Assessing regional economic performance in the southern Thailand Special Economic Zone using a Vine-COPAR model

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Abstract: Special economic zones can play an integral role in enhancing both regional and national economic growth. To explore the relationship between regional growth and the presence of the SEZ in Songkhla province, Thailand, the CD Vine-COPAR models were constructed using annual datasets of Songkhla’s economic performance from 1995 to 2016. The findings indicate that the D Vine-COPAR model produced better fitting predictions for the manufacturing sector, while the C Vine-COPAR models provided goodness of fit for the agriculture and service sectors. A five-year forecast (2017-2021) were also created. For Vine-COPAR-based Granger causality, GPP, FDI and Trade are evidently important contributors to regional economic development. Consequently, the government should adopt comprehensive strategies, to ensure comparative advantages for operating in the region based on favorable local factors.

Keywords: Vine Copulas; multivariate time series; forecasting techniques; evaluation of prediction model; Granger causality

JEL Classification:

1. Introduction

Under the new growth theory (Romer 1986; Lucas 1988), endogenous growth models emphasize technical progress (capital stock, human capital and innovation). From the early 1990s, foreign direct investment (FDI) has been a crucial source of enhancing economic growth in emerging economies. Thailand’s regional development has been enhanced by the development of Special economic zone (SEZ), which is viewed as an effective economic instrument to accelerate economic growth. Since 1961, the SEZ development policies have been implemented by developing major infrastructure projects, and regional development programs. The World Bank (2017) stated that creating the SEZ can stimulate economic expansion both within and outside the zone. Inside the zone, it attracts foreign investment as well as facilitate skills and innovation transfers, while outside the zone purposes to evoke synergies and knowledge spillovers to foster additional economic activity. Typically, the success of the SEZ depends on the SEZ characteristics, the structure and the regional and country contexts. Since the SEZ operates as geographic regions within countries, localized employment churn registered as job creation. Moreover, economic dynamism can account for variations in regional productivity and improve in the standard of living towards nations in turn (Slaper, 2014).
In 2014, the Thai government launched pilot SEZ projects in five border provinces, namely Tak, Aranyaprathet, Mukdahan, Songkhla, and Trat, in which the government granted investors special privileges including tax and non-tax incentives. The Gross Provincial Production (GPP), which accounts for the chain volume measures of production outputs at regional and provincial levels, is determine. The compilation of GPP is a part of System for National Accounts of Thailand by using a bottom-up approach to effectively compile and improve the indicators of provincial-level production. There are 16 economic activities including agriculture production (agriculture, hunting and forestry; fishing) and non-agriculture production (mining and quarrying; manufacturing; construction; sale; hotels and restaurants; Financial intermediation; real estate, renting and business activities, etc.) The change in real value added is employed for evaluating the changes of each production output. Looking more closely of economic performance through GPP, Songkhla produces many agricultural products (share 14% of GPP), which provide copious raw materials, this encourages agro-industries such as rubber, palm oil and sea-food processing (share 21% of GPP). Songkhla has a strategic location on the North-South Economic Corridor, which is directly connected to Malaysia and Singapore. It is a service-based economy (share 18% of GPP) (Government Public Relations Department, 2016). The values of cross-border trade are accounted more than 50% of Thailand’s total border trade. Therefore, the major sectors contributing to economic growth can be categorized into three groups: (1) manufacturing; (2) agriculture; and (3) service sector (Cherdchom et al. 2016). As a result, forecasting and measuring of the GPP, FDI and border trade are crucial for driving the SEZ operation.

