Enhanced Knowledge in Sciences and Technology Vol. 3 No. 2 (2023) 042-051

EKST

Homepage: http://publisher.uthm.edu.my/periodicals/index.php/ekst
e-ISSN : 2773-6385

A Study on Dependence Structure Between Bond Yields and Stock Prices During Lockdowns Using Bivariate Copula

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DOI: https://doi.org/10.30880/ekst. 2023.03.02.006
Received 15 January 2023; Accepted 19 February 2023; Available online 30 November 2023

Abstract: A copula is a multivariate cumulative distribution function in probability theory and statistics for which the marginal probability distribution of each variable is uniform on the range [0, 1]. Copulas are used to describe and model the inter-correlation or dependency between random variables. This research aims to study a copula- Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) approach to modelling joint distribution of two major assets which is Bursa Malaysia stock price and Malaysia ten-year bond yields during lockdowns. Our objectives are to analyse the dependence structure of two major asset classes between bonds yields and stock price and to investigate the effect of lockdowns to the bond yields and stock prices. R-studio is used for modelling the distribution and fit the data with Student-*t* distribution copula and Clayton copula and estimate the tail dependence. Our result show that value of log-likelihood for Student-*t* distribution copula higher than Clayton copula. Other than that, stock prices and bond yields is affected during lockdowns. Our result show that's the correlation between stock price and bond yields is increase overtime during movement control order.

Keywords: Dependence Structure, Bond Yields, Stock Prices, Copula, Tail Dependence.

1. Introduction

Dependence Structure represents the grammatical relations that hold between constituents. The significant change in dependence structure, the selection of pair copula families, and the associated parameter estimates can be observed [1]. A copula is a multivariate cumulative distribution function in probability theory and statistics for which the marginal probability distribution of each variable is uniform on the range [0, 1]. Dependence between random variables is important because it might

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indicate important statistical or causal linkages in real-world application such as social, physical, and biological systems [2]. Copula modelling is becoming a more values and attributes in finance for predicting asset returns. Copulas, in essence, allow us to extract the dependence structure from joint distribution function of a set of random variables while also isolating that dependence structure from univariate marginal behaviour [3]. The copula function is used to model the dependence structure of the random variables. Bond yields is the return of a capital investor. Bond yields are determined by expectations of inflation, economic growth, default probabilities, and duration.

The purpose of this study is to analyse the dependence structure of two major asset classes which is the Bursa Malaysia stock price and Malaysia ten-year bond yields during lockdowns which means movement control order (MCO). Since the data of the bond and stock price are large, the bivariate Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) method are apply in this study. The first problem of this study is the data of bond yields and stock prices are large, when analysing the prior literatures, it notices that various type of copula has different characteristics of dependence structure between random variables. Certain copulas may have a perfect match according to one aspect of the data. However, they may not have perfect match of overall aspect, vice-versa.[4]. Hence, a copula for better describe the data to modelling the dependence structure of bond yields and stock prices during lockdowns in the joint distribution. Besides, the second problem is the effect of lockdowns to the bond yields and stock prices from the dependence structure. The objective of this study is to analyse the dependence structure of two major asset classes between bonds yields and stock price and to investigate the effect of lockdowns to the bond yields and stock prices.

Siddiqui and Rizvi identified the dependence structure between MENA Sukuk, Gulf Cooperation Council Sukuk, and Nifty 50 Shariah indices. GARCH model and Carnonical-Vine (C-Vine) Copula approach are used to analyse the daily data of the indices before and during COVID-19 pandemic which is from April 2017 to November 2020. [5]. Kang study the dependence structure between bonds and stock using a multivariate copula approach. This study applies a copula- Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) approach to model the joint distribution of excess return of four major assets which is one year and 10-year Treasury bonds, S&P 500, and Nasdaq indices [6]. Panchenko developed a goodness-of-fit test for copulas. The test's application to the US large cap stock demonstrated the Gaussian copula's inefficiency. The findings show that Student-*t* copula is more flexible used for the dependence modelling of multivariate collections of stock. More flexible copula forms will be created to capture dynamical changes in the dependency structure [7]. Kazemi study the best method to compare the result of parameter estimation for Archimedean copulas which is by using Kendal coefficient and Goodness of fit test. The result show that the goodness-of-fit test is the best method to have an estimation for copulas parameters [8]. Zorgati study the financial contagion phenomena in the subprime crisis context using a copula approach. Canonical Maximum Likelihood (CML) method is used to estimate the parameters of various copulas. The findings show that there is a contagion effect of daily return. The result show that American market gave a strong contagion intensity according to the data while compared to the other Asian counterparts [9].

