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Identification of Non-Oil and Gas Main Commodity Exports in Indonesia to Major Destination Countries Using PCA Biplot and CVA Biplot

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Abstrak

Ekspor merupakan salah satu modal suatu negara untuk menambah devisa negara. Penelitian ini difokuskan pada ekspor komoditas nonmigas berdasarkan tujuan utama negara yang memberikan sumbangan laba terbesar bagi Indonesia. Penelitian ini menggunakan biplot *principal component analysis* (PCA) dan *canonical variate analysis* (CVA). Penelitian ini bertujuan untuk mendeskripsikan komoditas ekspor nonmigas berdasarkan negara tujuan utama ekspor dan mengidentifikasi kelebihan dan kekurangan kedua metode tersebut. Data yang digunakan meliputi besarnya laba ekspor komoditas nonmigas pada negara tujuan utama. Biplot PCA menggunakan negara sebagai objek, sedangkan biplot CVA menggunakan kelompok negara. Hasilnya meliputi empat kelompok negara tujuan utama berdasarkan komoditas ekspor. Biplot PCA dapat menjelaskan 68,45% data aktual. Kelebihan biplot PCA adalah representasi negara yang baik, sedangkan kelemahannya adalah representasi komoditas ekspor yang buruk. Di sisi lain, kekuatan biplot CVA meliputi representasi variabel ekspor yang lebih baik dibandingkan dengan biplot PCA dan cukup dalam mewakili kelompok negara, sedangkan kelemahannya adalah representasi negara yang buruk.

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Abstract

Export is one of the capitals of countries to increase foreign exchange. This study focuses on the export of non-oil and gas commodities based on the main destination countries that contribute the highest profit to Indonesia. The research uses principal component analysis (PCA) biplot and canonical variate analysis (CVA) biplot. This study aims to describe non-oil and gas export commodities based on the main export destination countries and to identify the advantages and disadvantages of both methods. The data include the amount of non-oil and gas commodity export profit on the main destination countries. PCA biplot uses the state as an object, whereas the CVA biplot uses a

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group of countries. The result includes four groups of main destination countries based on export commodities. The PCA biplot can explain 68.45% of actual data. The advantage of PCA biplot is well representation of a country, whereas its weakness is poor representation of export commodities. On the other hand, the strengths of CVA biplot comprise is the better representation of export variables compared with those of PCA biplot and sufficient in representing country group, and its weakness is poor representation of countries.

1. Introduction

Export is one of the capitals for countries to obtain foreign exchange. More state exports indicate higher foreign exchange earnings. This condition will support the financing of economic development, which affects the economic growth and development of the country. Export commodities consist of oil and gas; and non-oil and gas commodities [1]. Non-oil and gas commodities are divided into three groups, namely, agriculture, processing industry and mining commodities.

In January–October 2016, non-oil and gas exports dominated Indonesian exports by 90.88%, and the rest was dominated by oil and gas commodities. The non-oil and gas commodity group, which yields the largest export result, includes the processing industry group, featuring a value of 76.55%. Similarly, in January–October 2017, non-oil commodities still dominated Indonesian exports by 90.66%, with the processing industry being the largest non-oil/gas commodity group. Thus, this research focuses more on non-oil commodity exports. Non-oil commodities involve numerous sectors of goods based on the Indonesian Business Field Classification (KLBI). Indonesia features 15 major non-oil and gas export commodities. The main commodities are selected based on the amount of profit earned (Free on Board, FOB) in USD units [1].

Indonesia presents extensive export coverage to various countries in the world, from Asia, Australia, Europe, America and Africa. Based on the Ministry of Industry, Indonesia deals with 30 main export destination countries as they are the most export-generating for Indonesia. The study is conducted to determine the non-oil and gas commodity exports that provide the highest amount of profits based on Indonesia's main export destination countries. Therefore, a method is needed to describe the main commodities of non-oil and gas exports based on the main export destination countries of Indonesia.

Biplot and correspondent analyses involve a multivariate analysis that can describe data in two dimensional graphs [2], [3]. The result of correspondence analysis can be observed in the form of correspondence plot [4] in this study, correspondence analysis is not used as characteristics of variables will be identified in-depth. The classical biplot method, often called the principal component analysis (PCA) biplot, is a graphical representation of PCA; it used to obtain linear combinations that successively maximise the total variance. However, if the data contain a group structure, then PCA biplot is not considered the right approach. Then the appropriate method for discrimination between groups is to use biplot canonical variate analysis (CVA). Therefore, this study used PCA biplot and CVA biplot to identify Indonesia's main non-oil commodity exports based on Indonesia's main export destination countries.

2. Literature Review

2.1. Export of Non-Oil and Gas Commodities

Exports are divided into two main commodities, namely, oil/gas and non-oil/gas commodities [1]. Non-oil and gas commodities are further divided into three groups of commodities, namely, agricultural export commodities, export commodity processing industry and mining export commodities. From the large number of non-oil and gas commodities, 15 major non-oil/gas export commodities exist. The main commodities are grouped based on the magnitude of the role of profit to non-oil and gas commodities. The FOB value of the goods is used in the export; it refers to the price (USD units) up to the port of loading after the goods are loaded onto the ship.

