months except for critical workers, closed cinemas, nightclubs, theaters, etc., and implemented a general lockdown to reduce COVID-19 transmission (Hadjidemetriou et al. 2020).

Recent study also showed that the implementation of the lockdown-like policy in Italy has a good impact on pandemic conditions; the policy has successfully reduced human mobility which results in a decrease in the number of infections and deaths due to COVID-19 (Panarello and Tassinari 2022). As a result of the successful implementation of the lockdown during the pandemic, Almulhim and Barahona (2022) made a decision support system to investigate important indicators that need to be considered in the reopening strategy.

2.2 Temporal dependency analysis using time-varying copula

Copula is a function that pairs one-dimensional distribution functions into a multivariate distribution function (Sklar 1959). One of the roles of the copula in multivariate analysis is to form a multivariate distribution function of interconnected random variables. The advantage of copula compared to conventional dependency measures, such as Pearson correlation, is that it can accommodate random variables that have both linear and nonlinear relationships and are free from the assumption of data normality.

Recent studies related to the COVID-19 issue using the copula method mostly focuses on the impact of the pandemic on the capital market. Studies that directly analyzes the factors that influence cases of COVID-19 or its spread using a copula is still limited. Some of them found in the literature are as follows. Jamshidi et al. (2021) analyzed the dependence structure between number of test and positivity rate using Clayton, Frank, Gumbel, and FGM copula. They used the classic copula model whose parameters are static. Lin and He (2021) analyzed the relationship between temperature and confirmed case by considering the impact of the number of potential infection using the semiparametric multivariate density estimation. The joint probability density between the two variables is formed using static Gumbel-Hoougard copula. D'Urso et al. (2022) identified the spatial dependence between COVID-19 infection rate with its covariates, such as life expectancy at birth, income, employment rate, total age dependency, etc, using D-Vine copula-based quantile regression.

According to the current developments in copula modeling, several studies show that the relationship between variables can be temporal. Therefore, the copula modeling which was originally static-describes the static relationship between variables-can be developed into a dynamic copula modeling, known as time-varying copula. There have been many developments in the time-varying copula model. Patton (2006) introduced a dynamic parameter of time-varying copula which follows an ARMA(1, 10) process. Similar approach has also been taken by Hafner and Manner (2012); Manner and Reznikova (2012). They assumed that the relationship between time on the same variable can be described by the autoregression process, while the relationship between variables can be described by the moving average process which is defined as the mean absolute difference between the cumulative distribution function of the two variables.

Some researchers use other approaches; Dias and Embrechts (2010) assumed that the dynamic parameter of time-varying copula follows an ARMA(1, 1) process, Xu et al. (2018) assumed that it follows a generalized autoregressive score of order (1, 1), Manner et al. (2019) assumed that it follows a latent Gaussian AR (1), and Ahdika et al. (2021) has generalized Patton (2006)'s approach by assuming that the parameters of the time-varying copula follow an ARMA (1, m) process.

3 Theoretical framework

3.1 Large-scale social distancing policies in Indonesia

The first COVID-19 case in Indonesia was confirmed on March 2, 2020. On March 31, 2020, the Indonesian government enacted regulations to control the transmission of COVID-19 by establishing the first large-scale social distancing policy (Pembatasan Sosial Berskala Besar 1/PSBB 1). This regulation is contained in Government Regulation of the Republic of Indonesia Number 21 of 2020 concerning Large-Scale Social Restrictions in the Context of Accelerating Handling of Corona Virus Disease 2019 (COVID-19). Under this regulation, the governor, regent, or mayor proposes the implementation of PSBB 1 to the minister who carries out government affairs in the health sector. The minimum restrictions include school and work holidays, the regulation of religious activities, and restrictions on activities in public places or facilities (Republik Indonesia 2020). However, these restrictions must consider educational needs, work productivity, population, and the fulfillment of peoples's basic needs. In Jakarta, the capital of Indonesia, PSBB 1 was initially implemented from April 10 to April 23, 2020 and then extended to June 4, 2020 because the case numbers had not subsided.

PSBB 1 continued from June 5 to September 10, 2020 and became a transition period for the community to lead a new normal life. The implementation of PSBB 1 during this period is known as Transitional PSBB 1. During Transitional PSBB 1, some activities–especially economic activities–were permitted. General protocols for social and economic activities during the Transitional PSBB 1 period include limiting the number of participants, visitors, workers, and business owners to less than 50% of a space's capacity, always maintaining a distance of 1 meter between people, and washing the activity area with disinfectant before and after work or activities (Pemprov DKI Jakarta 2020). When traveling, people were allowed to take private vehicles but were required to always wear masks, prioritize travel on foot and by bicycle, keep a distance of 1 meter when waiting for vehicles (e.g., in terminals, bus stops, and stations), and were prohibited from crowding. Other public transportation (e.g., motorcycle taxis and cars) were allowed to operate according to the COVID-19 protocol (Pemprov DKI Jakarta 2020).

Meanwhile, teaching and learning activities in schools could not be carried out. After considering the death rate, the number of beds in the isolation rooms, and the occupancy of beds in the ICU, the Jakarta provincial government again imposed a strict PSBB policy, like the policy before the Transitional PSBB1, from September 14 to October 11, 2020. This set of restrictions is known as PSBB 2. During the PSBB 2 period, educational activities in schools were not implemented, and there were temporary restrictions on work activities in the workplace and office. In particular, PSBB 2 imposed a capacity limit of 25% of people who are in the workplace at the same time. It is also temporarily stopped activities at the workplaces and offices for at least 72 hours if workers were found to be exposed to COVID-19 (Pemerintah Gubernur DKI Jakarta 2020). However, several sectors were excluded fromthis temporary limitation, including the offices of foreign country representatives and international organizations carrying out diplomatic and consular functions or other tasks protected by international law, state-owned or regional enterprises participating in the COVID-19 response or meeting the basic needs of the community; business actors engaged in 11 essential business sectors, and local and international community organizations involved in the disaster and the social sector. The 11 critical business sectors are (1) health, (2) food and beverage, (3) energy, (4) communication and information technology, (5) finance, (6) logistics, (7) hospitality, (8) construction, (9) strategic industries, (10) essential services, public utilities, and industries designated as vital national objects, and (11) daily needs (Pemerintah Gubernur DKI Jakarta 2020). Exceptions are given by allowing workplaces and offices with these categories to carry out activities with a maximum of 50% of capacity. After the strict implementation of PSBB 2, statistical data showed that the addition of positive cases of COVID-19 and the number of patients hospitalized and self-isolated remained stable. In addition, from October 6 to October 11, 2020, signs of a decrease in the number of positive cases were observed. Therefore, from October 12, 2020 to January 11, 2021, the Jakarta provincial government again allowed some community activities through the implementation of Transitional PSBB 2. Restrictions were loosened by allowing the business sector to resume production with a maximum of 50% capacity while still prohibiting educational activities (Gubernur Daerah Khusus Ibukota Jakarta 2020).