In this study, dependence structure between Bursa Malaysia stock price and Malaysia ten-year bond yields form 2nd May 2019 to 28th October 2021 is analyse using bivariate copula which is Student-*t* copula and Clayton copula. Besides, the effect to the stock prices and bond yields is also analyse.

2. Materials and Methods

This section will describe all the necessary information of materials and methods section that is required to obtain the results of the study.

2.1 Data

The data that used in this study is Bursa Malaysia stock price and Malaysia ten-year bond yields form 2nd May 2019 to 28th October 2021. The data in obtain form the internet (https://finance.yahoo.com/ , https://www.investing.com/).

2.2 Copula

$$h(x_1,\dots,x_n) = C\big(F_1(x_1),\dots,F_n(x_n)\big), \forall(x_1,\dots,x_n) \in \overline{\mathbb{R}}^n \qquad Eq.\ 1$$

Let $F_1(x_1),\dots,F_n(x_n)$ be the continuous marginal distribution functions and continuous in $x_1,\dots,x_n$ respectively, h be the joint distribution of $(x_1,\dots,x_n)$, and C be the Copula. Then H will be defined as a joint distribution function with marginal distributions $F_1(x_1),\dots,F_n(x_n)$. Differentiating the equation (3.2.1) with respect to $(x_1,\dots,x_n)$ leads to the joint density function of random variables in terms of copula density. It is stated as below:

$$\mathrm{H}(x_1,\dots,x_n|\Omega_{t-1}) = C(F_1(x_1|\Omega_{t-1}),\dots,F_n(x_n|\Omega_{t-1})|\Omega_{t-1}) \prod_{i=1}^{n} f_i(x_i), \forall(x_1,\dots,x_n) \in \overline{\mathbb{R}}^n \qquad Eq.\ 2$$

Ω_{t-1} will be the information set up to time t, $F_1(x_1|\Omega_{t-1})$ be the continuous marginal distribution functions conditional on Ω_{t-1}. C be the Copula and H will be defined as a joint distribution function with marginal distributions $F_1(x_1),\dots,F_n(x_n)$.

2.3 Pearson correlation and Kendall's rank correlation test

The Pearson correlation test measures the strength of the linear relationship between two variables. Kendall's rank correlation test measures the strength between stock price and bond yields.

2.4 Modeling marginal distributions

The data is undergoing the weighted Ljung-Box test on standardized residuals and standardized squared residuals, weighted lagrange multiple tests for autoregressive conditional heteroskedastic, Nyblom stability test and Sign Bias test. A proper specification for marginal distributions of individual series is important for building a copula model. Let $x_{1,t}$ & $x_{2,t}$ be the data of the bonds and stock market. The equation (3.3.1) and (3.3.5) is stated conditional mean as below, where $\eta_{1,t}$ & $\eta_{2,t}$ are innovation terms and $\sigma_{1,t}$ & $\sigma_{2,t}$ are the standard deviation of bond and Stock Market index. $\sigma_{1,t}^2$ & $\sigma_{2,t}^2$ is the specification of conditional variance for the bond and Stock market index, where$1\big(\eta_{i,t-1} < 0\big)$ is an indicator function. Skewed t distribution is better than normal distribution when fits the financial time series (Hansen, 1994). Then, we assume that $\eta_{i,t} \sim ST(\eta_{i,t}|\nu_{i,t}, \lambda_{i,t})$ with mean and variance value $= 0$. Lastly, let $K(\cdot)$ and $\Lambda(\cdot)$ denoted as lagged residual and yields spread for the bond and only lagged residuals for the stock.

