THE 20TH EDITION OF THE INTERNATIONAL CONFERENCE
EUROPEAN INTEGRATION
REALITIES AND PERSPECTIVES

Green Economy and
Sustainable Development

Application of a Principal Component Analysis Within the Economic Circularity Indicators Framework

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Abstract: In this article, it has been tested the correlation relationships between the normalized values of main circular economy indicators for EU27 countries, for the period 2010-2023. Thus, a principal component analysis has been applied, (PCA), in EViews 9 to check the eigenvalues, the eigenvectors loadings of the correlation matrix. The goal of this methodology was to identify the degree of correlation between the chosen variables and to reduce the dimension of variation between the variables by eliminating the factors. It has been found that in terms of dimensionality reduction, factors 1, 2 and 3 have an eigenvalues greater than 1. More exactly factor 1 has a value of 3.854 and factor 2 has a value of 1.629, and factor 3 has a value of 1.162. Thus, the factors retained are three. Concerning eigenvalues figures, we have found that the proportion for factor 1 is 38.55% and for factor 2 is 16.29% and for factor 3 is 11.62% of the total variance. The first three components namely account for 66.46% of the total variation.

Keywords: circular economy; correlation matrix; Principal component analysis (PCA)

JEL Classification: C38; F64; O13; O44; Q53; R11

1. Introduction

According to the European Parliament, the circular economy is a concept that aims to improve the production and consumption model by extending the life cycle of products through sharing, reusing, renting, reconditioning, repairing and recycling materials and products. At the same time, a practical goal of the circular economy is to reduce waste to a minimum, by incorporating products again and again in the production cycle (transition to circularity), saving raw materials through recycling and saving energy. Over the past few decades, the concept of the circular economy has been extremely often approached in theory, but also in practice, with the development of numerous specific methodologies

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and indicators. Thus, by researching these circularity indicators through the Principal Component Analysis (PCA) method, we can effectively analyze a large data sets or data with many features, facilitating the identification of trends, patterns, or outliers.

The analysis of the main components (PCA) is a mathematical procedure that converts into a set of values of the uncorrelated variables called the main factors a set of observations of the variables correlated by the method of orthogonal transformation. The PCA is a method that tries to reduce the size of a large set of data in a smaller data set that still keeps the information of the initial data set, providing valuable information through graphs that describe the loading of components and scores. In general, the PCA is based on the decomposition of a correlation or covariance matrix values. Therefore, when using different variables, with different units of measure, for the proper use of the PCA, there must be a data normalization procedure.

By analyzing the size of the data set using PCA, common problems in data analysis are also addressed, such as: multicollinearity, which occurs when there are strong relationships between variables in the data set, and overfitting, i.e. the abundance of data specific to the data set. Reducing the size of the data set using PCA helps eliminate redundant features induced by multicollinearity, or irrelevant features specific to overfitting.

The work is ordered as follows: first describes the methodology used and the description of the data, then in the second part is proceeded to analyze the statistical and econometric tests and in the end the conclusions are presented.

2. Related Work and Problem Statement

The circular economy is a continuously expanding field of concern, a veritable toolbox, improving the understanding and functioning of areas such as poverty reduction, health, pollution, labor, the informal economy, waste, gender equality, education, including contributing to achieving sustainable development goals with which the circular economy has a direct or indirect connection. (Ahmed & Ali, 2004; Wilson, Velis & Cheeseman, 2006; Medina, 2007; Horbach, Rennings & Sommerfeld, 2015; World Health Organization, 2018; Schroeder, Anggraeni & Weber, 2019; Kumar et al., 2021; Andrew et al., 2022; Korsunova et al., 2022).

In this context, a pragmatic, quantitative analysis is also extremely important, by selecting specific circularity indicators that describe at a macroeconomic, mezzo or microeconomic level the specific features of the field, its stage and especially what the prospects for improvement may be (Park & Chertow, 2014; Ellen MacArthur Foundation and Granta Design, 2015; Elia et al., 2017; Cayzer, Griffiths & Beghetto, 2017; Parchomenko et al., 2017; Huysman et al, 2017; Saidani et al., 2019 etc.).

The application of the methodology of the main components has often been approached in the economic literature with mathematical and econometric profile. Thus, authors such as: Humphreys and Montanelli (1975), Kendall and Dickinson (1990), Sokal and Rholf (1995), Jolliffe (2002), Aitchison and Greenacre, (2002), Guirguis (2018), Dinu et al. (2023). The specialized literature also benefits from works that deal with means and aspects for adjusting the results of the principal components analysis Konishi (2025).