In light of the recent developments in COVID-19 cases worldwide and the presence of new COVID-19 variants in several countries, the central and local governments have published several regulations to control COVID-19 by restricting activities that may cause COVID-19 transmission. These regulations are called the Implementation of Restrictions on Community Activities (Pelaksanaan Pembatasan Kegiatan Masyarakat/PPKM). The policy is effective from January 11, 2021 and regulated in the Instruction of the Minister of Home Affairs Number 01 concerning the Enforcement of Activity Restrictions to Control the Spread of Corona Virus Disease (COVID-19). The implementation of PPKM is explicitly delegated to regional heads on the islands of Java and Bali, which generally have a high incidence of COVID-19 in Indonesia. Some restrictions include workplace and office restrictions by implementing work from home (WFH) by 75% of workers and work from office (WFO) by 25% of workers through stricter health protocols. In addition, teaching and learning activities are carried out online. Operating licenses for essential sectors related to the community's basic needs allow 100% operation with working hours, capacity, and stricter implementation of health protocols. Restaurant activities are limited to 25%

capacity for dine-in, and the operating hours of shopping centers and malls are limited to 7:00 PM. Construction activities are allowed to fully operate and activities in places of worship can be carried out by setting a capacity limitation of 50% with the implementation of the better health protocols (Menteri Dalam Negeri Republik Indonesia 2021).

3.2 Temporal interdependencies analysis

According to Kavanagh (2013), temporal dependence predicts that the likelihood of an intervention at one time is a function of interventions in previous time. In the context of the dependency analysis in this paper, temporal interdependence shows two types of dependencies (Patton 2006). The first is the dependence between two different variables. The second is the dependence of the same variable on itself in previous times. Therefore, in this paper, we intend to identify the dependence between the percentage change in human mobility with the number of active COVID-19 cases and the dependence of each variable on itself in previous times.

We explore the temporal interdependencies between percentage change in human mobility in public areas and active COVID-19 cases. The public areas considered in this study include grocery stores, parks, transit stations, retail areas, and workplaces. In addition, we also use the percentage change in human mobility in residential area which is definitively the change in the length of time people spend at home compared to normal conditions. Human mobility and active COVID-19 cases are modeled using the time-series ARIMA model, which combines the autoregressive model (AR) and moving average model (MA). The AR model is a model that describes a dependent variable that is influenced by the variable itself in the previous period. The order of p expresses the number of historical periods used in the AR, usually known as AR(p), and is written as follows (Cryer and Chan 2008):

$$Y_t = \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \varepsilon_t, \tag{1}$$

where $\phi_1, \ldots, \phi_p \in \mathbb{R}$ is the autoregressive coefficient and $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$. In this context, Y_t is the value of the percentage change in human mobility and the number of active COVID-19 cases. Meanwhile, the error term is the difference between the actual value and the predicted value of the modeling results-both the percentage change in human mobility and the number of active COVID-19 cases-.

The MA model is quite different from the AR model. The difference lies in the independent variables, which are the residual values in the previous period. The MA model of order q, often denoted by MA(q), has the following general form (Cryer and Chan 2008).

$$Y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}, \tag{2}$$

where $\theta_1, \ldots, \theta_q \in \mathbb{R}$ is the moving average coefficient and $\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)$.

The ARMA model combines the AR(p) and MA(q) models so that the autocorrelation function's (ACF) characteristics will be the same as the autoregressive model. At the same time, the partial autocorrelation function's (PACF) form will follow the aspects of the moving average model. The general form of ARMA(p, q) is as follows (Swaraj et al. 2021; Sun 2021):

$$Y_t = \phi_1 Y_{t-1} + \ldots + \phi_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \tag{3}$$

If the coefficient of AR(p) is moved to the left-hand side, it becomes:

$$Y_t - \phi_1 Y_{t-1} - \ldots - \phi_p Y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} \tag{4}$$

With the backshift operator, the equation becomes:

$$\left(1 - \sum_{t=1}^{p} \phi_t B^t\right) Y_t = \left(1 + \sum_{t=1}^{q} \theta_t B^t\right) \varepsilon_t \tag{5}$$

where $B^n Y_t = Y_{t-n}$ is the backshift operator. Meanwhile, if the data has been differentiated because of non-stationarity, the ARIMA(p, d, q) model has the following notation (Yang et al. 2021).

$$\left(1 - \sum_{t=1}^{p} \phi_t B^t\right)(1 - B)^d Y_t = \left(1 + \sum_{t=1}^{q} \theta_t B^t\right) \varepsilon_t \tag{6}$$

Now, the temporal interdependencies between human mobility and COVID-19 active cases are modeled using a time-varying copula model. Suppose that X_t denotes the percentage change of human mobility in each public area and Y_t denotes the number of active COVID-19 cases, each of which is modeled with an ARIMA(p, d, q) model. Then, suppose that $u_t = F(x_t)$ and $v_t = F(y_t)$ are the cumulative distribution functions of X_t and Y_t, respectively, and $H(x_t, y_t)$ is the joint distribution function of X_t and Y_t. There exists a copula C such that (Sklar 1959; Nelsen 2006)

$$H(x_t, y_t) = C(F(x_t;\eta_1), F(y_t;\eta_2)) \tag{7}$$

where $\eta_1 = \{\phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q\}_{X_t}$ and $\eta_2 = \{\phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q\}_{Y_t}$ are the parameters of the ARIMA(p, d, q) models for X_t and Y_t, respectively.

The copula function used in this study is the time-varying Gaussian copula model defined by (Nelsen 2006; Jondeau and Rockinger 2006)

$$C(u_t, v_t;\rho_t) = \Phi_{\rho_t}(\Phi^{-1}(u_t), \Phi^{-1}(v_t)) \tag{8}$$

where $\Phi_{\rho_t}(\cdot)$ and $\Phi(\cdot)$ are the bivariate and univariate standardized Gaussian cumulative distribution functions, respectively, and ρ_t is the dynamic parameter of the time-varying Gaussian copula model, $-1 < \rho_t < 1$.

The corresponding copula density function for the time-varying Gaussian copula is defined by (Jondeau and Rockinger 2006)

$$c(u_t, v_t;\rho_t) = \frac{1}{\sqrt{1 - \rho_t^2}} \exp\left\{-\frac{1}{2}\psi^T (R^{-1} - I_2)\psi\right\} \tag{9}$$

where $\psi = (\Phi^{-1}(u_t), \Phi^{-1}(v_t))^T$ and R is the correlation matrix.