Bonds :

$$x_{1,t} = \alpha_1 x_{1,t-1} + \sigma_{1,t}\eta_{1,t} \qquad Eq.\ 3$$

$$\sigma_{1,t}^2 = \alpha_2 + \alpha_3\, \sigma_{1,t-1}^2 + \alpha_3\, \sigma_{1,t-1}^2 \eta_{1,t-1}^2 \qquad Eq.\ 4$$

$$\nu_{1,t} = K(\alpha_4 + \alpha_5 \alpha_{1,t-1}\eta_{1,t-1}) \qquad Eq.\ 5$$

$$(\lambda_{1,t} = \Lambda(\alpha_6 + \alpha_7 \alpha_{1,t-1}\eta_{1,t-1}) \qquad Eq.\ 6$$

Stock :

$$x_{2,t} = \alpha_8 x_{2,t-2} + \alpha_8 x_{2,t-3} + \alpha_{9,t-12} + \sigma_{3,t}\eta_{3,t} \qquad Eq.\ 7$$

$$\sigma_{2,t}^2 = \alpha_{10} + \alpha_{11}\sigma_{2,t-1}^2 + \alpha_{12}\sigma_{2,t-1}^2\eta_{2,t-1}^2 1(\eta_{2,t-1} < 0) \quad \textit{Eq. } 8$$

$$v_{2,t} = K(\alpha_{13} + \alpha_{14}\sigma_{2,t-1}\eta_{2,t-1}) \quad \textit{Eq. } 9$$

$$\lambda_{2,t} = \Lambda(\alpha_{17} + \alpha_{16}\sigma_{2,t-1}\eta_{2,t-1}) \quad \textit{Eq. } 10$$

2.5 Modelling dependence structure

Elliptical copulas are used to provide time-varying correlation matrix. Student-*t* copula are used to modeling the joint distribution of random variable. Let T_ν^{-1} be the inverse of standardlized univariate Student-*t* distribution T_ν with the degree of freedom $\nu > 2$ and $T_{R,\nu}$ be the n-dimensional standardized Student-*t* distribution with the correlation matrix R and degrees of freedom parameter ν. The n-dimensional Student-*t* copula is Eq.11, and its density function is Eq.12.

$$C(\mu; R, \nu) = T_{R,\nu}(\mathrm{T}_\nu^{-1}(\mu_1), \ldots, \mathrm{T}_\nu^{-1}(\mu_n)) \quad \textit{Eq. } 11$$

$$C(\mu; R, \nu) = \frac{\Gamma\left(\frac{\nu+n}{2}\right)\left[\Gamma\left(\frac{\nu}{2}\right)\right]^{n-1}}{\sqrt{\det(\mathrm{R})}\left[\Gamma\left(\frac{\nu+1}{2}\right)\right]^{n}}\left(1 + \frac{\varsigma' R^{-1}\varsigma}{\nu}\right)^{-\frac{\nu+n}{2}} \prod_{i=1}^{n}\left(1 + \frac{\varsigma_i^2}{\nu}\right)^{\frac{\nu+1}{2}} \quad \textit{Eq. } 12$$

Archimedean copulas are also a great a method to modelling bivariate distribution. Clayton copula are used in modelling dependence structure. The joint distribution function is stated as below as Eq.13 and its density form is Eq.14.

$$f(x_1, x_2) = C_1(\mu_1, \mu_2) \quad \textit{Eq. } 13$$

$$f(x_1, x_2) = c_2\big(C_1(\mu_1, \mu_2)\big)c_1(\mu_1, \mu_2) \prod_{i=1}^{2} f_i(x_i) \quad \textit{Eq. } 14$$

2.6 Estimation

Estimation of Akaike Information Criterion, Bayesian Information Criterion, and Log-likelihood function to determine the data is fit for Student-*t* distribution copula or Clayton copula. Estimation of correlation for the elliptical copula is stated as below:

$$L(R_t, \nu) = -\frac{1}{2}\sum_{t=1}^{T}\log(\det(R_t)) + Tlog\left(\Gamma\left(\frac{\nu+4}{2}\right)\right) + 3Tlog\left(\Gamma\left(\frac{\nu}{2}\right)\right) - 4Tlog\left(\frac{\nu+1}{2}\right) - \left(\frac{\nu+4}{2}\right)\sum_{t=1}^{T}\log\left(1 + \frac{\varsigma_t' R_t^{-1}\varsigma_t}{\nu}\right) + \frac{\nu+1}{2}\sum_{t=1}^{T}\sum_{i=1}^{4}(1 + \frac{\varsigma_{i,t}^2}{\nu}) \quad \textit{Eq. } 15$$

Estimation of correlation for the hierarchical copula is stated as below:

$$[\widehat{\rho_1}] = \arg max \sum_{t=1}^{T} C_1(\widehat{\mu_{1,t}}, \widehat{\mu_{2,t}} | X_{t-1}, \rho_1) + \sum_{t=1}^{T} c_1(\widehat{\mu_{1,t}}, \widehat{\mu_{2,t}} | X_{t-1}, \rho_1) \quad \textit{Eq. } 16$$

where ρ_1 is the dependence parameter of C_1.