Regarding the implementation of the principal component, clusters and other additional methodologies, more or less improved, whether it concerns individual indicators or a composite index, numerous authors (Hao et al., 2013; Parchomenko et al., 2018; Kayal, 2019; Banghiore, 2024; Yobe, 2024) demonstrate the value of these approaches to understanding the field.

3. Solution Approach

In this article, we will test the relationship of the indicators of the circular economy by applying a main analysis of the components (PCA). The PCA aims to reduce the dimensionality of the data set by performing a covariance analysis between the factors, by a linear orthogonal approach, based on the correlation or covariance matrix. Basically what is taken into account is the variance and the first component, the most significant is on the first coordinate, the second on a second coordinate and so on, up to the last components that have the slightest amount of total variation. The main components are not correlated with each other, and each factor of the main component explains in successive ways the largest amount of total variation.

The main components are orthogonal, and the covariance matrix is diagonal, their own vectors being a linear combination of the main components that aim to reduce the data size, but keeping the initial significance and simplifying the understanding of the importance of variables within the components. Because the variables included in the analysis have different measurements, even if they are from the same sphere of circularity, they have previously proceeded to a relatively simple normalization of data sets.

The data are obtained from the Eurostat database, for the period 2010-2023. Where the data were absent, the interpolation was done, where the data set stopped in 2022, the extrapolation was for 2023, and the systematization of the information is Panel, taking into account all the countries of the European Union with 27 countries (EU27). Lack of data and adjustments, can make the study results viewed with caution.

In the analysis, we will start with a description of the macroeconomic variables that we will use in the analysis of the main components.

Table 1 Presentation of variables for circular economy

Variables name	Acronym	Unit of measure	Data source
Resource productivity	RP	Euro per kilogram, chain linked volumes (2015)	Eurostat, [cei_pc030]
Waste generation per capita	WGcapita	Kilograms per capita	Eurostat, [cei_pc034]
Recycling rate of waste of electrical and electronic equipment (WEEE) separately collected	WEEE	Percentage	Eurostat, [cei_wm060]
Circular material use rate	Cmur	Percentage	Eurostat, [cei_srm030]
Trade in recyclable raw materials	Trrm	Tonne	Eurostat, [cei_srm020]
Private investment and gross added value related to circular economy sectors	PiGVACES	Million euro	Eurostat, [cei_cie012]
Persons employed in circular economy sectors	PECES	Full-time equivalent (FTE)	Eurostat, [cei_cie011]
Patents related to recycling and secondary raw materials	Prelrsrm	Number	Eurostat, [cei_cie020]
Consumption footprint	Cf	Single weighted score, Index, 2010=100	Eurostat, [cei_gsr010]
Greenhouse gases emissions from production activities	Ggepa	Kilograms per capita	Eurostat, [cei_gsr011]
N in front of variables describes the data normalization procedure (i.e. the minimum value on the difference between the maximum and minimum value).			

Source: Eurostat indicators, selection made by authors

4. Analysis of Results

Descriptive statistics it is presented and to test for normality, it is analysed the Jarque – Bera statistic test. The null hypothesis (H0) is that the selected variables are distributed normally, and the alternative hypothesis (H1) is that they are not. According to table 2, the Jarque - Bera 2 information for all the selected variables are very statistically significant at the significance of 5%, confirming the normal distribution. But if we assume that the null hypothesis requires Skeweness to be 0 and Kurtosis will be 3, it is rejected. Thus, Skewness is generally over 1, except NRP and NWEEE indicators, and Kurtosis is positive and extremely high (over 3) for most indicators, except NWGCapita and NCMUR, indicating a leptokurtic distribution. If we consider that for a normal distribution the value of the mean and the median are close, suggesting a relatively symmetrical distribution of the series, the null hypothesis is confirmed. At the same time, the standard deviation also oscillates around the mean and median values, which indicates that the values are spread in a small, almost average range around the mean.