Generally, development is measured using aggregated models based on centralized data. However, a top-down framework can frequently result in ineffective measures at a local level. In fact, regional performance can better be measured to explore economic convergence based on specific local characteristics (Ascani et al. 2012; Wei Xuan 2016). Many empirical studies of dependent of economic growth employed Granger’s theorem (Engle and Granger 1987) or vector autoregressive (VAR) models (Hamilton 1994; Tsay 2002; Lutkepohl 2005). However, classical VAR models can capture only linear and symmetric dependences in time and between series. In a small degree of freedom, if the dependences of the system are modeled with longer lags, those larger estimated parameters might be misspecification. It is a weakness of the traditional VAR models (Pyndick and Rubinfeld 1997). Unbiasedness is a part of properties of an estimator. Recently, research into the relationship between regional growth and SEZ remains limited (Chi-Keung 2010; Ho 2004). To address this issue, Vine-Copula autoregressive (Vine-COPAR) models are constructed to overcome such limitations as constants in dependency. The Vine-COPAR models have been verified as a flexible model with high-dimensional patterns (Brechmann and Czado 2013; Brechmann and Czado 2015). This approach allows arbitrary marginal distributions. To mean interdependencies among multivariate time series, we exploited a fully integrated Granger causality test of Vine-COPAR models.

The objectives of this study are as follows: (1) to construct upon the so-called Vine-COPAR models. More precisely, we test the Vine pair-copula decompositions including Canonical vine (C-vine) and Drawables vine (D-vine) to optimally quantify the dependence structures, (2) to evaluate the performance of the prediction methods, (3) to forecast the economic performance over a five-year period (2017-2011), and (4) to analyze the patterns of causality among economic growth, FDI and border trade. The contributions of the paper are twofold. First, it is the first study applying Vine COPAR to analyze the dependent between economic growth and the SEZ operation. Second, adoptions of appropriate policies regarding to GPP, FDI and border trade can provide new insights to highlight opportunities for competitive advantages within regional economy. This paper is structured as follows: In Section 2 introduces the C and D Vine copulas, and the Vine-COPAR-based Granger causality. Section 3 presents data and empirical findings. Finally, Section 4 offers conclusions along with policy recommendations.
2. Methodology

2.1 Vine copula models

A copula function can be used to model multivariate distributions with given univariate margins. For a random vector \( X = (X_1, \ldots, X_d) \sim H \) along with \( H_i, i = 1, \ldots, d \) Sklar’s theorem can be written as:

\[
H(X_1, \ldots, X_d) = C(F_1(X_1), \ldots, F_d(X_d)),
\]

where \( H \) is \( n \)-dimensional distribution with marginal \( F_i, i = 1, 2, \ldots, d \). \( C \) is \( d \)-dimensional copula linked to form a joint distribution. Sklar’s theorem with a bivariate copula is implemented as:

\[
H(u_1, u_2) = C(F^{-1}_1(u_1), F^{-1}_2(u_2)),
\]

where \( u_1, u_2 \in [0, 1] \) and \( F \) is the distribution of invertible margins \( F_1 \) and \( F_2 \).

2.1.1 C and D Vine Copulas

For multivariate analysis, C and D Vine copulas, which were initially proposed by Joe (1996), are utilized to estimate dependency. The factors are \( X = x_1, x_2, x_3 \) within the marginal distribution functions. For instance, C Vine copulas can be formed by Eq.(1.3):

\[
f(x_1, x_2, x_3) = f_1(x_1)f_2(x_2)f_3(x_3|x_1, x_2)
\]

followed by Sklar’s theorem (1.1) such that

\[
f(x_1| x_2) = \frac{f(x_1, x_2)}{f_2(x_2)}
\]

and

\[
f(x_3|x_1, x_2) = \frac{f(x_2, x_3|x_1)}{f(x_2|x_1)}
\]

\[
= c_{1,2}\{F_1(x_1), F_2(x_2)\}f_2(x_2),
\]

\[
= c_{2,3\mid 1}(F(x_2|x_1), F(x_3|x_1)).
\]

2.2 VAR model

Since the SEZ is considered as the economic transformation, the FDI and border trade are viewed as a proxy for the SEZ performance. The Gross Provincial Production, Foreign Direct Investment and border trade are denoted by GPP, FDI and TRADE, respectively. All relevant variables are transformed into logarithms in order to stabilize the variance of a series. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is used to test the stationary time series. We propose a VAR framework which consists of the three endogenous variables: \( Y = (GPP, FDI, TRADE) \). The \( VAR(p) \)-process can be defined in the basic form as:

\[
lnY_t = \beta_0 + \beta_1 lnY_{t-1} + \ldots + \beta_p lnY_{t-p} + \varepsilon_t, t = p + 1, \ldots, T,
\]

where \( \beta_0 \) is a \( k \)-dimensional constant vector, \( \beta_i \) are \( k \times k \) real-valued matrices for \( i = 1, \ldots, p \) and \( \varepsilon_t \) is a \( k \) dimensional white noise vector process with a time-variant definite covariance matrix \( E(\varepsilon_t \varepsilon_t') = E_\varepsilon \) for \( t = p+1, \ldots, T \).

