

Indonesia Stock Exchange Composite Modelling With Gaussian Copula Marginal Regression

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ABSTRACT

This study discussed the modelling of Indonesia Stock Exchange Composite Index (ICI) in Indonesia Stock Exchange (IDX) with Gaussian Copula Marginal Regression (GCMR). In this study, secondary data, which was monthly data from 2010 to 2015 was used. Estimator of Copula parameters was to identify the relationship between ICI with macroeconomic factors. To estimate the parameters of Copula, Kendall's Tau approach was used. Another thing that was studied in this research was to determine the model predictions of GCMR on Gaussian Copula. The structure of dependencies between ICI and its macroeconomic factors largely followed Copula family. In addition, the predicted results with the ICI line plot approached the real data from actual data with the estimator data using GCMR models.

Keywords— Copula Gaussian, Gaussian Copula Marginal Regression, Indonesia stock exchange composite index

I. INTRODUCTION

Stock is one instrument of the most popular financial markets. On the other hand, the stock is an investment instrument chosen by investors because it is able to provide an attractive level of profits. Investment is an attempt to delay consumption in the present and place their funds in an asset during a certain period to get a certain rate of return in the future. In the secondary market or in activities of daily stock trading, stock prices fluctuated either increase or decrease. Stock price formation occurs because of the demand and supply of the stock. In other words, the stock price is formed by supply and demand of the stock. Supply and demand of stock occurs because of many factors, both of which are specific for the stock (performance of the company and the industry in which the company is engaged) and the macro factors such as inflation, exchange rates, interest rates,

non-economic factors such as social and political conditions, and other factors¹.

In a study on the finance, non linear data and abnormalities in the data are often found. The assumption of normality distribution in statistical methods is necessary, due to the ease in estimation methods of calculation.

In general, non-normal distribution cases have little attention or even forced assuming normal distribution. One of method in the dependence model very popular today is Copula which was first introduced by Sklar in 1959. Some of the advantages of Copula is not strict on the assumption of distribution (particularly normal distribution), can explain non-linear dependencies, easy to build distribution with it because the marginal distribution of random variables can be different or even unknown². Some of the advantages of Copula method attract the attention of researchers and continue to grow in the field of science. Copula has been widely used to model the structure of relationships in climatology and meteorology³, risk management⁴, and in other fields.

A development of regression-based Copula method is Gaussian Copula Marginal Regression (GCMR). GCMR can be utilized to identify the effect of extremes. Previous study about regression-based Copula used a Gaussian Copula Marginal Regression (GCMR) which is modelling the extreme rainfall data⁵. Copula parameter estimation can be carried out using various approach like Spearman's Rho, Kendall's Tau, and maximum likelihood estimation (MLE). Therefore, this study will assess GCMR parameter estimation and the method is applied to the movement of the Indonesia stock exchange composite index (ICI) in the Indonesia Stock Exchange (IDX).

II. METHODOLOGY

The data used in this research was secondary data of ICI in IDX from January 2010 to December 2015.

Banking financial statements studied can be accessed on www.bi.go.id and www.imf.org. In this study, ICI was a response variable, while the independent variables suspected to affect the response variable was:

- X₁ : Inflation (%)
- X₂ : Exchange Rate of IDR/USD
- X₃ : Interests Rate (%)

The steps undertaken in conducting analysis and predictive modelling JCI with macroeconomic factors were as follows:

- (i) Data description.
Early stage of the research was descriptive statistical analysis to explain the data description of all variables that would be included in the research model.
- (ii) Identified the relationships between variables with Pearson, Kendall's Tau, and Spearman correlation.
Correlation aimed to measure the strength of relationship between ICI and inflation, the exchange rate, and interest rate.
- (iii) Transformed among variabls to a uniform [0,1].
- (iv) Estimated Copula parameter among variables with Kendall's Tau approach
- (v) Modelled among variables with GCMR
- (vi) Calculated prediction of ICI and its macroeconomic factors

III. PRIOR APPROACH

In general, Gaussian Copula Marginal Regression model was described as follows,

$$Y_i = g(x_i, e_i; \lambda), i = 1, 2, \dots, n$$

g(.) is appropriate function of regression, e_i was error of model, and λ was parameter. From any possibility of g (.), model selection was,

$$Y_i = F_i^{-1}\{\Phi(e_i); \lambda\}, i = 1, 2, \dots, n$$

Φ(.) was cumulative function of distribution from Y_i that was given by x_i. Based on integral theorem of transformation, regression model on Kendall's Tau was,,

$$\tau = 1 + 4 \int_0^1 \frac{\theta(u)}{\theta'(u)} du$$

to ensure the marginal distribution of Y_i. For example using the formula in equation of Gaussian linear model,

$$Y_i = x_i^T \beta + \sigma e_i \quad \text{in appropriate with}$$

$$F_i = (Y_i; \lambda) = \Phi\{(Y_i - x_i^T \beta / \sigma)\} \quad \text{with}$$

λ = (β^T σ)^T. When model uses weibull distribution, then μ_i = exp(x_i^T β)⁶, with λ̄ = β̄.