Unlike the standard copula model, the value of the dynamic parameter ρ_t of the time-varying Gaussian copula model changes throughout the observation period. The basic concept of the dynamic parameter of the time-varying copula model was introduced by Patton (2006). In his study, Patton assumed that the dynamic parameter ρ_t of the time-varying Gaussian copula model follows an evolution equation following an ARMA(1, 10)-type process such that (Patton 2006)

$$\rho_t = \tilde{\Lambda}\left(\omega_\rho + \beta_\rho \cdot \rho_{t-1} + \alpha \cdot \frac{1}{10}\sum_{j=1}^{10} \Phi^{-1}(u_{t-j}) \cdot \Phi^{-1}(v_{t-j})\right) \tag{10}$$

where $\tilde{\Lambda}(x) = (1 - e^{-x})(1 + e^{-x})^{-1}$ is defined to maintain the value of ρ_t in $(-1, 1)$ all the time.

However, Ahdika et al. (2021) extended the dynamic parameter ρ_t of the time-varying Gaussian copula into four extended functions so that the parameter has the following form (Ahdika et al. 2021)

$$\rho_{k,t} = \Lambda\left(\omega_\rho + \beta_\rho \cdot \rho_{k,t-1} + \alpha \cdot \xi_k(u_t, v_t)\right) \tag{11}$$

where

$$\xi_k(u_t, v_t) = \begin{cases} \frac{1}{m}\sum_{j=1}^{m} |u_{t-j} - v_{t-j}|, & \text{for } k = 1 \\ \frac{1}{m}\sum_{j=1}^{m} (u_{t-j} - v_{t-j})^2, & \text{for } k = 2 \\ \sqrt{\frac{1}{m}\sum_{j=1}^{m} (u_{t-j} - v_{t-j})^2}, & \text{for } k = 3 \\ \frac{1}{m}\sum_{j=1}^{m} (X_{t-j+1} - X_{t-j})(Y_{t-j+1} - Y_{t-j}), & \text{for } k = 4 \end{cases} \tag{12}$$

Therefore, there are four parameters to be estimated, $\{\omega_\rho, \beta_\rho, \alpha, m\}$, where the first three parameters are continuous and the fourth is an integer. In other words, the extended dynamic functions of ρ_t proposed by Ahdika et al. (2021) are assumed to follow an ARMA(1, m) process with four kinds of forcing variables.

The parameters are estimated by maximizing the following likelihood function:

$$\mathcal{L}(\eta_1, \eta_2, \rho_t) = \sum_{t=1}^{T} \mathcal{L}_t(\eta_1, \eta_2, \rho_t) \tag{13}$$

where

$$\begin{aligned} \mathcal{L}_t(\eta_1, \eta_2, \rho_t) &= \log(h(x_t, y_t; \rho_t)) \\ &= \log\left(\frac{\partial^2 H(x_t, y_y; \rho_t)}{\partial x_t \partial y_t}\right) \\ &= \log\left(\frac{\partial^2 C(F(x_t; \eta_1), F(y_t; \eta_2); \rho_t)}{\partial x_t \partial y_t}\right) \\ &= \log\left(f(x_t; \eta_1) \cdot f(y_t; \eta_2) \cdot c(F(x_t; \eta_1), F(y_t; \eta_2); \rho_t)\right) \\ &= \log(f(x_t; \eta_1)) + \log(f(y_t; \eta_2)) + \log(c(F(x_t; \eta_1), F(y_t; \eta_2); \rho_t)) \\ &= \mathcal{L}_{f_{1t}}(\eta_1) + \mathcal{L}_{f_{2t}}(\eta_2) + \mathcal{L}_c(\rho_t) \end{aligned} \tag{14}$$

The parameters of η_1, η_2, and ρ_t are estimated in two steps, as follows:

$$\hat{\eta}_i = \arg\max_{\eta_i} \sum_{t=1}^{T} \mathcal{L}_{f_{it}}(\eta_i), \quad i = 1, 2 \tag{15}$$

$$\hat{\rho}_t = \arg\max_{\rho_t} \sum_{t=1}^{T} \mathcal{L}_c(\rho_t) \tag{16}$$

4 Results and discussion

We use the data on human mobility in public areas–specifically, in grocery stores, parks, transit stations, retail, residences, and workplaces–obtained from Google's COVID-19 Community Mobility Reports, which can be accessed at https://www.google.com/covid19/mobility/ (Google Community Mobility Reports 2021). The mobility reports shows movement by region, across different categories of places, specifically, the movement in public areas such as grocery stores, parks, transit stations, retail areas, and workplaces. It also shows the change in time spent by people at home. The data show how lengths of stay and visits at specific locations change over time compared to a baseline. The change calculation utilizes the same type of aggregated and anonymous data used to display popular times for places in Google Maps. Anonymous data come from users that have enabled the Location History feature. Each day's changes are compared to a baseline value for that day of the week. For the corresponding day of the week, the baseline is the median value during the five weeks, Jan 3-Feb 6, 2020. The datasets illustrate trends over several months, with the most current data reflecting about 2-3 days ago-the length of data to be produced (Google Community Mobility Reports 2021).

Furthermore, we obtain data on active COVID-19 cases from kaggle.com/hendratno/covid19-indonesia (Hendratno 2021) with the following data references: covid19.go.id, kemendagri.go.id, bps.go.id, and https://bnpb-inacovid19.hub.arcgis.com/apps/provinsi-dki-jakarta/explore https://tiny.cc/Datacovidjakarta.

Figure 2 presents the percentage change in human mobility compared to pre-pandemic baseline recorded in five public areas and in residences from March 28, 2020 to July 9, 2021. The percentage change in human mobility at grocery stores, parks, transit stations, retail areas, and workplaces is the change in the number of visitors at those sites compared to the baseline. Meanwhile, the percentage change in the area of residence is the change in the duration of time spent at home (Google Community Mobility Reports 2021). A positive sign indicates an increase in human mobility, while a negative sign indicates a decrease. Figure 2 shows that mobility in five public places experienced a significant decline in the early days of the pandemic (i.e., after the first Covid-19 case in Indonesia was announced on March 2, 2020). This is indicated by the negative percentage change of human mobility around March to May 2020; after this period, human mobility slowly increased, especially in grocery stores, parks, transit stations, and retail areas. Meanwhile, human mobility did not experience a significant increase in workplaces as in the previous four types of public areas. This may be due to the work-from-home (WFH) policy, which is well adhered to by employers. Even at the beginning of the pandemic, the governor of Jakarta carried out inspections at workplaces. He gave warnings to employers who did not comply with the government's WFH rules. Thus, mobility in the workplace tends to have a regular pattern of following the instructions given by the government.

