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New Data Mining approach for clustering Export Credit Agencies (ECAs) based on performance criteria: a bibliometric citation analysis for the period 2005 to 2020

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Abstract. Nowadays, ECAs have a crucial role in the export of production, creating job opportunities for countries and growth of economic indicators.This research aims first to estimate the performance of ECAs based on covering all countries of the world and ranking the countries based on the issue of export credit according to their performance and clustering techniques. For evaluation performance of these ECAs, clustering techniques are used to put them in the categories according to their performance between 2005 to 2020 in the fourth quarter. The context of clustering shows the rank of each cluster, and then exporters can choose a better choice from them. Moreover, for reinsurance,other ECAs can find out which ECAs have high performance. The result indicates that ranking the ECAs and show the performance of each cluster.

2020 *Mathematics Subject Classification.*
Key words and phrases. Export Credit Agencies (ECAs), Clustering techniques, performance ECAs, K-means method, economic growth, risk.

1. Introduction

In this hectic world, all countries are looking forward to growing the economic indicators (Pradhan, 2019 [22]). These indicators demonstrate which one is developed and which one is developing (Melo et al., 2020 [17]). One way to reach these indicators is that the balance between export and import will be positive (Kartikasari, 2017 [11]). It means the country satisfies their needs by itself (decrease import) and the amount of export increase dramatically (Schaffartzik et al., 2019 [25]). This work also creates more job opportunities and decreases the unemployment rate (Masipa, 2018 [16]). For protecting the exporter from commercial and political risks, ECAs have a crucial role, and they ensure exporters support them in all situations (Petrová et al., 2021 [20]).

After funded ECAs in countries, many exporters and importers (In EXIM BANKS) are keen to use the services and products of these ECAs. Statistics demonstrate the trend of using ECAs' services increases dramatically in the world (Qerimi & Sergi, 2017 [24]).

Many factors affect the amount of credit export. One of them is the cost of issue credit. This cost is varied in each country. If this cost is low, many exporters tempt to get them. The second factor is that most exporters want to export their products

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into high-risk countries because they need their services and goods. Hence, the rate of claiming will increase, and most ECAs do not like to cover this credit.

Each ECA had especial performance in its country. As we will explain in the next section, based on the related literature, there are a few papers that have been published about ECAs in the world. As per our knowledge, there is a little evidence that analyzed their performance. The solely paper that can be found about ECAs performance is paper related to Yazdi et al.(2019) [29] which they used DEA and some inputs and outputs for evaluated some, not all ECAs in the specific time (a year). The contribution of this paper is to evaluate the performance of ECAs by data mining technique for clustering these ECAs during 2005 to 2020 for all ECAs.

This research aims to cluster ECAs by volume of insurance issues during 15 years by K-means algorithm and also rank them.

The research questions of this research are:

1. How many clusters are these data needed?
2. What is the attitude of each cluster?

This paper consists of these parts. After the introduction section, section two relates to the literature review. Section three pointed out to research methodology. Data analysis is demonstrated in section four. And final section reveals the conclusion.

2. Literature review

Blackmon (2016) [1] evaluated the role of ECAs in the shortterm during the 2008 financial crisis. The author claimed that during this crisis, the role of ECAs was increasing dramatically in the part of short term insurance among OECD countries. Janda et al.(2013) [9] performance of ECAs in central European countries. In this research, the advantages and disadvantages of ECAs are evaluated. They concluded that the countries witha small distance to markets and high GDP led to an increase in the performance of its ECA.Wright(2011) [28] evaluated the role of ECAs in the market of energy. In this paper, he pointed out three challenges that OECD faced. First, the non-OECD countries' performance strong effect on OECD countries. Second, there is tension among ECAs performance and economic indicators. And the final challenge is ECAs attempted to persuade developing countries to decrease Carbone dioxide emissions for energy supply. Janda(2014) [8] demonstrated the role of ECA of Czech and its power in that country. He pointed out that this ECA has suitable relationship with banks of Czech country especially commercial banks. For absorbing these banks, ECA decrease the rate of low-profit margin. Chauffour et al.(2010) [2] evaluated the role of ECAs in developing countries, especially during financial crises. In this paper, some economic factors are considered. Consequently, the result showed that if the economic factors such as financial capacity, institutional capacity, and government are in a good mood, establishing the ECA is worthy.