Table 2. Descriptive statistics for circular economy indicators selected

	NRP	NWGCAPITA	NWEEE	NCMUR	NTRRM	NPIGVACES	NPECES	NPRELRSR...	NCF	NGGEPA
Mean	0.286626	0.231684	0.442743	0.261536	0.165657	0.097496	0.182797	0.103078	0.319855	0.307910
Median	0.218136	0.143069	0.449629	0.207483	0.064363	0.021912	0.080207	0.036100	0.293103	0.241545
Maximum	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Minimum	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Std. Dev.	0.210859	0.236564	0.099684	0.216366	0.212346	0.171321	0.234915	0.166123	0.144122	0.228992
Skewness	0.808225	1.415557	-0.256084	1.109023	1.637238	2.857042	1.737651	2.781970	1.528091	1.098793
Kurtosis	2.896381	3.873623	7.490846	3.737963	5.144478	11.69358	4.900749	11.71856	7.070044	3.487992
Jarque-Bera	41.32245	138.2602	321.7727	86.06296	241.3054	1704.608	247.1264	1684.789	408.0117	79.81345
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	108.3448	87.57671	167.3568	98.86054	62.61832	36.85348	69.09731	38.96363	120.9052	116.3899
Sum Sq. Dev.	16.76194	21.09785	3.746246	17.64904	16.99917	11.06527	20.80485	10.40399	7.830681	19.76883
Observations	378	378	378	378	378	378	378	378	378	378

Source: Eurostat data, authors' processing

According to the correlation matrix table, most of the correlation coefficients of the macroeconomic variables are less than 0.5 and have a relatively weak positive and negative linear correlation, thus eliminating the questions related to collaintarity. Only, for example, the NCMUR is correlated positively and strongly with no (0.661), NTRRM is correlated positively and strong with no (0.574) and with NCMUR (0.581), but also Npigvaces, NPECESM, NRESLRSRM with NTRRM and between them. Thus, the purpose of the article is to reduce dimensionality by eliminating variations, correlating factors by analyzing PCA.

Table 3. Correlation matrix for circular economy indicators selected

	NRP	*NWGcapita*	*NWEEE*	*NCmur*	*NTrrm*	*NPiGVA CES*	*NPECES*	*NPrelrs rm*	*NCf*	*NGge pa*
NRP	1									
NWGcapi ta	-0.041	1								
NWEEE	-0.115	0.057	1							
NCmur	0.661	0.101	-0.212	1						
NTrrm	0.574	-0.166	-0.189	0.581	1					
NPiGVA CES	0.467	-0.112	-0.106	0.484	0.602	1				
NPECES	0.236	-0.181	-0.044	0.296	0.636	0.814	1			
NPrelrsr m	0.325	-0.045	-0.068	0.392	0.624	0.792	0.832	1		
NCf	0.104	0.050	-0.043	0.126	-0.118	-0.035	-0.058	-0.061	1	
NGgepa	0.195	0.316	0.108	0.138	0.015	-0.119	-0.212	-0.011	0.055	1

Source: Eurostat data, authors' processing on EViews 9 software

Also, it has been checked for stationary of the series by applying a pooled unit root summary test to calculate and compare the statistical values with the p-values. In order to reduce the number of ADF tests from 10 to 1, it has been used the pooled unit root summary test.

Using a common Unit root method, the study has been notice that all the statistical methods mentioned in table 4 in terms of Levin, Lin & Chu T*, IM, Pesaran and Shin W-Stat, ADF-FISHER Chi-Square and PP-Fisher Chi-Square have significant statistics and probabilities. For example, ADF - Fisher Chi - Square has a statistical value of 156,909 and a probability of 0.0000. In other words, the selected indicators are presented as a stationary series.

Table 4. Pool unit root test for circular economy selected indicators

Group unit root test: Summary				
Series: NRP, NWGCAPITA, NWEEE, NCMUR, NTRRM, NPIGVACES, NPECES, NPRELRSRM, NCF, NGGEPA				
Date: 03/23/25 Time: 02:46				
Sample: 1 378				
Exogenous variables: Individual effects				
Automatic selection of maximum lags				
Automatic lag length selection based on SIC: 0 to 14				
Newey-West automatic bandwidth selection and Bartlett kernel				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.89949	0.0097	10	3711
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-9.89933	0.0000	10	3711
ADF - Fisher Chi-square	156.909	0.0000	10	3711
PP - Fisher Chi-square	311.125	0.0000	10	3770
** Probabilities for Fisher tests are computed using an asymptotic Chi				
-square distribution. All other tests assume asymptotic normality.				

Source: Authors' calculation based on EViews 9 software. Significant p-values recorded at the 5% significance level.