We applied a VAR to forecast economic performance. The assumption of random repressors is uncorrelated with errors. For forecasting of the final period \( (T) \), vector \( Y_t \) and \( Y_{t-1} \) are essential. Pecan (2010) consigned a forecast for one-period as follow:

\[
Y_{(T+1)/T} = E(y_{T+1}/y_T, y_{T-1}, \ldots) = \beta_1 y_T + \beta_p y_{T-p+1}.
\]

2.3 Granger Causality

Since the Gaussian assumption is constant variance, so this method can merely capture linear and symmetric dependence in time and between series. Therefore, we employed the Vine-COPAR
model based Granger causality, which determines interdependencies among multiple time series, to deal with high-order causality. The Vine-COPAR\(p\)-based Granger causality was then built up in the following form:

\[
\ln Y_{kt} = \beta_{k0} + \sum_{i=1}^{s} \beta_{ki} \ln Y_{1t-i} + \sum_{j=1}^{q} \beta_{kj} \ln Y_{2t-j} + \sum_{l=1}^{n} \beta_{kl} \ln Y_{3t-l} + \varepsilon_{kt}. \tag{1.10}
\]

where \(\beta_{k0}\) (for \(k=1,2,3\)) is the interception term. \(\beta_{ki}, \beta_{kj}\) and \(\beta_{kl}\) are the estimated coefficient of the lagged variables. \(s, q\) and \(n\) are the optimal serial lag lengths and \(\varepsilon_{kt}\) refers to random disturbance terms.

The Log-likelihood ratio (LR) tests of unrestricted (\(L_u\)) and restrictions (\(L_r\)) models are imposed with the null hypothesis of no Granger causality \(H_0: \beta_{k1,1} = \beta_{k2,2} = \ldots = \beta_{k3,3} = 0\). Then, we employed the maximum likelihood method to maximize the Vine-COPAR models to obtain the estimated parameters and it is better than a two-step estimation.

3. Data and Empirical Results

In Section 3.1, the data is described and the empirical findings are reported in Section 3.2, including the accuracy of the prediction models, the forecast under the Vine-COPAR, and the Granger causality based on the Vine-COPAR models.

3.1. Data

The annual datasets of GPP and TRADE time-series data were obtained from the Bank of Thailand database, whilst the FDI data was acquired from the Thai Board of Investment over the period 1995-2016. Before that time, those statistical datasets were incomplete. The GPP was accounted at chain volume measures (the reference year at 2002), the TRADE was measured at the FOB prices and the FDI was counted at current prices. Figure 1 shows Songkhla economic performance. The GPP has been increasing for the manufacturing and trade sectors. While the agriculture sector has been slowing down due to the agricultural price fluctuation especially in rubber, which is the most important cash crop in the south as Fig. 1 (a-c). Since 2005, Thailand Board of Investment has started to approve Inward Thai Direct Investment and FDI at in southern Thailand. Afterwards, the FDI volumes seem to be surges and stops into neighboring countries like Vietnam, Indonesia to seek cheaper resources of materials or labor offshore.

![Figure 1 The Regional Economic performances in the Southern Thailand SEZ.](image)
3.2 Empirical Results

3.2.1 CD-Vine COPAR models

The dependent of economic data was explored within (1) manufacturing, (2) agriculture and (3) service sector. Macro-economic time-series data are usually non-stationary (Nelson and Plosser 1982). Hence, the KPSS test is utilized within the null hypothesis of a stationary against a unit root alternative. All variables are stationary at an alpha level of 0.01 in all these cases (for example, in the manufacturing sector for the GPP, it gives KPSS level of 0.166, truncation lag parameter of 2 and p-value of 0.121; for the FDI, it reports KPSS level of 0.168, truncation lag parameter of 2 and p-value of 0.152 and for the TRADE, it informs KPSS level of 0.199, truncation lag parameter of 2, p-value of 0.136). Consequently, the VAR specification in level is sufficient.