Yazdi et al.(2019) [29] evaluated the performance of ECAs by Data Envelopment Analysis. They considered some inputs and outputs, and then based on those, these ECAs are evaluated. The result demonstrated that among these ECAs, which one has efficiency and which one is inefficiency and how inefficiency ECAs can be changed to efficiency ECA.Karbassi Yazdi et al.(2019) [29] suggested how can did credit risk in an uncertain environment. They did this model by Fuzzy Inference System (FIS).Dinh &

Hilmarsson(2012) [4] demonstrated how companies use the services of ECAs in emerging companies. They depicted many companies want to invest in emerging markets. However, these markets had high risk, and most ECAs do not want to cover this issue. They pointed out how to cope with this issue.Hur & Yoon(2021) [7] evaluated the effect of ECAs on export and companies performance. By evaluating companies of South Korea, they found out that ECAs had related and strong effect on companies performance and ECAs are useful for them. Darouich et al., (n.d.) [3] pointed out the role of ECA (Euler Hermes) in Paris agreement (climate change). They depicted that Hermes has restriction policy against fossil fuels cover and attempted to meet the standard of governmental about Paris agreement.

Kustra & Wiktor-Sułkowska (2020) [14] show the role of ECAs in global mining. They demonstrate that the mining industries need to financial support for develop their performance. Thanks to banking system, however, ECAs are better than banking system because of chipper credit, long term credit and tax exemption. Köksal(2018) [13] shows the role of ECAs in developing countries such as Turkey and IMT countries. He analyzed the relationship between the role of ECAs and amount of exports and GDP of countries by VAR method. Polat & Yeşilyaprak(2017) [21] investigate about the role of ECA and export performance in Turkey. They point out that export insurance positive effect on Turkish export by using regression, Poisson fixed effect, Poisson Pseudo maximum likelihood estimation (PPML) methods.

Hayat et al. (2021) [6] have defined the concept of economic growth as the capacity of a certain country to increase the level of output. Nayak et al. (2021) [18] suggested that economic growth represents a key factor in achieving sustainable development, especially in emerging countries. Moreover, Qaiser Gillani et al. (2021) [23] highlighted the major importance of an appropriate environment both for maintaining the health of the population and for achieving sustainable development.

3. Research methodology

3.1. Data Mining Technique-Clustering. Nowadays, people face too much data that they know how to manage and use (Susanto et al., 2020 [26]). Hence, these data will be not used or misuse. To cope with this problem, science data and especially data mining techniques emerged(Triguero et al., 2019 [27]). These techniques help managers to use data appropriately and accurately. One of the branches of data mining is clustering. In this method, the information which is the similarity to others is put into the same category.There are generally two types of clustering algorithms; hierarchical and nonhierarchical. In hierarchical clustering, clusters create in a predefined form up to down. In nonhierarchical algorithm, clusters create by merging or splitting clusters. Gülagiz and Shahin (2017) [5] compare and evaluate clustering methods. One of the popular non-hierarchical clustering methods is K-means which has the low error of clustering method(Olukanmi & Twala, 2017 [19]). For the implementation of this method, it needs how many clusters it needs. For finding the number of clusters, many methods exist (Kodinariya & Makwana, 2013 [12]).

This method is used as well as following procedure:
First: consider sets of data which are $X = \{x_1, x_2, ..., x_n\}$, $x_n \in \mathbb{R}^d$.
Second: the subset of this data are $c_1, c_2, ..., c_n$.
Third: Euclidian distance between each x_i data-centred of m_k of subset of C_k that

contain x_i are computed. This is clustering error and strongly related cluster center $m_1, m_2, ..., m_M$.
Fourth: Clustering algorithm does it as follow as

$$E(m_1, ..., m_M) = \sum_{i=1}^{N} \sum_{K=1}^{M} I\left(x_i \in C_k \|x_i - m_k\|^2\right)$$

where $I(X) = 1$ if X is true or otherwise equal to 0(Likas et al., 2003 [15]).