2.2. Biplot Analysis

Biplot is one effort to describe the data contained in the summary table for the two-dimensional graph. Biplot analysis is descriptive with two dimensions that can present visually as a piece of objects and variables in one graph. With this presentation, the characteristics of the variables and object of observation and the relative position between the observed object and variables can be analysed [5].

Biplot analysis can examine the relationship between objects and variables in an image [6]. The information that can be obtained from biplot analysis include the following:

1. Proximity between objects. The proximity of position between objects is interpreted as the similarity between their properties. A closer distance between object positions indicates a higher similarity between objects.
2. Variability of variables. This information is used to determine the length of a variable vector that is proportional to the diversity of the variable. A longer variable vector denotes greater variability of variables.
3. The relationship between variables (correlation). This information is used to determine how a variable affects other variables. The angle value of two vector variables describes the correlation of two variables. A narrower angle between two variables indicates a higher correlation. If the angle formed is perpendicular, then the correlation is low. If the angle is blunt and counterclockwise, then the correlation is negative.
4. Value of a variable on an object. This information is used to identify the benefits of each object.

2.3. PCA Biplot

PCA biplot is a mapping method in multivariate analysis that contains information in a data table; it shows the main structure of the data [7]. The graph in biplot analysis is based on PCA, that is, by describing singular-value decomposition (SVD).

The value of the principal component or PCA is given by $z = \boldsymbol{a'y}$, where a refers to the characteristic vector of covariant matrix S, and y denotes the p x 1 observation vector. A vector characteristic of $\boldsymbol{a}_1, \boldsymbol{a}_2, \dots, \boldsymbol{a}_p$ and principal component $z_1, z_2, \dots, z_p$ exist for every vector observation $\boldsymbol{y_i}$, i = 1, 2, …, n. Then, the vector observation is transformed into $z_{ij} = a'_j(\boldsymbol{y}_i - \overline{\boldsymbol{y}}) = (\boldsymbol{y}_i - \overline{\boldsymbol{y}})'\boldsymbol{a}_j$, where i = 1, 2, …, n, and j = 1, 2, …, p. Every p x 1 vector observation $\boldsymbol{y_i}$ is transformed into p x 1 vector of the principal component:

$$\boldsymbol{z}_i' = \left[(\boldsymbol{y}_i - \overline{\boldsymbol{y}})'\boldsymbol{a}_1, (\boldsymbol{y}_i - \overline{\boldsymbol{y}})'\boldsymbol{a}_2, \dots, (\boldsymbol{y}_i - \overline{\boldsymbol{y}})'\boldsymbol{a}_p\right]$$
$$= (\boldsymbol{y}_i - \overline{\boldsymbol{y}})'\left(\boldsymbol{a}_1, \boldsymbol{a}_2, \dots, \boldsymbol{a}_p\right) = (\boldsymbol{y}_i - \overline{\boldsymbol{y}})'\boldsymbol{A} \quad (1)$$

where $\boldsymbol{A} = \left(\boldsymbol{a}_1, \boldsymbol{a}_2, \dots, \boldsymbol{a}_p\right)$ represents matrix pxp, and the column is the eigen vector of S. Z and X are defined as follows:

$$\boldsymbol{Z} = \begin{pmatrix} \boldsymbol{z}_1' \\ \boldsymbol{z}_2' \\ \vdots \\ \boldsymbol{z}_n' \end{pmatrix};\ \boldsymbol{X} = \begin{pmatrix} (\boldsymbol{y}_1 - \overline{\boldsymbol{y}})' \\ (\boldsymbol{y}_2 - \overline{\boldsymbol{y}})' \\ \vdots \\ (\boldsymbol{y}_n - \overline{\boldsymbol{y}})' \end{pmatrix} \quad (2)$$

Equation (2) can then be written as follows:

$$\boldsymbol{Z} = \boldsymbol{XA} \quad (3)$$

Matrix $\boldsymbol{A} = \left(\boldsymbol{a}_1, \boldsymbol{a}_2, \dots, \boldsymbol{a}_p\right)$ is orthogonal matrix, and $\mathbf{A}'\mathbf{A}$ = I. Equation (3) is multiplied with $\mathbf{A}'$, thus obtaining the following:

$$\boldsymbol{X} = \boldsymbol{ZA}' \quad (4)$$

The best two-dimensional representation of X is given by using the first two columns of Z and A. Z2 is the coordinate for n observations, and A2 is the coordinate for variable p.

Equation (4) can also be obtained by describing the SVD value. To obtain the SVD, the equation using the X matrix of size n x p containing n objects and p variables, corrected-averaged and occupies rank r can be written as follows:

$$\boldsymbol{X}_{nxp} = \boldsymbol{U}_{nxr}\boldsymbol{L}_{rxr}\boldsymbol{A}'_{rxp} \quad (5)$$

where U and A′ is a matrix with orthonormal columns (U'U = A′A = Ir), and Ir is an identity matrix of dimension r. L is a diagonal matrix of size (r x r) with the diagonal elements being the square root of the X′X eigen value.