Table 5. Results of the principal component analysis (PCA), computed by using ordinary correlations for the selected circular economy indicators

Principal Components Analysis
~~Date:~~ 03/23/25 Time: 00:33
Sample: 1 378
Included observations: 378
Computed using: Ordinary correlations
Extracting 10 of 10 possible components

Eigenvalues: (Sum = 10, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.854969	2.225880	0.3855	3.854969	0.3855
2	1.629089	0.466834	0.1629	5.484057	0.5484
3	1.162254	0.205549	0.1162	6.646312	0.6646
4	0.956706	0.084303	0.0957	7.603017	0.7603
5	0.872403	0.250463	0.0872	8.475420	0.8475
6	0.621939	0.281490	0.0622	9.097360	0.9097
7	0.340449	0.044028	0.0340	9.437809	0.9438
8	0.296421	0.133782	0.0296	9.734230	0.9734
9	0.162639	0.059509	0.0163	9.896869	0.9897
10	0.103131	---	0.0103	10.00000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10
NRP	0.328297	0.378655	-0.183151	-0.095954	0.384099	0.212778	-0.438503	0.486302	-0.183219	0.225699
NWGCAPITA	-0.073643	0.444731	0.387813	0.030279	-0.645698	0.391910	0.055260	0.262498	0.054591	0.004047
NWEEE	-0.103166	-0.037728	0.647804	0.342888	0.573489	0.320097	0.117084	-0.052353	-0.001560	-0.053917
NCMUR	0.346891	0.388657	-0.188406	-0.067120	0.051272	0.352555	0.195107	-0.711499	-0.032925	0.127690
NTRRM	0.431879	0.034338	-0.040172	-0.209989	0.137754	-0.041593	0.686836	0.371059	0.177215	-0.324117
NPIGVACES	0.451609	-0.114643	0.109646	0.130337	-0.096452	0.026930	-0.499729	-0.123996	0.495656	-0.482792
NPECES	0.422165	-0.292595	0.188022	0.187446	-0.143964	-0.120179	0.091514	0.054570	0.263436	0.741455
NPRELRSRM	0.431747	-0.123038	0.259143	0.125880	-0.197053	-0.212721	-0.037528	-0.064091	-0.769953	-0.181747
NCF	-0.014262	0.266202	-0.361005	0.859341	-0.031789	-0.153984	0.139787	0.098069	0.022091	-0.075984
NGGEPA	-0.022769	0.566058	0.338292	-0.131402	0.123197	-0.698939	-0.045710	-0.125975	0.150233	0.055946

Ordinary correlations:

	NRP	NWGCAPITA	NWEEE	NCMUR	NTRRM	NPIGVACES	NPECES	NPRELRSR...	NCF	NGGEPA
NRP	1.000000									
NWGCAPITA	-0.040641	1.000000								
NWEEE	-0.114915	0.056939	1.000000							
NCMUR	0.661130	0.101360	-0.211762	1.000000						
NTRRM	0.574368	-0.166422	-0.188984	0.580743	1.000000					
NPIGVACES	0.467487	-0.112023	-0.105581	0.484485	0.601803	1.000000				
NPECES	0.236028	-0.181237	-0.044198	0.296206	0.636068	0.813789	1.000000			
NPRELRSRM	0.324689	-0.044711	-0.067970	0.391921	0.624417	0.792085	0.832049	1.000000		
NCF	0.103930	0.049888	-0.042686	0.125642	-0.117825	-0.035124	-0.058304	-0.061491	1.000000	
NGGEPA	0.194693	0.316186	0.108138	0.138036	0.015163	-0.118973	-0.212490	-0.010884	0.054546	1.000000

Source: Authors' calculation based on EViews 9 software

The PCA table results in the first section, summarizes eigenvalues or the standardized variance associated with each factor, and the last two sections shows the loading of eigenvectors and the correlations. For example, the proportion for factor 1 is 38.55% and for factor 2 is 16.29% of the total variance. The proportion of the first factor is calculated as 3.854969 / 10 = 0.3854. The first two components namely account for 54.84% of the total variation. If we take into account also the third component, the cumulative proportion is 66.46%.

The patterns in the data are shown by the loadings of eigenvectors. For example, the eigenvectors loading of the first principal component labeled as PC1 is 0.32 for NRP and 0.43 for NPRELRSRM. The first component, considering the eigenvectors loadings, is having 4 negative values out of 10. The PC2 principal component shows four negative and six positive values. For example, NCMUR has a value of 0.35 at the PC1, then a value of 0.39 at the PC2, then -0.19 at PC3, then a value of -0.07 at PC4, a value of 0.05 at PC5, 0.20 at PC6, a value of -0.71 at PC8, -0.03 for PC9 and finally 0.13 at PC10. The correlation matrix shows that most of the correlation coefficients of the circular economy indicators are strong and positive, but there is also weak linear negative and positive correlation between the variables.

The decision on how many factors to retain it can be based on the eigenvalues. As we can see from Table 5, the factors 1, 2 and 3 have an eigenvalues greater than 1. Specifically, factor 1 has a value of 3.854 and factor 2 has a value of 1.629, and the factor 3 has a value of 1.162. Thus, the factors that we will retain are three.