Table 1 summarize that the dependencies between two variables belong to several copula families (Gaussian, Clayton, Frank, Joe, Rotated Joe, rotated Clayton, and Rotated Gumbel). Since the pair-copula constructions decompose a multivariate probability density towards bivariate copulas for a good selection choice to build more powerful tree sequences. We then inform the bivariate copula families serving as building blocks for vine copulas. For instance, the optimal pair-copula constructions based on the C-Vine COPAR between the GPP(1) and FDI (2), the GPP(1) and TRADE (3), and the FDI-TRADE (23) and GPP (1) in the manufacturing sector is Joe, rotated Joe and Frank families, respectively etc. The Kendall’s tau reported both positive and negative dependencies. For tail dependencies in manufacturing sector (D-Vine COPAR), the GPP and FDI have a great dependence in the upper tail, indicating that GPP is likely to raise together with FDI; besides, the GPP and TRADE are similar. For the agriculture sector (C-Vine COPAR), the GPP and TRADE have dependence in the lower tail. Furthermore, we can see that the AIC to penalize copula families with more parameter for D Vine-COPAR model (59.125) produced a better performance in case of the manufacturing sector, while the C Vine COPAR models (100.422 and 111.162) provided properly good fit models for the agriculture and the service sectors. After choosing the independence copula, the optimal lag of the Vine COPAR(p*) models are the D-Vine COPAR(3), C-Vine COPAR(3) and C-Vine COPAR(2) for (1) the manufacturing, (2) the agriculture and (3) the service sectors, respectively.

Table 1 CD-Vine COPAR models, Kendall’s correlation, and upper-lower tail dependence.

<table>
<thead>
<tr>
<th>SEZ economic performance</th>
<th>Manufacturing</th>
<th>Agriculture</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C-Vine COPAR</td>
<td>D-Vine COPAR</td>
<td>C-Vine COPAR</td>
</tr>
<tr>
<td>pair-copula¹</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5.470 (12= Joe)</td>
<td>4.682 (12= Joe)</td>
<td>-0.010 (12= rotated Clayton)</td>
</tr>
<tr>
<td></td>
<td>1.221 (13= rotated Joe)</td>
<td>-2.303 (23= Frank)</td>
<td>1.581 (13= Rotated Joe)</td>
</tr>
<tr>
<td></td>
<td>-4.583 (231= Frank)</td>
<td>1.276 (132= Clayton)</td>
<td>-16.812 (231= Frank)</td>
</tr>
<tr>
<td>Kendall’s tau</td>
<td>0.700</td>
<td>0.660</td>
<td>-2.516</td>
</tr>
<tr>
<td></td>
<td>0.380</td>
<td>-0.243</td>
<td>0.245</td>
</tr>
<tr>
<td>tail dependence²</td>
<td>[0.0,0.865]</td>
<td>[0.0,0.840]</td>
<td>[0.0]</td>
</tr>
<tr>
<td></td>
<td>[0.0,0.587]</td>
<td>[0.0]</td>
<td>[0.480,0]</td>
</tr>
<tr>
<td></td>
<td>[0.0]</td>
<td>[0.581,0]</td>
<td>[0.0]</td>
</tr>
<tr>
<td>AIC</td>
<td>76.254</td>
<td>59.125</td>
<td>100.422</td>
</tr>
</tbody>
</table>

Note: 1. pair-copula: GPP(1). FDI(2), TRADE(3)
2. tail dependencies: [lower, upper]
3. selection for appropriate lags for the manufacturing: AIC (-5.25e+01), HQ (-5.35e+01), SC (-5.21e+01), and FPE (7.45e-23); for the agriculture: AIC (-5.24e+01), HQ (5.31e+01), SC (-5.26e+01), and FPE (7.24e-23); for the service: AIC (-5.15e+01), HQ (5.41e+01), SC (-5.27e+01), and FPE (7.18e-23)
3.2.2 Evaluation of the performance of the prediction models

Since the traditional VAR models can handle only linear and symmetric dependence structures. We then develop the novel CD-Vine COPAR models, which allow for asymmetric modelling of serial and between-series dependencies to advocate superior predictive ability of the CD-Vine COPAR models over the classical VAR models as the benchmarking purpose. The prediction performance of the D-Vine COPAR model was compared to that of a classical VAR based model employing the out-sample (2012-2016). For evaluation of performance, the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) are measured are shown in Table 2. The CD Vine-COPAR has better prediction accuracy with the smaller RMSE and MPE.