The diagonal elements of matrix L are called the singular value of matrix X. The columns of matrix A are eigen vectors of X′X. The columns for U matrix are obtained from the following:

$$\boldsymbol{u}_i = \frac{1}{\sqrt{\lambda_i}}\boldsymbol{a}_i \quad (6)$$

Where:
u_i = matrix columns U, i = 1, 2, ..., r
a_i = column matrix A, i = 1, 2, ..., r
λ_i = the i-th eigen value of the matrix X′X, i = 1, 2, ..., r
The UL matrix in Equation (5) equals the principal component matrix Z in (3). To prove this point, we multiply UL by A, which is an orthogonal matrix, in Equation (5), as its matrix element is the eigen vector of X′X. Then, we obtain the following:

$$\boldsymbol{XA} = \boldsymbol{ULA'A} = \boldsymbol{UL} \tag{7}$$

The matrix A in SVD is equal to the matrix A in Equation (3), whose elements contain the eigen vector of matrix S. Then, Equation (7) transforms as follows:

$$\boldsymbol{XA} = \boldsymbol{Z} = \boldsymbol{UL} \tag{8}$$

Thus, Equation (2.4) can be written as follows:

$$\boldsymbol{X} = \boldsymbol{ZA'} = \boldsymbol{ULA'} \tag{9}$$

Then, the SVD gives the same value in Equation (4) based on the principal component [8].

2.4. CVA Biplot

The CVA biplot is a graphical representation to achieve simultaneous results between groups and variables; it not only determines differences among groups but also describes variables that are dominant in differentiating among groups [9].

The points on the CVA biplot can be determined with the following steps [10], [11]:

a. Let Xnxp be the data matrix, where n is the number of samples, and p is the number of variables. If the data contains a different unit, transform X into $\widetilde{\boldsymbol{X}}$ to achieve the same data unit.
b. Divide n sample observations into g groups, where n = n1 + n2 +…+ ng, to obtain matrix N = diag (n1, n2, …, ng).
c. Calculate the average of observations in each group based on $\widetilde{\boldsymbol{X}}$ matrix to obtain the average matrix of group $\overline{\overline{\boldsymbol{X}}}_{gxp}$.
d. Calculate the inter-group matrix (between groups).

$$\boldsymbol{B} = \overline{\overline{\boldsymbol{X}}}^T \boldsymbol{N} \overline{\overline{\boldsymbol{X}}} \tag{10}$$

e. Calculate the in-group matrix (within groups).

$$\boldsymbol{W} = \widetilde{\boldsymbol{X}}^T \widetilde{\boldsymbol{X}} - \overline{\overline{\boldsymbol{X}}}^T \boldsymbol{N} \overline{\overline{\boldsymbol{X}}} \tag{11}$$

f. The normalised eigenvector corresponding to the eigenvalue of W-1/2BW-1/2 matrix is the column element of Vtemp matrix. Then, with $\boldsymbol{V} = \boldsymbol{W}^{-1/2}\boldsymbol{V}_{temp}$, the interpolation base matrix $\boldsymbol{V}_{r,int}$ consists of the first column r of matrix V. In the case of interpolative and predictive biplot, each sample of observation is represented as points in the coordinate space $\boldsymbol{Y} = \widetilde{\boldsymbol{X}}\boldsymbol{V}_{r,int}$.

2.5. Size of Biplot Goodness

2.5.1 Size of PCA Biplot Goodness

The size of X matrix approach is formulated in the following form [12]:

$$\rho^2 = \frac{(\lambda_1 + \lambda_2)}{\sum_{k=1}^{r} \lambda_k} \tag{12}$$

where λ1 is the first largest eigenvalue, λ2 is the second largest eigenvalue, and λk with k = 1, 2, ..., k is the k-th largest eigenvalue. When ρ2 is close to 1, the biplot gives an improved presentation of actual data information. The measure of goodness can also be observed in the plot of point predictivities and axis predictivities by examining the distribution of dots; the top right of the line indicates that the points can be represented well, and vice-versa [13]. The plot point predictivities value is the diagonal value of the following:

$$diag\left(\hat{\tilde{\boldsymbol{X}}}\hat{\tilde{\boldsymbol{X}}}^T\right) diag\left(\tilde{\boldsymbol{X}}\tilde{\boldsymbol{X}}^T\right)^{-1} \tag{13}$$

where $\hat{\tilde{\boldsymbol{X}}} = \tilde{\boldsymbol{X}}\boldsymbol{V}_r\boldsymbol{V}_r^T$. The plot value of axis predictivities is a diagonal value calculated by the following:

$$diag\left(\hat{\tilde{\boldsymbol{X}}}^T\hat{\tilde{\boldsymbol{X}}}\right) diag\left(\tilde{\boldsymbol{X}}^T\tilde{\boldsymbol{X}}\right)^{-1} \tag{14}$$