3. Results and Discussion

The section will present data and analysis of the study. In this section, ‘R-studio’ was used for the entire analysis.

3.1 Statistical analysis

Table 1: Statistical analysis of stock prices and bond yields before during and after MCO

Data	Min	Max	Skewness
Stock prices Before MCO	-0.0184409	0.0130183	-0.467301
Stock prices During MCO	-0.0773778	0.0399972	-1.256593
Stock prices After MCO	-0.0180178	0.0199251	0.05802283
Bond yields Before MCO	-0.040431	0.030917	-0.7737936
Bond yields During MCO	-0.0655552	0.0819783	0.106053
Bond yields After MCO	-0.098283	0.094214	-0.03066704

Table 1 shows that the data set of stock price return before, during and after movement control order (MCO) is skewed to the left, left and right respectively. Besides, data set of bond yields before, during and after movement control order (MCO) is skewed to the left, right and left respectively.

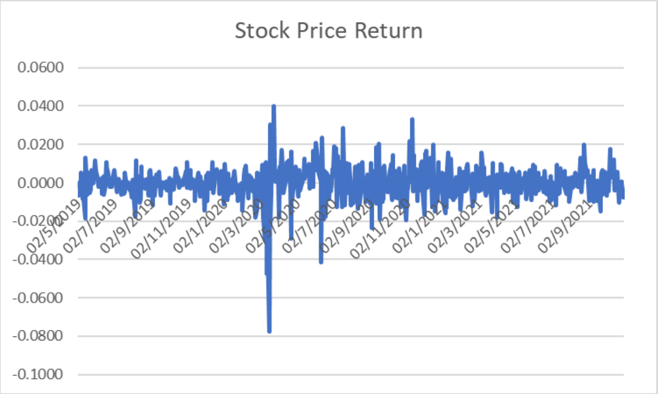

Figure 1: Daily return of stock price from 02/05/2019 to 28/10/2021

Figure 1 shows that the daily return of stock index in percentage from 2nd May 2019 to 28th October 2021. From this figure, its shows that the stock return is unstable start in April 2020. This is because the movement control order began on 18th March 2020. It is affected by the movement control order since everybody must be sat at home. Malaysians are not allowed to go out consume and spend their money. It will cause economy Malaysia recession. On the other sides, all the international traveller, capitalist and businessman and are not all allow to visit our country. It was a huge financial loss to Malaysia.

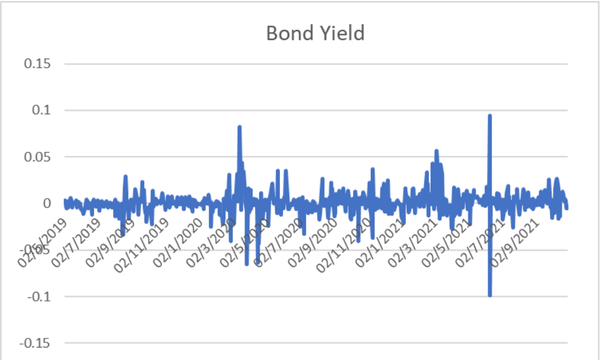

Figure 2: Bond yields from 02/05/2019 to 28/10/2021

Figure 2 shows that the bond yields in percentage from 2nd May 2019 to 28th October 2021. From Figure 2, the bond yields are unstable start form MCO. Bond yields is based on a bond coupon's payment divide by its price market. Hence, bond yields are inversely proportional to the stock price.

3.2 Pearson correlation and Kendall's rank correlation test

Table 2: Pearson correlation test

Data	P-value	Correlation
Before MCO	0.3448	-0.06647782
During MCO	0.3095	-0.0709796
After MCO	0.2856	0.07568232

Table 2 shows that the value of Pearson correlation between stock price return and bond yields before, during and after MCO. The value of Pearson correlation of before, during and after MCO is -0.06647782, -0.0709796 and 0.07568232. Negative value of Pearson means the stock price return increase, the bond yields decrease and vice versa. Therefore, the stock price is linear inversely proportional to bond yields before and after MCO. After MCO, the stock price is directly proportional to bond yields. Since the Pearson correlation is not zero, therefore there is correlation between these two variables.