Number of Clustering

The number of clusters in the K-means algorithm is one of the most critical parts of this algorithm. The wrong choice will be lead to incorrect computation and, finally, wrong decision. There are many techniques choosing for this work. One of them is the elbow chart which is when the trend is broken, and the number shows the clustering number. One of the essential techniques for finding the number of clustering is the silhouette method. The following steps describe this model:
Step 1: Dissimilarity: consider data I in cluster A so we have

$$S(i) = \text{ dissimilarity}$$

I=data belongs to cluster a
$A(i)$= dissimilarity average of I to all data of a
$D(I, c)$=average dissimilarity of I to all data of c
$B(i)$=minimum $d(I, c)$ where $c \neq a$
C= cluster that $c \neq a$
B= Cluster b that minimum neighbor distance of data i
$S(i) = \frac{b(i)-a(i)}{\max\{a(i),b(i)\}}$
The number of $S(i)$ is computed by a combination of $a(i)$ and $b(i)$ as follow as
$S(i) = \begin{cases} 1 - \frac{a(i)}{b(i)}, & \text{if } a(i) < b(i) \\ 0 & \text{if } a(i) = b(i) \\ \frac{b(i)}{a(i)} - 1, & \text{if } a(i) > b(i) \end{cases}$

$$S(i) \text{ is } -1 \leq S(i) \leq 1.$$

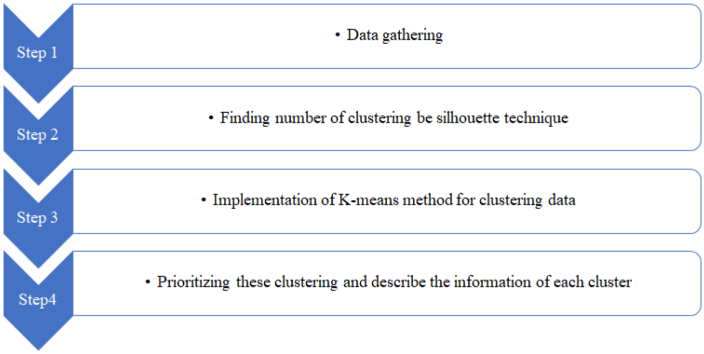
Step 2: finding similarity

Consider similarity $a'(i), d'(I, c)$ and put $b'(i)$=maximum $d'(I, c)$, where $C \neq A$. The numbers of $s(i)$ is (Kodinariya & Makwana, 2013 [12])

$$S(i) = \begin{cases} 1 - \frac{b'(i)}{a(i)}, & \text{if } a'(i) > b'(i) \\ 0 & \text{if } a'(i) = b'(i) \\ \frac{a'(i)}{b'(i)} - 1, & \text{if } a'(i) > b'(i) \end{cases}$$

In this research, the IBM SPSS Modeler version 18 is used to auto cluster data by silhouette technique and IBM SPSS 24 to describe each cluster's attitude.

Figure 1. The procedure of research



Data of this research will be an endorsement. Since these data are enormous, we cannot add them to the paper.

4. Data analysis

To find the number of clustering and we mentioned above, we use IBM SPSS MODELER 18, section auto clustering.

The result indicates as follow:

Method	Build time	Silhouette	Number of Clusters Smallest Cluster	Smallest Cluster	Smallest Cluster(%)	Largest Cluster	Largest Cluster (%)	Smallest/Largest
K-means	<1	0.761	5	1	0	142	71	0.007

Table 1. The number of clustering

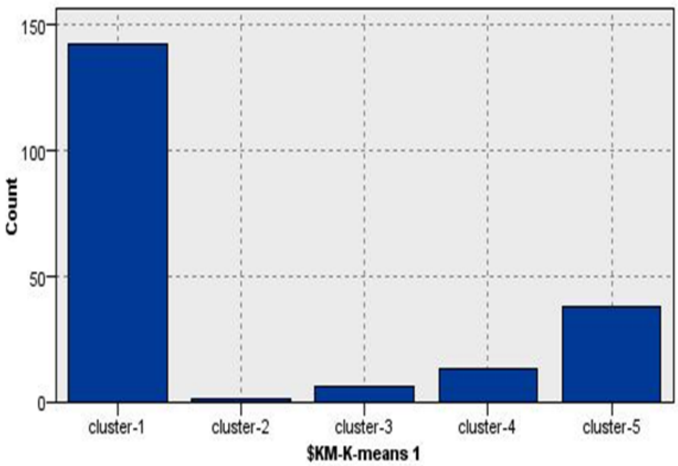


Figure 2. The number of countries in each cluster

Figure 2 demonstrates the numbers of countries in each cluster.

Table 2. The number of clustering in the table

Number of Cases in each Cluster

Cluster	1	1.000
	2	2.000
	3	10.000
	4	157.000
	5	30.000
Valid		200.000
Missing		.000

Table 3 points out that only one country (united States) is included in cluster one, the smallest cluster. In the second cluster two countries which are Germany and United Kingdom, are included. Cluster three includes 10 countries. In the largest cluster there are 157 countries existed. In the last cluster 30 countries are included.