In contrast to the five public areas, which experienced a significant decline at the start of the pandemic, percentage change in time spent at residences continued as normal. This happens because people usually work approximately 8 hours a day and most of their time is spent at home. The changes that occur are not significant because even though the work

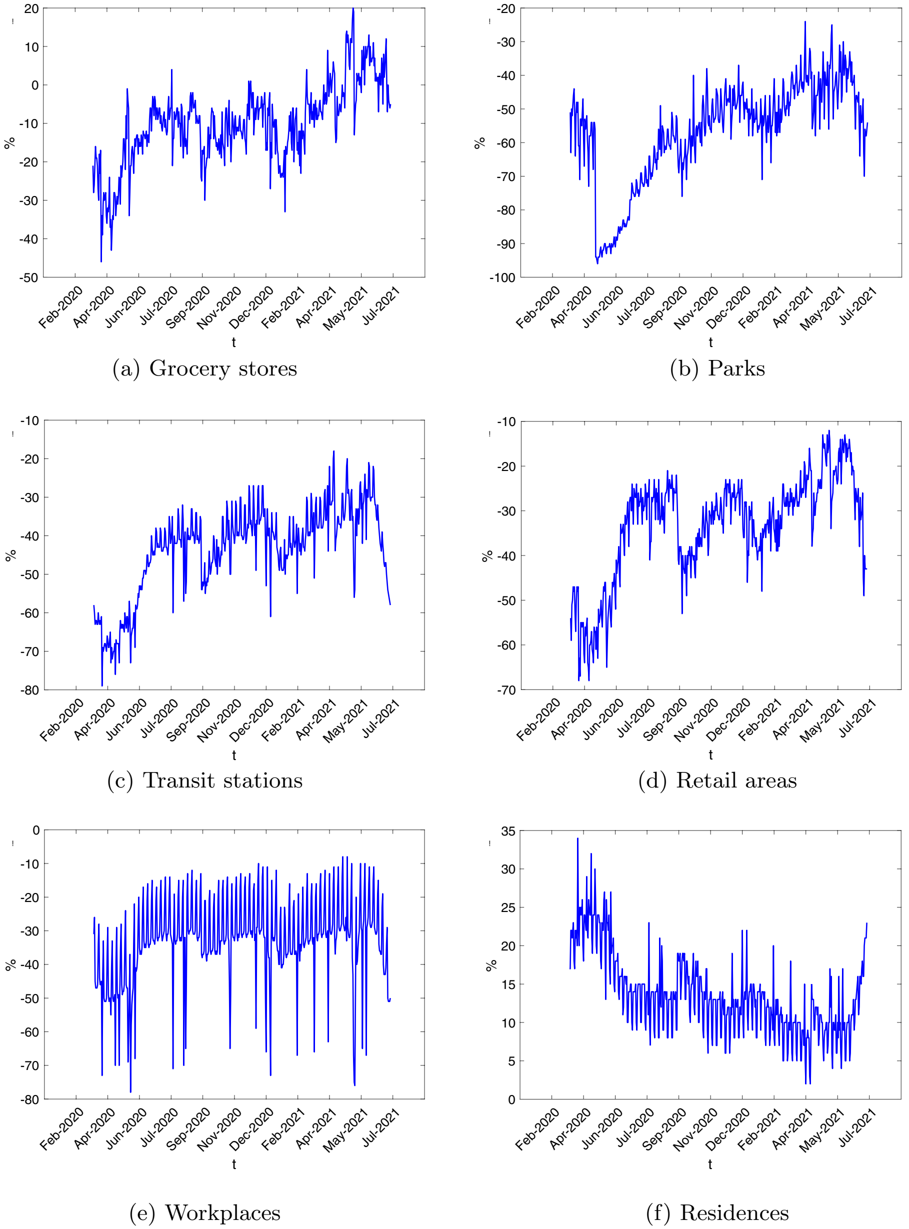


Fig. 2 Percentage change of human mobility at five public areas and time spent at home compared to a pre-pandemic baseline

from home rule is enforced, the additional time has a relatively small proportion compared to the remaining 16 hours that are usually spent at home. According to Google Mobility Reports, the biggest change that can occur on weekdays is probably just +50% and even less on weekends (Google Community Mobility Reports 2021).

Fig. 3 Active COVID-19 cases in Jakarta, Indonesia

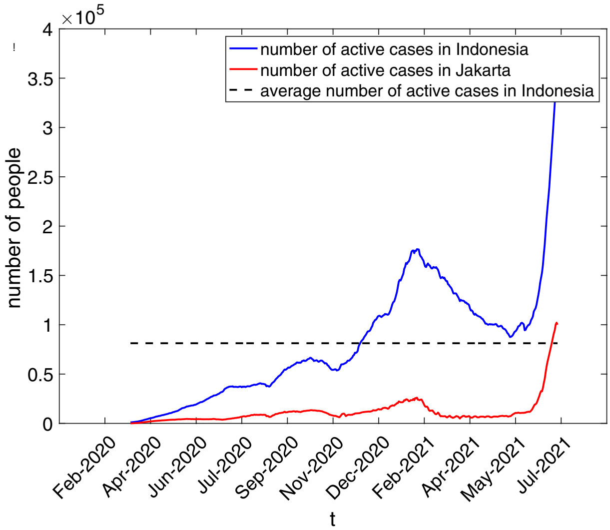


Table 1 Summary statistics of the percentage change of human mobility in public areas and time spent at home, and active COVID-19 cases

Variables	Mean	Std.	Min	Max
Human mobility in grocery stores (%)	−10.03	10.50	−46	20
Human mobility in parks (%)	−56.93	15.26	−96	−24
Human mobility in transit stations (%)	−43.59	11.60	−79	−18
Human mobility in retail (%)	−33.50	11.63	−68	−12
Human mobility in workplaces (%)	−32.80	12.56	−78	−8
Human mobility in residences (%)	13.59	5.28	2	34
COVID-19 active cases	11,703	13,828	24	102,101

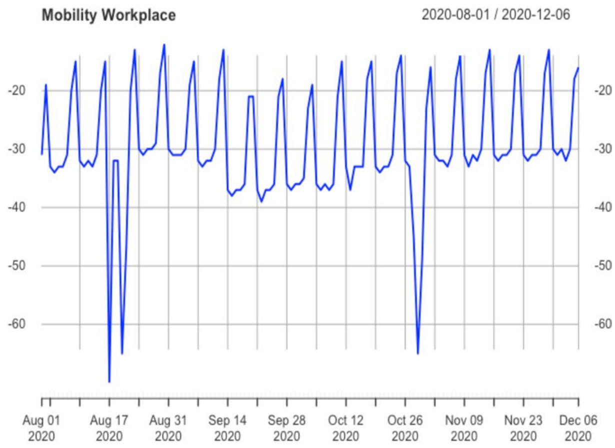
Figure 3 shows the daily data on the number of active COVID-19 cases in Jakarta during the study periods, compared to total active cases in Indonesia and its average number. The pattern of increase and decrease in the number of cases in Jakarta is generally the same as that in Indonesia as a whole. Specifically, the daily active cases were consistently below 10,000 until the first week of September 2020. Cases slowly increased until their first peak in mid-October 2020, with 13,386 cases, and then declined until November 2020. After this decline, the number of active cases increased somewhat significantly until it reached a second peak in early February 2021, with a total of 26,097 active cases. The figure experienced another slow decline until mid-February. From mid-February 2021 to the end of May 2021, the number of cases remained around 10,000 and then experienced a very significant increase until early July 2021, with the number of active cases reaching 102,101.