IV. OUR APPROACH

Based on the analysis performed, the parameter estimators Copula between JCI and macroeconomic factors used was obtained as shown in the following table :

TABLE I
ESTIMATOR OF COPULA PARAMETERS
BY KENDALL'S TAU APPROACH

Variables	Type of Copula	Paramaters	P-Value
ICI and Inflation	Gumbel	1.225	0.000
	Clayton	0.45	0.027
	Frank	1.701	0.000
	Gaussian	0.285	0.000

Variables	Type of Copula	Paramaters	P-Value
ICI and Exchange Rate	Gumbel	2.188	0.000
	Clayton	2.377	0.000
	Frank	6.579	0.000
	Gaussian	0.753	0.000

Variables	Type of Copula	Paramaters	P-Value
ICI and Interests Rate	Gumbel	-	-
	Clayton	-0.238	0.054
	Frank	-1.236	0.000
	Gaussian	-0.211	0.085

Note: **Bold** indicates significant at α=0.05

There was a connection between ICI and macroeconomic factors by the identified Copula in table 1. If the relationship follows the Gaussian Copula, then it shows that there is a linear relationship between them two.

If a relationship follows gumbel, clayton, or frank copula, it means that there are extreme events and there is a relationship at the extreme point. Gumbel copula is a copula that has a relationship tail at the top. In other hand, clayton copula illustrates that there are extreme events at a low value, and there is a relationship between two variables when value of them are low, the higher value of observations at the variable, then the relationship between them is getting weaker because copula has tail relationship in bottom part.

Similar with relationship between ICI and inflation, both exchange and interests rate followed clayton copula. Unlike other copula, frank copula does not have a tail relationship at the top and bottom part, which from the point of observation of the picture, this copula resembles the gaussian copula. Frank copula showed that a very close relationship between ICI and inflation, exchange rate, and interest rate only occurred when their value were both very high and very low.

5000 data points were generated based on the parameter estimator to see the pattern of relationships

between ICI and its macroeconomic factors. Relationships between ICI and inflation, exchange rate, and interests rate followed the pattern of gaussian, clayton, gumbel, and frank copula as shown on Figure 1 below.

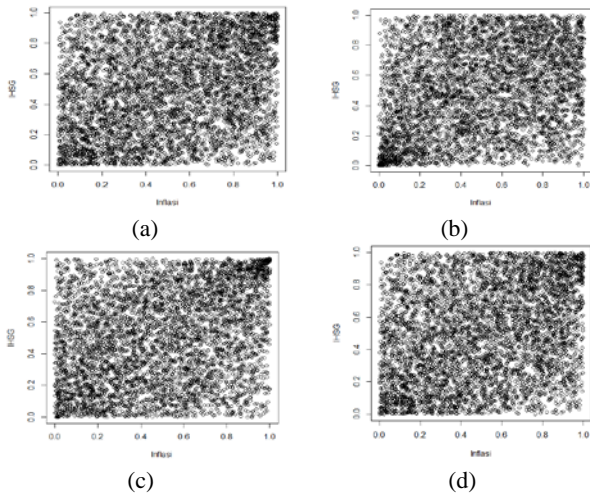


Figure 1 : Scatter plot rank copula with n = 5000 between ICI and inflation following the copula of gaussian (a), clayton (b), gumbel (c), dan frank (d)

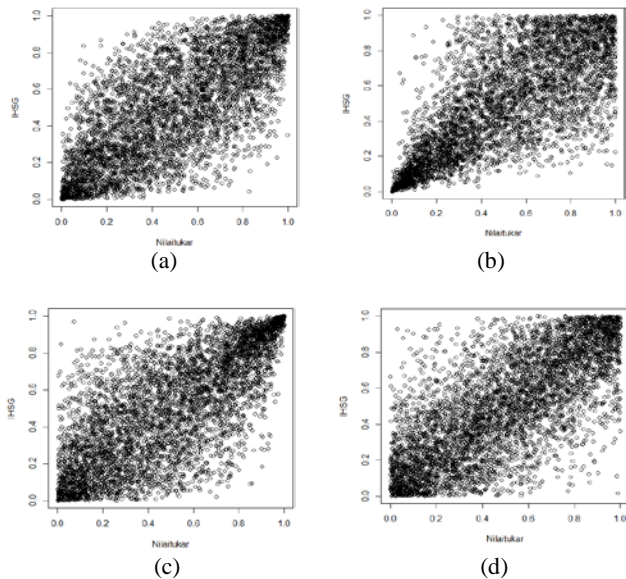


Figure 2 : Scatter plot rank copula with n = 5000 between ICI and the exchange rate following the copula of gaussian (a), clayton (b), gumbel (c), dan frank (d)