2.5.2 Size of CVA Biplot Goodness

1. Point Predictivities

The size of a CVA biplot can be observed from the plot of dimension r. All dots will lie around a diagonal line. The points at the top right-hand corner of the line indicate that the points are well represented by the CVA biplot, and vice-versa. If the points are at the lower left end of the line, then they cannot be well represented by the CVA biplot. The value of this plot is the diagonal value of obtained as follows:

$$diag\left(\hat{\boldsymbol{Y}}_g^T\hat{\boldsymbol{Y}}_g\right)\left\{diag\left(\boldsymbol{Y}_g^T\boldsymbol{Y}_g\right)\right\}^{-1} \tag{15}$$

where $\boldsymbol{Y}_g = (\boldsymbol{I} - \boldsymbol{G}(\boldsymbol{G}^T\boldsymbol{G})^{-1}\boldsymbol{G}^T)\tilde{\boldsymbol{X}}$, and G is the indicator matrix denoting the membership of the sample in the group formed. On the other hand, $\hat{\boldsymbol{Y}}_g = \boldsymbol{Y}_g\boldsymbol{V}_{r,int}(\boldsymbol{V}_{r,pr})^T$ [10] (Grange et al., 2009).

2. Group Predictivities

Similar to point predictivities, the goodness of group predictivities is identified from plots in dimension r. The value of this plot is the diagonal element of computed as follows:

$$diag\left(\hat{\tilde{\boldsymbol{X}}}^T\boldsymbol{W}^{-1}\hat{\tilde{\boldsymbol{X}}}\right)\left\{diag\left(\tilde{\boldsymbol{X}}^T\boldsymbol{W}^{-1}\tilde{\boldsymbol{X}}\right)\right\}^{-1} \tag{16}$$

where $\hat{\tilde{\boldsymbol{X}}} = \tilde{\boldsymbol{X}}\boldsymbol{V}_{r,int}(\boldsymbol{V}_{p,pr})^T$ (Rencher, 2002).

3. Axis Predictivities

Similar to the two previous measurements, the size of good axis predictivities is also observed from the plot on dimension r. The value of this plot is a diagonal element computed by the following:

$$diag\left(\hat{\tilde{\boldsymbol{X}}}^T\boldsymbol{N}\hat{\tilde{\boldsymbol{X}}}\right)\left\{\left(\tilde{\boldsymbol{X}}^T\boldsymbol{N}\tilde{\boldsymbol{X}}\right)\right\}^{-1} \tag{17}$$

Rencher (2002).

3. Data and Research Variables

The data used in this study are those obtained in January–October 2017, as sourced from the Central Bureau of Statistics (BPS) Indonesia. The data include the total profit of Indonesia's main non-oil and gas export commodities based on the main export destination countries. The variables in this research comprise the main commodity of non-oil and gas export; the objective of this research is the main export destination countries. Non-oil and gas exports use 15 primary commodities. On the other hand, the main destination country is selected based on the Ministry of Industry, which includes 30 countries as the main export destination of Indonesia.

Table 1 Research Variables (Million USD)

Variable	Label
X_1	Palm oil
X_2	Coal
X_3	Clothes
X_4	Rubber crumbs
X_5	Electrical equipment (electricity)
X_6	Basic organic chemicals sourced from agricultural products
X_7	Motorized vehicles with four or more wheels
X_8	Iron / steel
X_9	Copper Ores
X_{10}	Jewelry and valuables
X_{11}	Precious base metal
X_{12}	Sports shoes
X_{13}	Lignite
X_{14}	Four and more wheeled motor parts
X_{15}	Papper pulp

Table 2 Research Object

Object	Country	Object	Country
USA	United State	EGY	Egypt
BRA	Brasilia	AUS	Australia
MEX	Mexico	SGP	Singapure
NLD	Netherlands	MYS	Malaysia
DEU	Germany	THA	Thailand
CHE	Swiss	PHL	Philippines
GBR	United of Kingdom	VNM	Vietnam
ESP	Spain	CHN	Chinese
RUS	Russian	JPN	Japan
BEL	Belgium	KOR	South Korea
FRA	France	HKG	Hongkong
ITA	Italy	TWN	Taiwan
ARE	United Arab Emirates	IND	India
SAU	Saudia Arabia	PAK	Pakistan
TUR	Turkey	BGD	Bangladesh

Table 3 Group of Research Object

Group	Country	Group	Country
America	Amerika Serikat Brasilia Mexico	Africa	Egypt
		Australia	Australia
Europe	Netherlands German Swiss United of Kingdom Spain Russian Belgium Franch Italy	Southeast Asia	Singapure Malaysia Thailand Philippines Vietnam
		East Asia	Chinese Japan South Korea Hongkong Taiwan
West Asia	United Arab Emirates Saudia Arabia Turkey	South Asia	India Pakistan Bangladesh

Source: Map of the world

4. Results and Discussion

4.1. Descriptive Analysis

This descriptive analysis is conducted to provide a general description of the amount of non-oil and gas commodity export profit (million USD) based on the main destination countries in the form of statistical summary.