Table 1 presents the summary statistics of percentage change of human mobility and active COVID-19 cases in Jakarta, Indonesia.

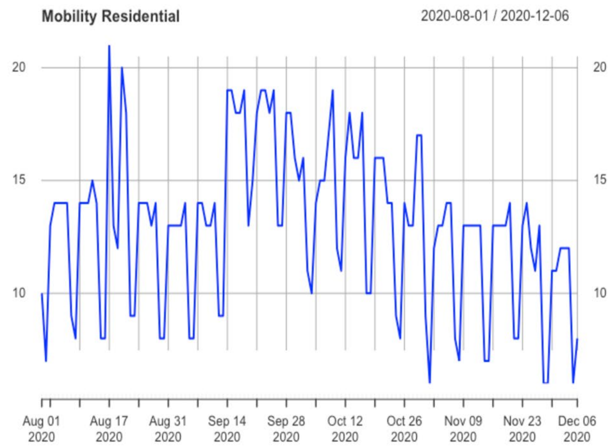
Table 1 shows the descriptive statistics measurements for community mobility report, i.e. mean, standard deviation, minimum, and maximum value. The mobility report shows relative change rather than actual numbers of visitors or length of stay. The positive scale of change implies the increase people visit a specific place compared to baseline. For example in Fig. 4, when we have long weekend due to holidays in August 17th–21th, the scale of change of the visit and the length of stay in workplace decreased into high negative value. In contrast, the change in the residential increased. It also happened in October 28th–30th. Larger changes do not necessarily imply more visitors, nor do lesser changes imply fewer visitors.

Table 2 shows the estimated parameters of each variable for ARIMA models employing OLS (Ordinary Least Square) method. For example, the best ARIMA model for data on percentage change of human mobility in grocery stores is ARIMA (3,1,2) with the estimated coefficient of the autoregressive process are 0.812, -0.284, and -0.183 for X_{t-1}, X_{t-2}, and X_{t-3} respectively. Furthermore, the estimated coefficient of the moving average process are -1.289 and 0.580 for ε_{t-1} and ε_{t-2} respectively.

Fig. 4 Mobility report (Google Community Mobility Reports 2021)



(a) Mobility in Workplaces



(b) Mobility in Residential

Table 2 Selected ARIMA model estimates

Variables	(p, d, q)	AR(1)	AR(2)	AR(3)	AR(4)	MA(1)	MA(2)	MA(3)
Percentage change of human mobility X_t								
Grocery stores	(3, 1, 2)	0.812	−0.284	−0.183	–	−1.289	0.580	–
Parks	(2, 1, 1)	0.336	−0.180	–	–	−0.713	–	–
Transit stations	(0, 1, 2)	–	–	–	–	−0.354	−0.346	–
Retail	(2, 1, 3)	−0.620	−0.810	–	–	0.211	0.405	−0.545
Workplaces	(4, 1, 2)	0.718	−0.872	0.133	–0.531	−1.247	0.994	–
Residences	(4, 1, 2)	0.607	−0.811	0.122	–0.607	−1.262	0.957	–
Active COVID-19 cases Y_t								
Active cases	(3, 2, 2)	0.998	−0.391	−0.196	–	−1.526	0.762	–

Table 3 Parameter estimates of the static and time-varying Gaussian copula model for percentage change in human mobility against active COVID-19 cases

Mobility components	$\hat{\rho}$	Time-varying Gaussian copula					
		Function k	$\hat{\omega}$	$\hat{\beta}$	$\hat{\alpha}$	$\hat{m}$	*AIC*
Grocery stores	−0.0178	1	0.6667	−0.8626	−1.8285	10	−2.1963
		2	0.4002	−1.4619	−1.9843	10	−1.6961
		3	1.7884	−2.0872	−3.5580	15	−5.7687
		4	**0.1829**	**−0.4836**	**0.2246**	**1**	**−56.4833**
Parks	0.0053	1	1.0411	−1.9995	−2.8328	9	−5.8384
		2	1.0818	−2.0601	−4.5604	15	−6.0482
		3	1.1614	−2.0534	−2.4178	9	−7.7355
		4	**0.1073**	**−0.9638**	**0.2630**	**1**	**−72.9842**
Transit stations	0.0025	1	1.0473	−1.8653	−2.7967	5	−11.7453
		2	0.6319	−1.7716	−2.8805	5	−8.4396
		3	2.6090	−2.0228	−5.4748	10	−12.4599
		4	**0.1548**	**−1.4673**	**0.2676**	**1**	**−56.6091**
Retail	0.0216	1	0.2576	−1.8798	−0.3550	1	−3.1275
		2	0.1296	−2.0538	−1.0084	5	−5.2950
		3	0.7702	−1.8825	−1.5740	5	−3.4049
		4	**0.1338**	**−0.9595**	**0.2506**	**1**	**−63.6746**
Workplaces	−0.0073	1	−0.7269	−0.6688	1.7727	5	−2.8179
		2	−0.2270	−0.9262	0.8157	2	−1.3572
		3	−0.3501	−0.5547	0.7045	2	−1.3175
		4	**0.1006**	**−0.5185**	**0.2493**	**1**	**−42.3755**
Residences	0.0110	1	−0.1413	1.7836	0.4129	15	−3.1184
		2	−0.0713	1.7795	0.4120	15	−2.8967
		3	−0.1387	1.7806	0.3378	15	−2.7278
		4	**−0.0720**	**−0.8792**	**0.3264**	**1**	**−73.5847**

The results in bold are the selected time-varying copula model with the smallest AIC value for each component

Table 3 provides the parameter estimates of the static and time-varying Gaussian copula for percentage change of human mobilitiy against the active COVID-19 cases in Jakarta, Indonesia during the study period.

Based on Table 3, the best dynamic parameter estimates of the time-varying Gaussian copula are those from the fourth dynamic parameter function ($k = 4$), as this function has the smallest *AIC* value. Since the parameter estimation results presented in Table 3 cannot be directly interpreted, the parameter estimates ω, β, α, and m are converted into the temporal interdependency $\rho_{k,t}$ using Eqs. (11) and (12). The values of $\rho_{k,t}$ are then represented in graphical form in Fig. 5. Figure 5 divides the temporal dependencies between human mobility in the six types of areas and the active COVID-19 cases based on the implementation periods of large-scale social distancing policies.