<table>
<thead>
<tr>
<th>Accuracy</th>
<th>Manufacturing</th>
<th>Agriculture</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>D-Vine COPAR</td>
<td>Classical VAR</td>
<td>C-Vine COPAR</td>
</tr>
<tr>
<td>RMSE</td>
<td>0.679</td>
<td>0.685</td>
<td>0.998</td>
</tr>
<tr>
<td>MAE</td>
<td>0.480</td>
<td>0.482</td>
<td>1.106</td>
</tr>
</tbody>
</table>

3.2.3 Five-Year Forecast of the SEZ’s economic performance

It is questionable whether economic models represent accurate forecasting techniques. To consider this issue, the statistical test of a model’s forecast performance is technically conducted by divided a given data set into the in-sample period using for initial parameter estimation, and the out-of-sample period using for evaluating forecasting performance. Empirical evidence relied on out-of-sample forecast performance offers more trustworthy and reflection of the information in real time than evidence based on in-sample performance due to the sensitivity of outliers and the process of discovering pattern in the data sets (Ehling and Körner, 2015). In this study, the in-sample data (1995-2011, roughly 70% of the data) was used to construct the estimation, while the out-of-sample data (2012-2016, the remaining 30% of the entire data set) was employed to produce the prediction.

The classical VAR versus Vine-COPAR models were compared using RMSE and MPE to evaluate their predictive power. Ultimately, a five-year forecast was produced. Figure 2 displays the five-year forecast in terms of GPP, FDI and TRADE over the period 2017-2021 using the D Vine-COPAR for the manufacturing sector and the C Vine-COPAR for the agriculture and service sectors. Interestingly, the FDI seems to increase in value especially in the manufacturing and service sectors, while the TRADE stays constant over the three sections. Somehow, the GPP and FDI flows exhibit high levels of volatility.

Figure 2 Five-Year Forecast of the SEZ economic performance.
3.2.4 Vine COPAR-based Granger causality

The results of the LR tests is shown in Table 3 under null hypothesis of non-causality. For the manufacturing sector, Granger-bidirectional causality exists between GPP and FDI, besides TRADE is Granger-causal FDI. Consistently with the agriculture sector, Granger-bidirectional causality occurs between FDI and TRADE, as well as GPP is Granger-causal Trade. In addition for the service sector, Granger-bidirectional causality take places among GPP and FDI as well as GPP and TRADE, while FDI is Granger-causal TRADE.

Table 3 Vine COPAR-based Granger causality test results.

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Statistics</th>
<th>Manufacturing</th>
<th>Agriculture</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>FDI does not Granger-cause GPP</strong></td>
<td>LR test</td>
<td>13.406</td>
<td>0.367</td>
<td>22.287</td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.004***</td>
<td>0.947</td>
<td>5.683e-05***</td>
</tr>
<tr>
<td><strong>Trade does not Granger-cause GPP</strong></td>
<td>LR test</td>
<td>0.361</td>
<td>4.368</td>
<td>24.438</td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.948</td>
<td>0.224</td>
<td>2.023e-05***</td>
</tr>
<tr>
<td><strong>GPP does not Granger-cause FDI</strong></td>
<td>LR test</td>
<td>17.956</td>
<td>3.714</td>
<td>23.443</td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.000***</td>
<td>0.294</td>
<td>3.265e-05***</td>
</tr>
<tr>
<td><strong>TRADE does not Granger-cause FDI</strong></td>
<td>LR test</td>
<td>10.301</td>
<td>13.814</td>
<td>19.852</td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.016**</td>
<td>0.003***</td>
<td>0.000</td>
</tr>
<tr>
<td><strong>GPP does not Granger-cause TRADE</strong></td>
<td>LR test</td>
<td>2.924</td>
<td>34.975</td>
<td>23.205</td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.404</td>
<td>1.233e-07***</td>
<td>3.660e-05***</td>
</tr>
<tr>
<td><strong>FDI does not Granger-cause TRADE</strong></td>
<td>LR test</td>
<td>3.550</td>
<td>33.741</td>
<td>23.930</td>
</tr>
<tr>
<td></td>
<td>P-value</td>
<td>0.314</td>
<td>2.247e-07***</td>
<td>2.583e-05***</td>
</tr>
</tbody>
</table>