Table 4 Summary of statistics of major non-oil and gas export commodity profit variables

Variable	Minimum	Maximum	Mean	Standar deviation
Palm oil (X_1)	0	4139.840	479.230	826.003
Coal (X_2)	0	3818.710	478.230	886.631
Clothes (X_3)	0.059	2851.152	173.583	518.881
Rubber crumbs (X_4)	0	851.465	127.120	220.304
Electrical equipment (electricity) (X_5)	1.957	887.883	127.531	197.369
Basic organic chemicals sourced from agricultural products (X_6)	0	638.13	115.32	168.595
Motorized vehicles with four or more wheels (X_7)	0	1064.431	86.863	209.517
Iron / steel (X_8)	0.242	1403.406	90.582	254.438
Copper ores (X_9)	0	3435.600	185.400	642.156
Jewelry and valuables (X_{10})	0	1048.560	81.297	233.402

Variable	Minimum	Maximum	Mean	Standar deviation
Precious base metal (X_{11})	0	1251.724	76.765	260.347
Sports shoes (X_{12})	0	607.502	66.927	124.027
Lignite (X_{13})	0	1944.140	70.120	354.455
Four and more wheeled motor parts (X_{14})	0	537.586	61.938	111.573
Papper pulp (X_{15})	0	134.409	61.982	243.995

Based on Table 4, almost all the major non-oil/gas export commodity variables feature a minimum value of 0 million USD, indicating the lack of profit from these variables. Furthermore, the X1 (palm oil) variable exhibits the highest maximum profit of 4139.84 million USD value among other variables. Meanwhile, variable X15 earns the smallest maximum profit value (Papper pulp) that is equal to 134.409 million USD. Variable X2 presents the largest standard deviation value (coal) amounting to 886.6341 million USD, denoting a large variation within data on the variable. X14 yields the smallest standard deviation (four or more wheeled motor parts) of 111.5729 million USD, showing the small difference between data (state) in this variable.

4.2. Biplot Analysis

4.2.1. PCA Biplot

Based on Figure 1, the information obtained include the following:

1. Relationship among objects

The relationship among objects can be identified from the proximity of object positions. Objects with distant positions between other objects or countries are the People's Republic of China and India and South Korea, whose positions are also distant but located in different quadrant areas. This finding means that these countries possess characteristics different from those of other countries. On the other hand, adjacent objects or countries indicate a similarity of characteristics between these countries.

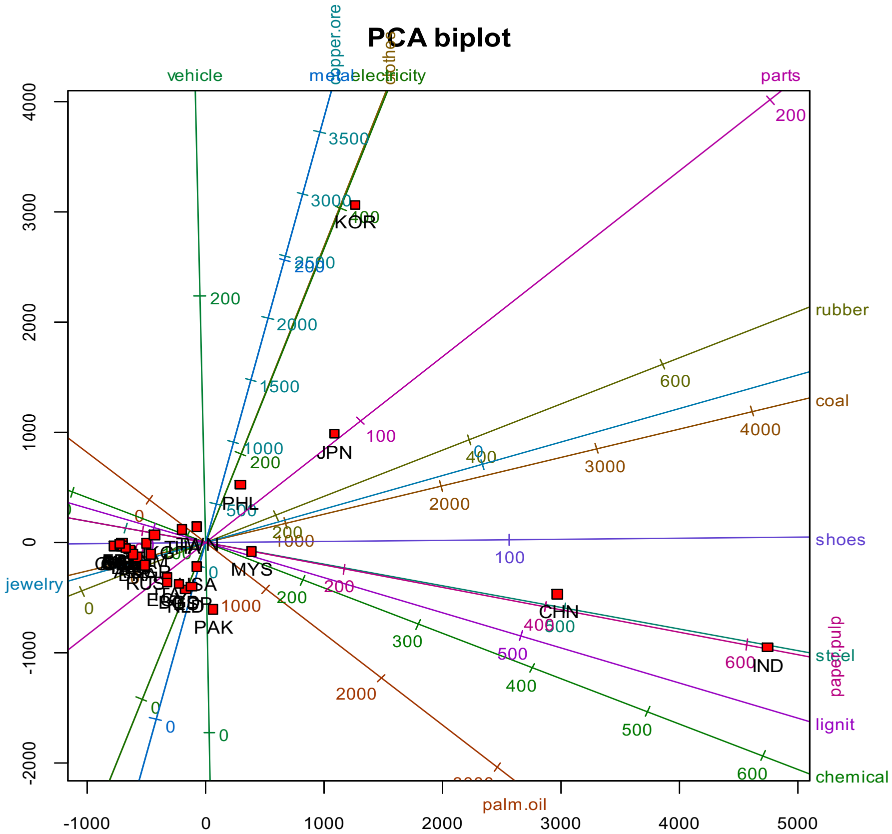

Figure 1 PCA biplot based on major non-oil and gas export commodities and major destination countries.