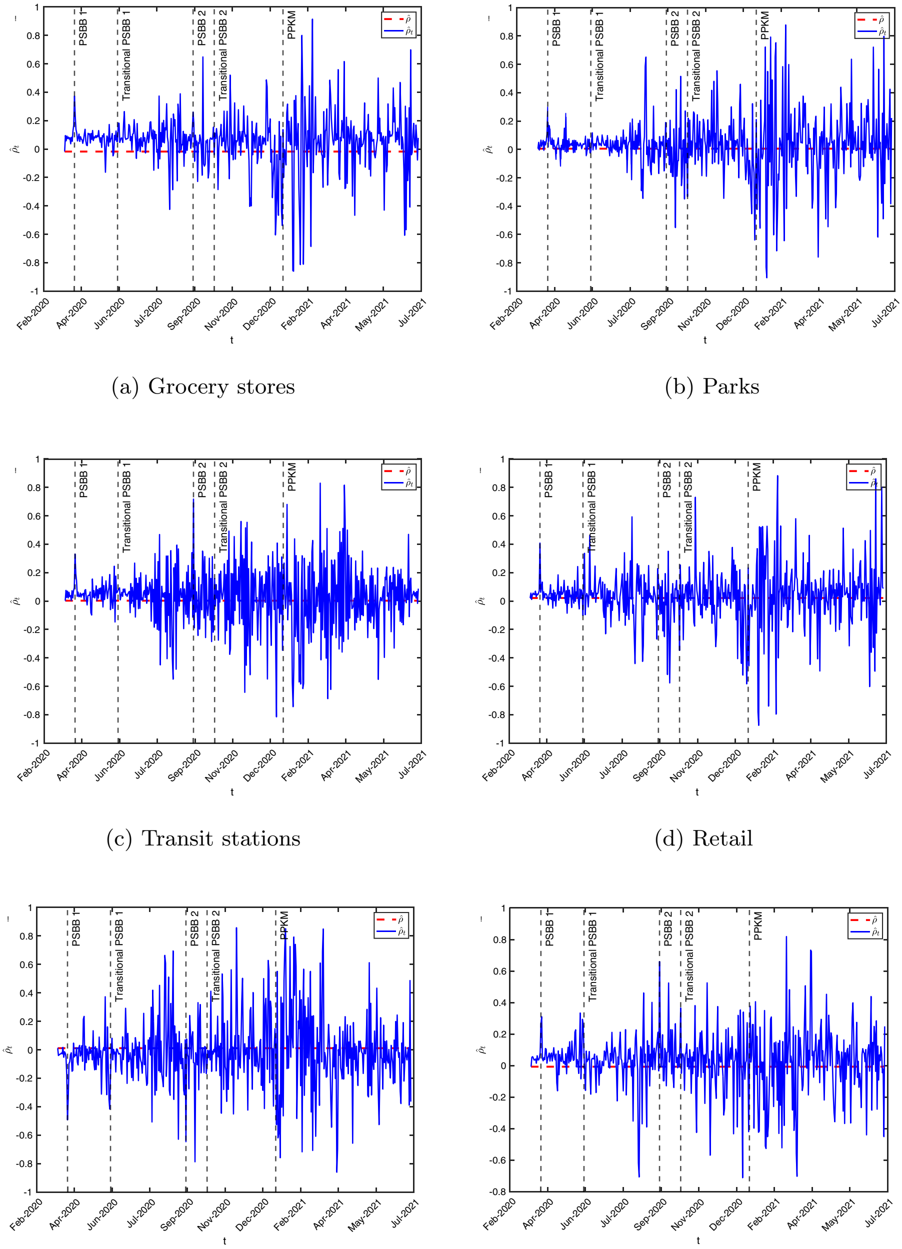
Our analysis produced several interesting findings. In the early period of large-scale social distancing policy, particularly during the implementation of PSBB 1, the temporal dependencies between human mobility and the number of active COVID-19 cases are not very strong. They tend to be positive, with a value of about −0.2 to 0.4, particularly in grocery stores, parks, transit stations, retail, and workplaces. This may reflect the relatively low number of active cases during this period; in addition, the government has implemented an isolation policy for those infected by COVID-19. Therefore, human mobility does not yet have a strong relationship with the number of active COVID-19 cases.

The temporal dependencies between human mobility and the number of active cases in residences in the pandemic tend to be negative. This means that although mobility in residential areas began to decline, the number of active COVID-19 cases in residential areas has increased. This indicates that other causes influence the growth in active cases in the residential environment besides mobility in the area; one of the most likely causes is family transmission.

Temporal dependencies strengthen during the Transitional PSBB 1 period, with values around −0.6 to 0.6 for all public places. This is possible because the restrictions on social activities were relaxed while the virus spread, causing the number of active cases to increase. Thus, in this period, the temporal dependence of the intensity of human movement significantly affects the increase in the number of active cases.

Furthermore, during the implementation period of PSBB 2, the temporal dependencies between human mobility and the number of active COVID-19 cases weaken in the range of −0.4 to 0.4. During this period, the number of active COVID-19 cases tended to be flat (Fig. 3). This shows that the tightening of activity restriction rules was quite proper, even though the relationship between the two variables is weak. The number of these flat cases is possible due to stricter restrictions. Namely, the workplace capacity was limited to a maximum of 25%. Still, travel was permitted as long as people continued to observe the health protocols implemented in the Transitional PSBB 1 period. In addition, the exceptions in some industrial sectors allow for human mobility. Therefore, because health protocols and restrictions were tightened but still allowed for human mobility during this PSBB 2 period, human mobility does not strongly influence the addition of active cases. On the other hand, the tightening was fairly effective, as evidenced by the stable number of cases.

During the Transitional PSBB 2 period, the temporal dependencies are again more substantial, as the dynamics fluctuate in a more extensive range between −0.7 to 0.8. The easing of activity restrictions made this possible. This effect is also strengthened by a significant increase in the number of active cases during this period and an increase in the movement of people. Furthermore, in the early period of PPKM implementation, the temporal dependencies are fairly strong, at values of around −0.8 to close to 1. This shows that the tightening of regulations in several sectors has succeeded in reducing the number



(a) Grocery stores

(b) Parks

(c) Transit stations

(d) Retail

(e) Residences

(f) Workplaces

Fig. 5 Dynamic dependencies between human mobilities against the active COVID-19 cases in relation to the social distancing policies in Jakarta, Indonesia of positive cases of COVID-19, this is evidenced by the number of active cases that has decreased since the implementation of PPKM and has been flat during late February to early July. However, the number of positive cases spiked again in early July 2021. This may happen because the PPKM regulation relaxes some restrictions and allows some activites at 100%. In general, negative dependencies indicate that human mobility does not always cause the number of active cases to increase; case numbers can rise due to other factors, such as family transmission, viral mutations that cause higher transmission rates, or environmental and meteorological parameters.