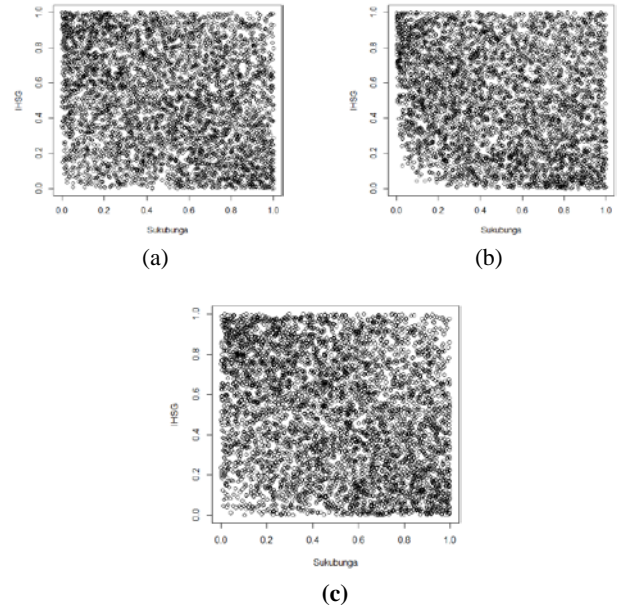


Figure 3 : Scatter Plot scatter rank plot with n = 5000 between ICI and interests rate following the copula of gaussian (a), clayton (b), dan frank (c)

Gumbel copula could not be estimated because the values of parameter calculation was $\theta < 1$, which was supposedly $\theta \in [1, \infty)$ (Figure 3). It was because Kendall's Tau correlation was negative (-).

The results of fitting copula with MLE for each significant copula. The best model for each pair of variables was selected based on the highest log-likelihood fitting. Model of the relationship between ICI and inflation followed clayton copula because the value of its log-likelihood was higher than the others. Similarly, relationship between ICI and interest rate followed clayton copula, illustrating that there were extreme events at a low value. There was also a relationship between two variables when the value of them are low. The higher value of observations at the variable, then the relationship between the two was getting weaker. It was because this copula had a relationship tail at the bottom such as relationship between ICI and both of inflation and interests rate. In contrast, the highest log-likelihood value of relationship between ICI and the exchange rate followed frank copula which showed a very close relationship between ICI and the exchange rate. It occurred when their value were both very high and very low. This shown on Table II below.

TABLE II
RESULTS OF FITTING COPULA WITH MLE

Variables	Type of Copula	Estimators	log-likelihood
ICI and Inflation	Gumbel	1.217	2.532
	Clayton	0.562	4.857
	Frank	1.894	3.468

	Gaussian	0.373	4.523
ICI and Exchange Rate	Gumbel	1.809	17.330
	Clayton	1.103	13.300
	Frank	6.936	28.250
	Gaussian	0.680	20.110
ICI and Interests Rate	Gumbel	-	-
	Clayton	-0.268	2.459
	Frank	-1.149	1.326
	Gaussian	-0.263	2.100

Note: **Bold** indicates highest log-likelihood

The next step was the relationship modelling between ICI and its macroeconomic factors. According to the Table 1, most of relationship between ICI and inflation, exchange rate, and interests rate followed copula family. In this study, ICI model followed gaussian copula using GCMR. ICI modelling by its macroeconomic factors with GCMR method was shown as follows,

$$ICI = \exp(0.4896280 + 0.003561 \text{Inflation} + 0.897384 \text{ExchangeRate} - 0.070241 \text{InterestsRate}) \\ = 1.631709(0.996439^{\text{Inflation}}) (1.897384^{\text{ExchangeRate}}) (0.929759^{\text{InterestsRate}})$$

If the Exchange Rate (x + 1), then ICI tend to rise by exp (0.897384) = 1.897384 times and vice versa. To see the size of goodness of the regression model with copula, then line plot of ICI with comparing actual data of ICI and estimator results was shown in Figure 4 as below,

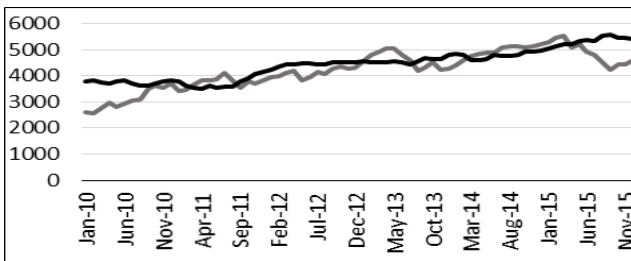


Figure 4 : Line Plot of Actual ICI (gray line) and estimator ICI (black line)

Predicted ICI approached the actual data and MAPE model goodness size was 0.107, while the correlation between the actual and estimation data was 76.679% (Figure 4). GCMR is good to model non-normal distribution response variable with tendency large skew.

V. CONCLUSION

From the results of study and discussion that has been conducted can be conclude that:

- a. Relationship pattern between ICI and its macroeconomic factors in IDX using copula parameter estimation with Kendall's Tau approach with the results of the highest log-likelihood fitting showed a relationships pattern which followed clayton copula ICI with Inflation and Interests Rate whereas ICI with Exchange Rate followed frank copula.
- b. ICI predicted by line plot approached actual data which had 0.107 MAPE model goodness size.

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