4. Conclusions and Policy Implications

This paper examined the relation between economic growth and the SEZ in Songkhla Province, including evaluating the accuracy of the prediction approach, forecasting the economic performance of the SEZ, and examining the causal influences among GPP, FDI and TRADE using Vine-COPAR based Granger causality. The main finding can be drawn:

1) The appropriate specification for a forecasting method using a Vine-COPAR model provides better results than a single time series since evaluating more dependent structures leads to more accurate predictions. Moreover, the Vine-COPAR based Granger Causality can accommodate high-order moment causality and this approach thus provides effective long run performance.

2) For five-year forecast (2017-2021), the FDI and TRADE appear to be the important contributions towards the SEZ. However, the GPP and FDI display sharp fluctuations, and the TRADE behaves constantly. Therefore, the government should encourage their competitiveness and maintain continuity of foreign investment and trade policies.

3) Granger causality and bidirectional causality exist between the GPP, FDI and TRADE all sectors.

This study has some policy implications; government should promote FDI-friendly policies and trade promotion in the SEZ since these policies can play a crucial role in boosting regional economic growth. The core of the development should focus on the favorable privileges towards FDI; in addition the Free Trade regime should be supported by eliminating a whole range of non-tariff barriers. Particularly bearing in mind, the FDI based-enterprises within SEZ are ordinarily accorded more liberal operating conditions.
Consequently, the findings from the provincial level suggest that Songkhla province should be promoted as one of the nine industrial centers in Thailand since it has great potential for a considerable acceleration of its economic growth based on the SEZ policy which could contribute towards the enhancement of the regional economy.

Author Contributions: A.R. designed the main writer of the paper, conducted the research findings, and revised the manuscript. J.L. constructed the model analysis and source coding for the R software. P.C. and P.P. took action of the field interviewing, data collecting and analyzed the results. S.S. dedicated the overall research and revised the policy recommendations. All authors revised and approved the final manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

References


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Response to Reviewer 1 Comments

**Point 1:** The authors use PP test to examine the unit root property of GPP, FDI and Trade variables. What is the outcome of the results? Are these variables stationary? Or non-stationary? If they are stationary, then VAR specification in level is appropriate. If they are non-stationary and they cointegrated then it can be estimated in VECM specification. On the other hand, if they are non-stationary and not cointegrated then the VAR in difference form is sufficient. It is not clear to the readers if they are stationary or not. Why do you choose PP test as opposed to other alternatives? Why don’t you consider the stationary null (KPSS) as well to make sure that the results are not affected by the lack of statistical power.

**Response 1:** Hence, the KPSS test is utilized within the null hypothesis of a stationary against a unit root alternative. All variables are stationary at an alpha level of 0.01 in all these cases (for example, for the GPP in the manufacturing sector, it gives KPSS level of 0.166, truncation lag parameter of 2 and p-value of 0.121; for the FDI, it reports KPSS level of 0.168, truncation lag parameter of 2 and p-value of 0.152 and for the TRADE, it informs KPSS level of 0.199, truncation lag parameter of 2, p-value of 0.136). Consequently, the VAR specification in level is sufficient.

**Point 2:** In equation (1.8), both intercept and the coefficient of appears as . It should be fixed.

**Response 2:** 

\[ \ln Y_t = \beta_0 + \beta_1 \ln Y_{t-1} + \cdots + \beta_p \ln Y_{t-p} + \varepsilon_t, t = p + 1, \ldots, T, \]  

(line 121)

**Point 3:** The intercept is assumed as a column vector of order Mx1 while the coefficient matrix is of order KxK. The matrix operation is not confirmable when M ≠ K.