Table 3: Kendall's rank correlation test

Data	Tau
Before MCO	0.002077445
During MCO	0.007274606
After MCO	0.0356414

Table 3 shows that the value of Kendall's rank correlation between stock price and bond yields before, during and after MCO. Kendall's rank correlation is to measure the strength between stock price and bond yields. From Table 3, the Kendall's Tau of before, during and after MCO is 0.002077445, 0.007274606, and 0.0356414, respectively. Since the Kendall's Tau is not zero, therefore there is correlation between these two variables.

3.3 Modelling Marginal distribution

The stock prices and bond yields are undergoing the weighted Ljung-Box test on standardized residuals and standardized squared residuals. Weighted lagrange multiple tests for autoregressive conditional heteroskedastic results shows that there is no auto correlation between residuals. Besides, Nyblom stability test shows that there no zero variance between stock prices and bond yields. Furthermore, Sign Bias test shows the stock prices and bond yields has an impact of positive return shock on volatility.

3.4 Goodness of fit test

Table 4: Fit AR-GARCH model with normal distribution

Data	Log-likelihood	Goodness of fit test (P-value)	Elapsed time
Stock prices Before MCO	771.7095	0.9584	0.199507
Stock prices During MCO	629.9904	0.3343	0.327112
Stock prices After MCO	728.5853	0.9153	0.1137092
Bond yields Before MCO	726.0005	0.2043	0.125699
Bond yields During MCO	593.6617	0.00005161	0.08278108
Bond yields After MCO	588.9483	0.0005546	0.12467

From Table 4, the stock price before and during and after MCO has a p-value of 0.9584, 0.3343, 0.9153 respectively while the bond yields before MCO has a p-value of 0.2043. Since the data has a p-value of greater than 0.05, therefore the data is fit for the AR-GARCH model with normal distribution. For the data of the bond yields during and after MCO is less than 0.5 which is 0.00005161 and 0.0005546 respectively. Hence the data are nor fit with normal distribution.

Table 5: Fit AR-GARCH model with Student's t distribution

Data	Log-likelihood	Goodness of fit test (P-value)	Elapsed time
Stock prices Before MCO	777.1705	0.4953	1.698703
Stock prices During MCO	636.2349	0.8137	0.3122571
Stock prices After MCO	728.8711	0.9847	0.09571099
Bond yields Before MCO	747.4314	0.09082	0.111742
Bond yields During MCO	634.8482	0.22764	0.2463391
Bond yields After MCO	625.3093	0.5542	0.4403901

From Table 5, the stock price before and during and after MCO has a p-value of 0.4593, 0.8137, 0.9847 respectively while the bond yields before, during and after MCO has a p-value of 0.09082, 0.22764 and 0.55542 respectively. Since the data has a p-value of greater than 0.05, therefore the data is fit for the AR-GARCH model with Student's t distribution.

Table 6: Fit AR-GJR-GARCH model with normal distribution

Data	Log-likelihood	Goodness of fit test (P-value)	Elapsed time
Stock prices Before MCO	776.2933	0.5554	0.4740319
Stock prices During MCO	630.0646	0.3014	0.2702391

Stock prices After MCO	729.1099	0.9153	0.20948
Bond yields Before MCO	726.265	0.07271	0.2632561
Bond yields During MCO	597.1032	0.00004536	0.3889589
Bond yields After MCO	598.9943	0.053937	0.3132079

From Table 6, the stock price before and during and after MCO has a p-value of 0.5554, 0.3014, 0.9153 respectively while the bond yields before and after MCO has a p-value of 0.07271 and 0.053937 respectively. Since the data has a p-value of greater than 0.05, therefore the data is fit for the AR-GJR-GARCH model with normal distribution. For the data of the bond yields during MCO is less than 0.5 which is 0.00004536. Hence the data are nor fit with normal distribution.

Table 7: Fit AR-GJR-GARCH model with Student's t distribution

Data	Log-likelihood	Goodness of fit test (P-value)	Elapsed time
Stock prices Before MCO	778.4909	0.05791	0.5540481
Stock prices During MCO	636.5482	0.9376	0.7001729
Stock prices After MCO	729.4447	0.9970	0.387964
Bond yields Before MCO	747.5689	0.2344	0.4388268
Bond yields During MCO	630.5984	0.5996	0.405915
Bond yields After MCO	630.3643	0.3406	0.672204

From Table 7, the stock price before and during and after MCO has a p-value of 0.4593, 0.8137, 0.9847 respectively while the bond yields before, during and after MCO has a p-value of 0.09082, 0.22764 and 0.55542 respectively. Since the data has a p-value of greater than 0.05, therefore the data is fit for the AR-GARCH model with Student's *t* distribution.