Based on the results, we conclude that the increase in the number of active COVID-19 cases can be controlled through human intervention. Similar to the previous studies which have shown that human intervention such as increasing the number of tests (Jamshidi et al. 2021) and general practitioners (D'Urso et al. 2022) can reduce the rate of active cases, government intervention through strict regulations in large-scale social distancing also has an impact on reducing the number of active COVID-19 cases.

5 Conclusion

This research is a part of the anthroposphere study that contains useful information regarding the effect of the large-scale social distancing policies implemented in Indonesia, which limits human mobility, to the number of active COVID-19 cases. This study shows that the strictness of rules for restricting social activities generally affected the increase in the number of active COVID-19 cases, especially in the early days of the pandemic. Each large-scale social distancing policy caused different temporal dependencies between human mobility and the number of active COVID-19 cases. Among all large-scale social distancing policies, the policy that had the most significant influence on the number of active COVID-19 cases was the implementation of several restrictions during the PPKM period. This is indicated by the range of values of the temporal dependence between human mobility and the number of active cases of COVID-19, which are relatively strong. This means that implementing several strict regulations, including setting the percentage of WFH and WFO in the workplace, setting dine-in capacity in restaurants and operating hours in shopping areas, and online teaching and learning activities reduce the number of active COVID-19 cases. In general, cases rise again when restrictive regulations are relaxed. We hope that this research gives insight to the policy makers to control the spread of the COVID-19, especially in Indonesia, so that the virus's spread can be reduced effectively. The results of this study can also be used as one of the references in regulating the social restrictions for other countries to limit human mobility in order to reduce the addition of the positive COVID-19 cases.

However, as time goes on, people may become increasingly resistant to various activity restrictions. This may cause human mobility to increase over time, followed by an increase in the number of active COVID-19 cases. Finally, although large-scale activity restrictions are reasonably effective at reducing the number of active cases, many other factors also affect case numbers even when these regulations are implemented. Humans cannot control these factors, including the virus's ability to mutate–indeed, several variants are currently proliferating–and environmental and meteorological factors. Further research can be carried out by investigating the effect of vaccination on the number of active cases while still taking large-scale social distancing regulations into account. The time-varying copula can also be improved to analyze the temporal interdependency between human mobility, vaccination implementation, and the number of active COVID-19 cases by embedding dynamic parameters in the vine copula model that can accommodate the dependence of more than two variables.

Acknowledgements The authors would like to thank the Laboratory of the Department of Statistics, Universitas Islam Indonesia, for their financial assistance through a non-degree training (NDT) grant.

Author Contributions AA: Conceptualization, Methodology, Software, Formal Analysis, Writing Original Paper, Writing and Review. AHP: Data curation, Software, Formal Analysis, Writing and Review. FNA: Data curation, Software, Formal Analysis.

Funding The authors have not disclosed any funding.

Declarations

Conflict of interest We declare that we have no conflict of interest to disclose.

References

Aabed, K., Lashin, M.M.: An analytical study of the factors that influence COVID-19 spread. Saudi J. Biol. Sci. **28**(2), 1177–1195 (2021)

Abedi, V., Olulana, O., Avula, V., Chaudhary, D., Khan, A., Shahjouei, S., Li, J., Zand, R.: Racial, economic, and health inequality and COVID-19 infection in the United States. J. Racial Ethnic Health Dispar. **8**(3), 732–742 (2021)

Ahdika, A., Rosadi, D., Effendie, A.R., Gunardi: Measuring dynamic dependency using time-varying copulas with extended parameters: evidence from exchange rates data. MethodsX **8**, 101322 (2021)

Almulhim, T.S., Barahona, I.: Decision support system for ranking relevant indicators for reopening strategies following COVID-19 lockdowns. Quality Quantity **56**(2), 463–491 (2022). https://doi.org/10.1007/s11135-021-01129-3

Bhadra, A., Mukherjee, A., Sarkar, K.: Impact of population density on Covid-19 infected and mortality rate in India. Model. Earth Syst. Environ. **7**(1), 623–629 (2021)

Bontempi, E., Coccia, M.: International trade as critical parameter of COVID-19 spread that outclasses demographic, economic, environmental, and pollution factors. Environ. Res. **201**(June), 111514 (2021)

Cartenì, A., Di Francesco, L., Martino, M.: How mobility habits influenced the spread of the COVID-19 pandemic: results from the Italian case study. Sci. Total Environ. **741**, 140489 (2020)

CDC: new ICD-10-CM code for the 2019 novel Coronavirus (COVID-19). Technical report, CDC, Atlanta (2020)

Coccia, M.: Effects of the spread of COVID-19 on public health of polluted cities: results of the first wave for explaining the dejà vu in the second wave of COVID-19 pandemic and epidemics of future vital agents. *Environmental Science and Pollution Research*: 19147–19154 (2021)

Cryer, J.D., Chan, K.S.: *Time Series Analysis with Applications in R* (2 edn.), Volume 20. Springer Science+Business Media, Inc (2008)

Di Renzo, L., Gualtieri, P., Pivari, F., Soldati, L., Attinà, A., Cinelli, G., Cinelli, G., Leggeri, C., Caparello, G., Barrea, L., Scerbo, F., Esposito, E., De Lorenzo, A.: Eating habits and lifestyle changes during COVID-19 lockdown: An Italian survey. J. Transl. Med. **18**(1), 1–15 (2020)

Dias, A., Embrechts, P.: Modeling exchange rate dependence dynamics at different time horizons. J. Int. Money Financ. **29**(8), 1687–1705 (2010)

D'Urso, P., De Giovanni, L., Vitale, V.: A D-vine copula-based quantile regression model with spatial dependence for COVID-19 infection rate in Italy. Spat. Stat. **47**, 202 (2022). https://doi.org/10.1016/j.spasta.2021.100586

Google Community Mobility Reports. 2021. Google LLC "Google COVID-19 Community Mobility Reports"

Gubernur Daerah Khusus Ibukota Jakarta. 2020. Keputusan Gubernur Daerah Khusus Ibukota Jakarta tentang Perpanjangan Pemberlakukan Pembatasan Sosial Berskala Besar pada Masa Transisi Menuju Masyarakat Sehat, Aman, dan Produktif

Hadjidemetriou, G.M., Sasidharan, M., Kouyialis, G., Parlikad, A.K.: The impact of government measures and human mobility trend on COVID-19 related deaths in the UK. Transp. Res. Interdisc. Perspect. **6**(March), 100167 (2020)