2. Relationship between variables

The relationship between variables can be observed from the size of angle between variables. If the variables coincide or form an angle close to 0° or 360° in the same direction, then they form a positive correlation. If the variables form angles approaching 180° in the opposite direction, then they exhibit a negative correlation. If the variables form angles approaching 90° or 270°or are upright to each other, they possess no correlation. Variables with the smallest or tightest angle (high positive correlation value) are found between X15 (pulp) and X8 (iron/steel), X3 (textile clothing) and X5 (electrical equipment), and between variables X9 (copper ore) and X11 (precious metal base). On the other hand, the largest angle forms between X1 (oil palm) and X7 (motor vehicles with four or more wheels), X10 (jewellery and valuables) and X4 (crumb rubber), and X10 (jewellery and valuable goods) and X2 (coal), indicating the high negative correlation among these variables.

3. Relationship between objects and variables

The relationship between objects and variables is visible from the position of the object to the variable. The results obtained are as follows:

a. The first group is variable X14 (motorised parts with four or more wheels), and the closest object is the state of Japan, which means that Japan plays an important role to the advantage for that variable.

b. The second group is X3 (clothes/convection of textile) and X5 (electrical equipment), and the surrounding objects are South Korea and the Philippines, indicating that the country feature similar characteristics to those variables.
c. The third group is the X8 (iron/steel) and X15 (pulp) variables; the adjacent objects are Malaysia, the People's Republic of China and India.
d. The fourth group includes a number of countries spread across variable X10 (jewellery and valuables). Thus, most major destination countries contribute almost the same profit to that variable.

4.2.2. CVA Biplot

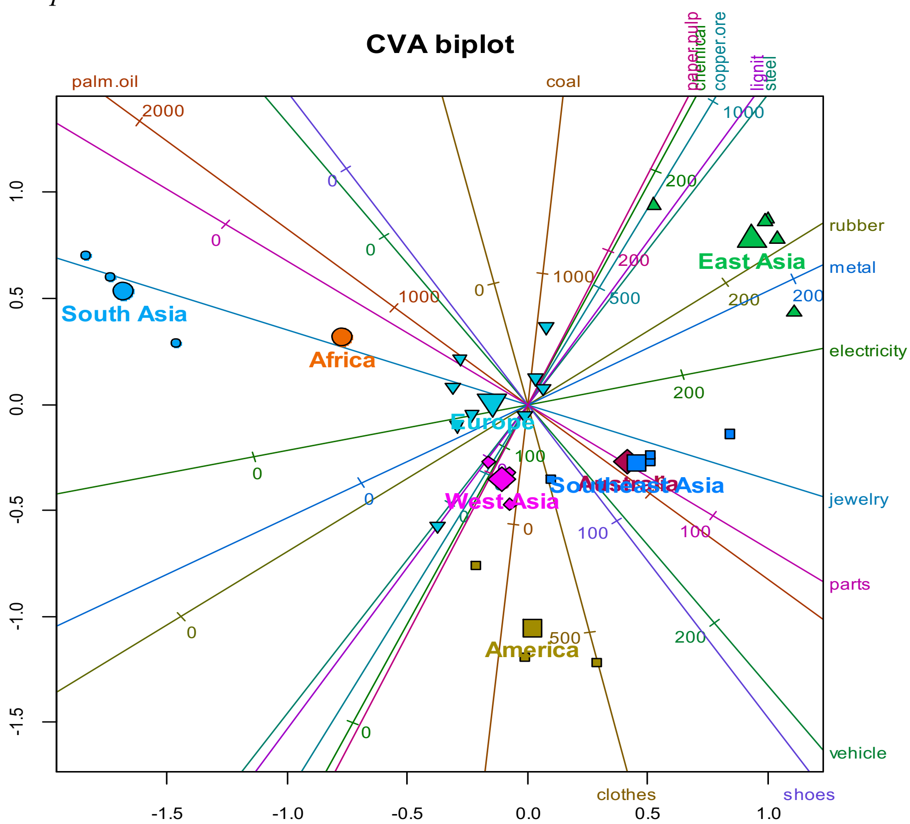

Figure 2 CVA biplot between main non-oil and gas export commodities and main destination countries.

Based on Figure 2, the information obtained is as follows:

1. Relationship between objects

The relationship between objects can be identified from the proximity of the position between objects. The objects whose positions are distant between objects or groups of other countries include South Asia and Africa and East Asia and America, whose positions also lie distantly but are in different quadrant areas. Such finding indicates that the four groups of countries possess characteristics different from those of the other groups. On the other hand, the object or group of adjacent countries indicate the existence of similar characteristics between groups of countries.

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2. Relationship between variables

The relationship between variables can be determined from the size of angle between variables. Variables with the smallest or coincident (high positive correlation value) angle are between X13 (lignite) and X8 (iron/steel) and X15 (paper pulp) and X6 (organic chemicals derived from agricultural products). A large angle (high negative correlation value) is identified between X1 (oil palm) and X14 (four or more motorised spare parts), X3 (clothes) and X2 (coal), and X1 (palm oil)) and X3 (clothes).