Table 3. The attitude of each cluster

Number of Cluster	Name of Countries	Range of covering(Million Dollar)
Cluster 1	United States	[60,861-256,407]
Cluster 2	Germany, United Kingdom	[38,761-128,880]
Cluster 3	Brazil,China, France, India,Italy, Netherlands Russian Federation, Spain, Switzerland, Turkey	[10900-87,516]
Cluster 4	Afghanistan, Albania, Algeria, American Samoa, Andorra, Armenia, Aruba, Azerbaijan, Bahamas, Bahrain, Bangladesh Barbados, Belarus, Belize, Benin, Bermuda, Bhutan, Bolivia Bosnia and Herzegovina, Botswana, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Cayman Islands, Chad, Colombia Comoros, Congo, Congo The Democratic Republic, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Djibouti, Dominican Republic, Ecuador, El Salvador Equatorial Guinea, Estonia, Eswatini, Ethiopia, Faroe Islands, Fiji, Finland, French Guiana, French Polynesia, Gabon	[0-32,070]

	Gambia, Georgia, Ghana, Gibraltar, Greece Greenland, Grenada, Guadeloupe, Guam Guatemala, Guinea, Guyana, Haiti, Honduras, Hungary, Iceland, Iran, Iraq, Israel, Jamaica, Jordan, Kazakhstan, Kenya, Korea, D.P.R. of, Kuwait Kyrgyz Republic, Laos, Latvia, Lebanon Lesotho, Liberia, Libya, Liechtenstein Lithuania, Luxembourg, Macau SAR, China, Madagascar, Malawi, Maldives Mali, Malta, Marshall Islands, Martinique Mauritania, Mauritius, Moldova, Monaco Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal New Caledonia, New Zealand, Nicaragua Niger, Nigeria, North Macedonia, Oman Panama, Papua New Guinea, Paraguay Peru, Philippines, Puerto Rico, Reunion, Romania, Rwanda, Saint Vincent and the Grenadines, Samoa, San Marino, Sao Tome and Principe, Senegal, Serbia, Seychelles, Sierra Leone, Slovak Republic, Slovenia, Solomon Islands, Somalia Sri Lanka, St. Lucia, Sudan, Suriname, Syrian Arab Republic, Tajikistan, Tanzania Togo, Trinidad and Tobago, Tunisia, Turkmenistan, Turks and Caicos Islands Uganda, Ukraine, Uruguay, Uzbekistan Venezuela, Virgin Islands, U.S., West Bank and Gaza, West Indies UK, Yemen Zambia, Zimbabwe	
Cluster 5	Angola, Argentina, Australia, Austria, Belgium, Canada, Chile, Czech Republic Denmark, Egypt, Hong Kong SAR, China, Indonesia, Ireland, Japan, Korea, Rep., Malaysia, Mexico, Norway, Pakistan, Poland, Portugal, Qatar, Saudi Arabia Singapore, South Africa, Sweden, Taiwan China, Thailand, United Arab Emirates, Vietnam	[52-45,457]

In the first cluster, the range of exports are the biggest among all countries. In the fourth cluster the lowest range we can see there. Other clusters range is between these ranges.

5. Conclusions

Nowadays, countries export goods and services to foreign countries to earn revenue and then invest in their countries' infrastructure, such as healthcare, education, IT, transportation, and so on. But the exporters faced various risks such as political and trade. For supporting them, ECAs are funded to help exporters with their export. ECAs attempted to cover their exporters by minimum risk and claim and help them to send their goods and services into low-risk countries. For this work, they provide internal and external guarantees to exporters. Moreover, they established many branches in the world to cover more exporters.

This research aims to determine how many countries are under cover of ECAs, and they are categorized and show the lowest to highest cover to each category by the K-means method. K-means method is one of the data mining methods used for category factors. In this research, the data of cover of ECAs to each country are demonstrated from 2005 to 2020.

The K-means model has been run, and the result pointed out these 200 countries can be categorized into 5 categories. The top of the category is United States which has the highest cover among all countries. The second category is related to Germany and United Kingdom countries which are the second-order about covering exporters. The fourth had the highest number of the country about covering exporters although the amount of coverage is the lowest among others.

The result pointed out that the risk of the United States, Germany and the United Kingdom are the lowest countries about risk credit, and most countries are eager to work with them. For future research, authors can use fuzzy C-means for clustering data in an uncertain environment.

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