Hafner, C.M., Manner, H.: Dynamic stochastic copula models: estimation, inference, and applications. J Appl Econom **27**(2010), 269–295 (2012)

Hassan, M.S., Bhuiyan, M.A.H., Tareq, F., et al.: Relationship between COVID-19 infection rates and air pollution, geo-meteorological, and social parameters. Environ. Monit. Assess. **1**, 193 (2021)

Hendratno. 2021. Covid-19 Indonesian Dataset

Jamshidi, B., Bekrizadeh, H., Rezaei, M.: Analysis of the number of tests the positivity rate and their dependency structure during COVID-19 pandemic. medRxiv **4**, 1–26 (2011d)

Jondeau, E., Rockinger, M.: The copula-GARCH model of conditional dependencies: an international stock market application. J. Int. Money Financ. **25**(5), 827–853 (2006)

Kavanagh, J.: Defining temporal dependence : a review of existing evidence, *Are U.S. Military Interventions Contagious over Time?*, 5–11. RAND Corporation (2013)

Lin, W., He, Q.: The influence of potential infection on the relationship between temperature and confirmed cases of covid-19 in China. Sustainability (Switzerland) **15**, 13 (2021). https://doi.org/10.3390/su13158504

Manner, H., Alavi Fard, F., Pourkhanali, A., Tafakori, L.: Forecasting the joint distribution of Australian electricity prices using dynamic vine copulae. Energy Econom. **78**, 143–164 (2019)

Manner, H., Reznikova, O.: A survey on time-varying copulas: specification, simulations, and application. Econom. Rev. **31**(6), 654–687 (2012)

Menteri Dalam Negeri Republik Indonesia.: Instruksi Menteri Dalam Negeri Nomor 01 tentang Pemberlakukan Pembatasan Kegiatan untuk Pengendalian Penyebaran Corona Virus Disease (COVID-19) (2021)

Nakada, L.Y.K., Urban, R.C.: COVID-19 pandemic: environmental and social factors influencing the spread of SARS-CoV-2 in São Paulo, Brazil. Environ. Sci. Pollut. Res. **28**(30), 40322–40328 (2021)

Nelsen, R.B.: An Introduction to Copulas, 2nd edn. Springer Science+Business Media Inc., New York (2006)

Oztig, L.I., Askin, O.E.: Human mobility and coronavirus disease 2019 (COVID-19): a negative binomial regression analysis. Public Health **185**, 364–367 (2020)

Pan, Y., Darzi, A., Kabiri, A., Zhao, G., Luo, W., Xiong, C., Zhang, L.: Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States. Sci. Rep. **10**(1), 1–9 (2020)

Panarello, D., Tassinari, G.: One year of COVID-19 in Italy: are containment policies enough to shape the pandemic pattern? Socio-Econom. Plann. Sci. **79**(2021), 56 (2022). https://doi.org/10.1016/j.seps.2021.101120

Patton, A.J.: Modelling asymmetric exchange rate dependence. Internat. Econom. Rev. **47**(2), 527–556 (2006)

Pemerintah Gubernur DKI Jakarta.: Peraturan Gubernur DKI Jakarta Nomor 88 Tahun 2020 Tentang Perubahan atas Peraturan Gubernur Nomor 33 Tahun 2020 tentang Pelaksanaan Pembatasan Sosial Berskala Besar dalam Penanganan Coronan Virus Disease 2019 (COVID-19) di Provinsi DKI Jakarta (2020)

Pemprov DKI Jakarta. Panduan Umum PSBB Transisi (2020)

Rahman, M.M., Thill, J.C., Paul, K.C.: COVID-19 pandemic severity, lockdown regimes, and people's mobility: early evidence from 88 countries. Sustainability (Switzerland) **12**(21), 1–17 (2020)

Republik Indonesia.: Peraturan Pemerintah Republik Indonesia Nomor 21 Tahun 2020 Tentang Pembatasan Sosial Berskala Besar dalam Rangka Percepatan Penanganan Corona Virus Disease 2019 (COVID-19) (2020)

Sánchez-Sánchez, E., Ramírez-Vargas, G., Avellaneda-López, Y., Orellana-Pecino, J.I., García-Marín, E., Díaz-Jimenez, J.: Eating habits and physical activity of the Spanish population during the Covid-19 pandemic period. Nutrients **12**(9), 1–12 (2020)

Sharif, N., Dey, S.K.: Impact of population density and weather on COVID-19 pandemic and SARS-CoV-2 mutation frequency in Bangladesh. Epidemiol. Infect. **21**, 149 (2021)

Sklar, A.: Distribution functions of n dimensions and margins. Publ. Inst. Stat. Univ. Paris **8**, 229–231 (1959)

Sun, J.: Forecasting COVID-19 pandemic in Alberta, Canada using modified ARIMA models. Comput. Methods Programs Biomed Update **1**(9), 100029 (2021)

Sun, Y., Hu, X., Xie, J.: Spatial inequalities of COVID-19 mortality rate in relation to socioeconomic and environmental factors across England. Sci. Total Environ. **758**, 143595 (2021)

Swaraj, A., Verma, K., Kaur, A., Singh, G., Kumar, A., Melo de Sales, L.: Implementation of stacking based ARIMA model for prediction of Covid-19 cases in India. J. Biomed. Inform. **121**(6), 103887 (2021)

Xu, D., Yuan, J., Xing, M.: A Time-varying Vine copula model for dependence analysis of failure system. In *IEEE* (2018)
Yang, H., Li, X., Qiang, W., Zhao, Y., Zhang, W., Tang, C.: A network traffic forecasting method based on SA optimized ARIMA-BP neural network. Comput. Netw. **193**(2020), 108102 (2021)
Zhou, P., Yang, X.L., Wang, X.G., Hu, B., Zhang, L., Zhang, W., Si, H.R., Zhu, Y., Li, B., Huang, C.L., Chen, H.D., Chen, J., Luo, Y., Guo, H., Jiang, R.D., Liu, M.Q., Chen, Y., Shen, X.R., Wang, X., Zheng, X.S., Zhao, K., Chen, Q.J., Deng, F., Liu, L.L., Yan, B., Zhan, F.X., Wang, Y.Y., Xiao, G.F., Shi, Z.L.: A pneumonia outbreak associated with a new coronavirus of probable bat origin. Nature **579**(7798), 270–273 (2020)

Authors and Affiliations

Atina Ahdika[1] · **Arum Handini Primandari**[1] · **Falah Novayanda Adlin**[1]

Arum Handini Primandari
primandari.arum@uii.ac.id

Falah Novayanda Adlin
falah.adlin@students.uii.ac.id

[1] Department of Statistics, Universitas Islam Indonesia, Jalan Kaliurang Km 14.5, Sleman Yogyakarta 55584, Indonesia