3. Relationship between objects and variables

The relationship between objects and variables is visible from the position of the object to the variable. The results obtained are as follows:

a. The first group is the variable X14 (motorised spare parts), and the closest objects are Australia and Southeast Asia, showing that the group of a country plays an important role to the advantage of that variable.
b. The second group is the X3 (clothes), and the closest objects are America and West Asia, which means that this group of countries exhibit similar characteristics to the variables.
c. The third group is X1 (oil palm), and the closest objects are Europe, Africa and South Asia. This result implies that the group of a country plays an important role to the benefit of the variable.

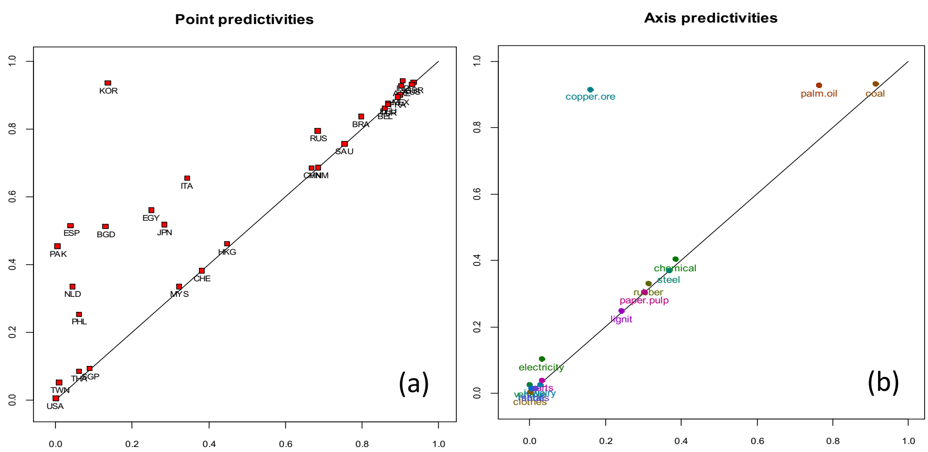

Figure 3 PCA biplot goodness measures. (a) Point predictivities and (b) axis predictivities

d. The fourth group is X4 (crumb rubber), and the closest object is East Asia, indicating that countries in the East Asian group feature similar characteristics to this variable.

4.2.3. Size of Biplot Goodness

PCA Biplot

1. Size of variability

Using the matrix approach X in Equation (12), the result obtained is 0.6845 or 68.45%. Thus, if the PCA biplot can explain or represent original data at 68.45%, it can be categorised well because its value is close to 1 or 100%.

2. Point predictivities

Based on Figure 3 (a), the objects are spread around the line, but one distant object is South Korea. An object is said to be represented by PCA biplot if the objects are either at the top right corner or are at point (1,1). Visibly, if many objects are spread on the upper right corner of the line, one of them acts similarly as Belgium. For the objects that are not well represented by the PCA biplot (United States and Taiwan), this result is attributed to the object or country spread in the lower left corner or value close to (0,0). However, overall, if the objects or the state can be represented properly by PCA biplot, many objects are spread at the upper right corner.

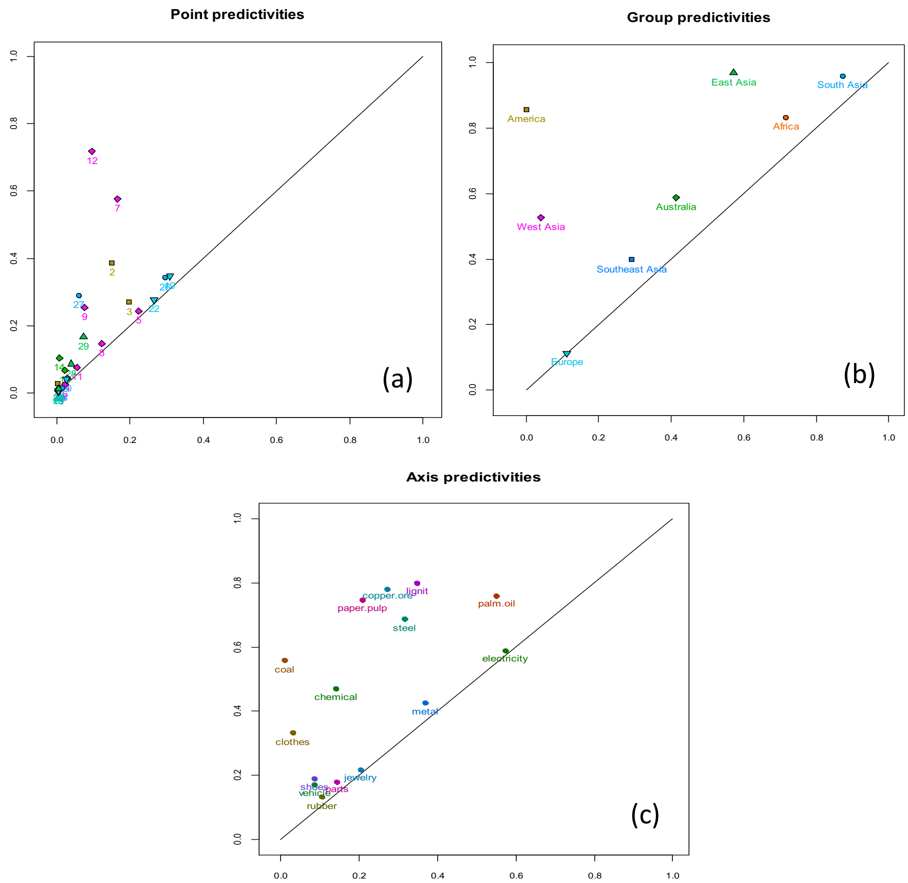

Figure 4 CVA biplot goodness sizes. (a) Point predictivities, (b) group predictivities and (c) axis predictivities.