**Response 3:** adjusted the equation (1.8) as

\[ \ln Y_t = \beta_0 + \beta_1 \ln Y_{t-1} + \cdots + \beta_p \ln Y_{t-p} + \varepsilon_t, t = p + 1, \ldots, T, \]  

(line 122-124)

**Point 4:** The section 2.3 doesn’t make any sense. What do you mean by higher-order causality?

**Response 4:** So this method can merely capture linear and symmetric dependence in time and between series. Therefore, we employed the Vine-COPAR model based Granger
causality, which determine interdependencies among multiple time series, to deal with high-order causality. (lines 130-134)

**Point 5:** In lines 106 and 107, the operator and the parameter are missing. It appears as “denotes the first difference”. Similarly, “refers to random disturbance term”

**Response 5:** adjusted the equation 10 as

$$\ln Y_{kt} = \beta_{k0} + \sum_{i=1}^{s} \beta_{ki} \ln Y_{1t-i} + \sum_{j=1}^{q} \beta_{kj} \ln Y_{2t-j} + \sum_{l=1}^{n} \beta_{kl} \ln Y_{3t-l} + \varepsilon_{kt}. \quad (1.10)$$

where $\beta_{k0}$ (for $k=1,2,3$) is the interception term. $\beta_{ki}, \beta_{kj}$ and $\beta_{kl}$ are the estimated coefficient of the lagged variables. s, q and n are the optimal serial lag lengths and $\varepsilon_{kt}$ refers to random disturbance terms.

(lines 135-138).

**Point 6:** The hypothesis in line 110 has no link to the working model represented by equation (1.10).

**Response 6:** $H_0: \beta_{k1,1} = \beta_{k1,2} \ldots = \beta_{k1,3} = 0$ (line 140)

**Point 7:** The results reported in Table 1 is not self-expository and the discussion of results in section 3.2. is not clear with reference to table 1.

**Response 7:** Since the pair-copula constructions decompose a multivariate probability density towards bivariate copulas for a good selection choice to build more powerful tree sequences. We then inform the bivariate copula families serving as building blocks for vine copulas. For instance, the optimal pair-copula constructions based on the C-Vine COPAR between the GPP(1) and FDI (2), the GPP(1) and TRADE (3), and the the FDI-TRADE (23) and GPP (1) in the manufacturing sector is Joe, rotated Joe and Frank families, respectively.

(lines 172-178)

**Point 8:** Seventeen years of annual data is used for estimation and then five years of data is used for forecast evaluation. It makes no sense to use small sample for estimation and then use the model for prediction.

**Response 8:** It is questionable whether economic models represent accurate forecasting techniques. To consider this issue, the statistical test of a model’s forecast performance is technically conducted by divided a given data set into the in-sample period using for initial parameter estimation, and the out-of-sample period using for evaluating forecasting performance. Empirical evidence relied on out-of-sample forecast performance offers more trustworth and reflection of the information in real time than evidence based on in-sample performance due to the sensitivity of outliers and the process of discoverign pattern in the data sets (Ehling and Körner, 2015). In this study, the in-sample data (1995-2011, roughly 70% of the data) was used to construct the estimation, while the out-of-sample data (2012-2016, the remaining 30% of the entire data set) was employed to produce the prediction.

(lines 206-214)
Point 9: The results illustrated in table 2 show that COPAR model is marginally better than classical VAR model. Are these differences statistically significant? It can be examined through block-bootstrapping. But again, it will not be beneficial given the small sample size.

Why classical VAR model is used as benchmark model for comparison? Why don’t you compare the other alternative models?

Response 9: Since the traditional VAR models can handle only linear and symmetric dependence structures. We then develop the novel CD-Vine COPAR models, which allow for asymmetric modelling of serial and between-series dependencies to advocate superior predictive ability of the CD-Vine COPAR models over the classical VAR models as the benchmarking purpose. (lines 196-199)