3.5 Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Log-likelihood function (LLF)

Table 8: Estimated value of parameter, LLF, AIC and BIC of Student-*t* distribution copula

Student-*t* distribution copula	LLF Value	AIC Value	BIC Value
Before MCO	0.1211659 (df=2)	3.757668	10.39391
During MCO	1.9358 (df=2)	0.1284005	6.793838
After MCO	0.5329871 (df=2)	2.934026	9.540636

Table 9: Estimated value of parameter, LLF, AIC and BIC of Clayton copula

Clayton copula	LLF Value	AIC Value	BIC Value
Before MCO	-0.002197294 (df=1)	2.004395	5.322515
During MCO	-0.1891466 (df=1)	2.378293	5.711012
After MCO	0.7734851 (df=1)	0.4530299	3.756335

From Table 8 and Table 9, we can compare the result. For the stock price and bond yields before MCO, in Student-*t* copula, the value of AIC and BIC is higher than Clayton copula. The value of log-likelihood function of Student-t copula is higher lower than the Clayton copula. Its means that the data is more fit to the Clayton copula than the Student-*t* copula. Besides, for the stock price and bond yields during MCO in Student-*t*, the value of AIC is lower than Clayton copula and BIC value is higher than Clayton copula. The value of log-likelihood function of Student-*t* copula is lower than Clayton copula. Its means that the data is more fit the Clayton copula than the Student-*t* copula. Moreover, for the stock price and bond yields during MCO in Student-*t*, the value of AIC and BIC is higher than Clayton copula. The value of log-likelihood function of Student-*t* copula is lower than Clayton copula. Its means that the data is more fit the Clayton copula than the Student-*t* copula.

3.6 Tail dependence

Table 10: Tail dependence coefficient for Student-*t* copula

Student-*t* distribution copula	Lower tail	Upper tail
Before MCO	2.434714e-07	2.434714e-07
During MCO	0.03993526	0.03993526
After MCO	4.606635e-161	4.606635e-161

For Table 10, the tail dependence coefficient for Student-*t* copula of stock price and bond yields before, during and after MCO is 0.00000024347, 0.03993526 and $4.606635\text{x}10^{-161}$ respectively.

Table 11: Tail dependence coefficient for Clayton copula

Clayton copula	Lower tail	Upper tail
Before MCO	4.993124e-73	-
During MCO	2.884373e-21	-
After MCO	0.001010334	-

The Clayton copula is the only copula shows the positive left tail dependence. Hence, there is no upper tail dependence. For Table 11, the tail dependence coefficient for Clayton copula of stock price and bond yields before, during and after MCO is 0.00000024347, 0.03993526 and 4.993124x10^(-73), 2.884373x10^(-21) and 0.001010334 respectively.

4. Conclusion

At the end of this study, we analyse the dependence structure between stick price and bond yields. The stock price and bond yields have correlation between each other determine by Pearson correlation test and Kendal's rank correlation test. We fit the data with AR-GARCH(1,1) model and AR-GJR-GARCH model with normal copula and Student-*t* copula. We assume that the degree of freedom parameter and skewness parameters are time-varying. For the copula, we found that Student-*t* copula yields higher log-likelihood than the Clayton copula. Besides that, the value of AIC and BIC of Clayton copula is higher than the Student-*t* distribution copula. Hence, the stock price and bond yields are more fit the Clayton copula than the Student-*t* distribution copula. The dependence structure between bond yields and stock market index shows tail dependence in table 10 and 11. Among these two copulas, Clayton copula is fit the dependence between stock price and bond yields.

On the other sides, during lockdown, stock price and bond yields have affected. We found that the correlation of stock price and bond yields before and during MCO is negative value. It is means that the while the stock price increase and bond yields decrease and vice versa. However, the correlation of stock price and bond yields before and during MCO is positive value. It's had a change between these two investments. Besides, the correlation between stock price and bond yields is increase overtime.

Acknowledgement

The authors would like to thank the Faculty of Applied Sciences and Technology, Universiti Tun Hussein Onn Malaysia for its support.

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