3. Axis predictivities

Based on Figure 3(b), the variables spread around the lower left corner, and two variables spread at the upper right corner, i.e. X1 (oil palm) and X2 (coal). A variable is said to be well represented by PCA biplot if it spreads at the upper right corner or is at point (1,1). By using PCA biplot, the variables, such as X3 (textile/clothes) and X12 (sports shoes), cannot be represented properly because the mean variables spread at the lower left corner or close to point (0,0). Thus, the PCA biplot performs poorly in representing these variables.

4.2.4. CVA Biplot

1. Point predictivities
Based on Figure 4(a), the objects spread at the lower left corner, and an Italian object (12) spreads far from other objects. An object is said to be well represented by a CVA biplot if it spreads at the top right corner or around point (1,1). The objects or countries are not well represented by a CVA biplot because almost all of them spread at the lower left corner or at around point (0,0), and none spread closely to the top right corner. Thus these objects cannot be represented properly when using CVA biplot.

2. Group predictivities
Based on Figure 4(b), several groups of countries spread at the upper right and lower left corners. A group is said to be well represented by a CVA biplot if it spreads at the top right corner or around point (1,1). The groups in the upper right corner are East Asia, Africa and South Asia. This result means that the CVA biplot can reproduce the group of countries well. However, one European group is included in the lower left corner, and one group lies distantly from the American group. This finding implies that the interpreted CVA biplot performs poorly in representing the groups. However, overall, the CVA biplot can represent the countries well based on the group.

3. Axis predictivities
Based on Figure 4(c), the variables spread around the middle and approach the bottom left corner. A variable is said to be well represented by a CVA biplot if it spreads at the upper right corner or around point (1,1). No plot is observed at the upper right corner or at point (1,1), but variables approach the top right corner, i.e. X5 (electrical equipment) and X1 (palm oil). No variables are found at the lower left corner or at point (0,0), but the variables are just as close as X4 (crumb rubber). Thus, the CVA biplot exhibits poor performance in representing variables.

4.2.5. Comparison of Size of Goodness Between PCA Biplot and CVA Biplot
Based on the results of the size of goodness that has been described, the result of comparison between PCA biplot and CVA biplot is obtained:

Table 5 Comparison of PCA and CVA biplots

PCA Biplot		CVA Biplot	
Size of Goodness	**Result**	**Size of Goodness**	**Result**
Variability size	PCA biplot can explain or represent original data of 68.45% (good enough)	Point predictivities	CVA biplot is not good in representing its objects
Point predictivities	PCA biplot can well represent its objects	Group predictivities	CVA biplot is well enough in representing its group
Axis predictivities	PCA biplot is not good in	Axis predictivities	CVA biplot is less good in

PCA Biplot		CVA Biplot	
Size of Goodness	**Result**	**Size of Goodness**	**Result**
	representing its variables		representing its variables

Based on the results in Table 5, the advantage of using PCA biplot is that point predictivities can represent the objects well. However, a disadvantage is that in axis predictivities, PCA biplot performs poorly in representing variables. When using a CVA biplot, the predominant advantage of axis predictivities can represent the major commodity export variables better than the PCA biplot. In addition to group predictivities, CVA biplot sufficiently represents country groups.

5. Conclusion

The conclusions of this study are as follows:

1. The following include the grouping results based on the relationship between non-oil and gas main commodities exports and major destination countries using PCA biplot:
   • Group 1 consists of Japanese countries with variables, namely, motorised spare parts with four or more wheels.
   • Group 2 consists of South Korea and Philippines, countries with variables of clothes and electrical equipment.
   • Group 3 consists of Malaysia, the People's Republic of China and India with variables of iron/steel and pulp.
   • Group 4 consists of nations other than the aforementioned countries with variables, such as jewellery and other valuables.
2. The following include the grouping results based on the relationship between non-oil and gas main commodities exports and main destination countries using CVA biplot:
   • Group 1 consists of Australian and Southeast Asian countries with variables of four or more motorised parts.
   • Group 2 consists of groups of American and Western Asian countries with their variable of clothes.
   • Group 3 consists of a group of European countries, Africa and South Asia with variable of palm oil.
   • Group 4 consists of East Asian country groups with variable of crumb rubber.
3. The advantage of PCA biplot is that it can represent the object (main destination country) well, whereas the CVA biplot exhibits superiority in representing variables (non-gas primary commodity exports) than the PCA biplot and adequately represents the main destination group.

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