Figure 1. The observed eigenvalue matrix of the principal component analysis (PCA) for selected circular economy indicators

Source: Authors' calculation based on EViews 9 software

By combining Figure 1 and Table 5, we can see the plotted number of eigenvalues. Thus, we should retain only three factors that their eigenvalues are greater than 1. If we consider only two factors for simplification, the results are presented as in Figure 2.

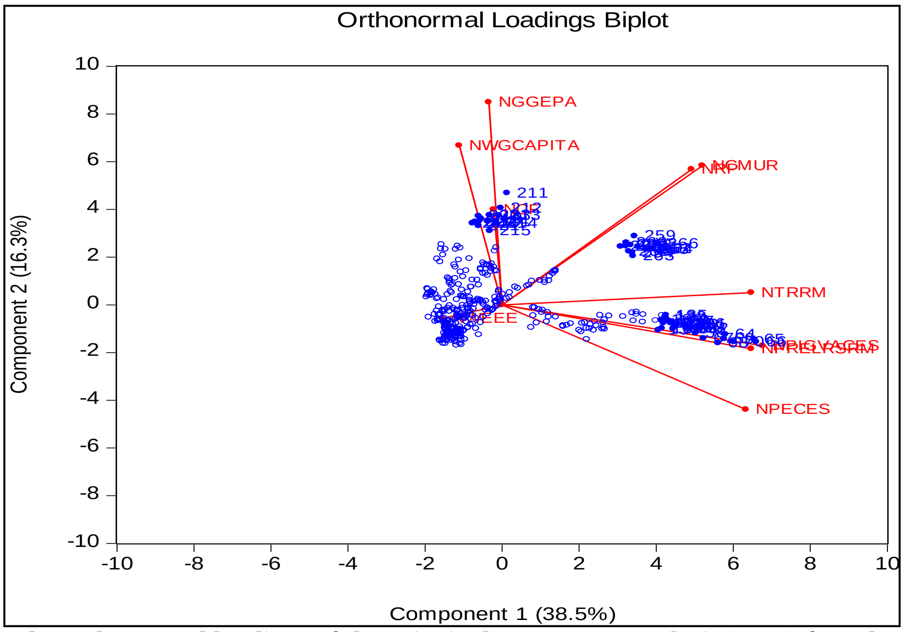

Figure 2. The orthonormal loadings of the principal component analysis (PCA) for selected circular economy indicators

Source: Authors' calculation based on EViews 9 software

According to Figure 2, the component scores are displayed as circles and the loadings of the macroeconomic factors are shown as lines. The first component has the highest proportion of total variation, which is 38.5% and positive loadings for six of the variables, except the variables NWEEE, NCF, NWGCAPITA, NGGEPA. The second component has a value of 16.3% of total variation. It has a positive variable loadings for six variables, and negative variable loadings for NWEEE, NPECES, NPRELRSRM, NPIGVACES.

5. Conclusions

The article tested the correlation relationships between the normalized values of main circular economy indicators. The total dataset includes annual data starting from 2010 to 2023, with systematized panel data for the 27 EU countries, thus total observations number is 378. The main data source is Eurostat.

Thus, it has been applied a principal component analysis (PCA), in EViews 9 to check the eigenvalues, the eigenvectors loadings of the correlation matrix. It has been found though the correlation matrix that most of the correlation coefficients of the circular economy indicators show strong positive linear correlation, but there is also weak linear negative and positive correlation between the variables.

In terms of dimensionality reduction, the study found that factors 1, 2 and 3 have an eigenvalues greater than 1. More exactly factor 1 has a value of 3.854 and factor 2 has a value of 1.629, and factor 3 has a value of 1.162. Thus, the factors that we will retain are three. Concerning, eigenvalues figures, we have found that the proportion for factor 1 is 38.55% and for factor 2 is 16.29% and for factor 3 is 11.62% of the total variance. The first three components namely account for 66.46% of the total variation. The orthonormal loadings show that the first component has the highest proportion of total variation, namely 38.5% and positive loadings for most of the chosen variables. The second component has a value of 16.3% of total variation, and it has positive variable loadings for six variables from ten selected.

6. Future Work

Although the paper focuses mainly on the circular economy indicators proposed by Eurostat, the list of indicators tracked may be longer or shorter. For example, in a later phase, in another study, perhaps one or two subdomains of circularity may be analyzed through the lens of the principal component.

At the same time, the geographical area could be extended, at a regional, continental or even planetary level, or on the contrary it could be investigated in a narrower area, at a country or even local, county level. Also, the data may cover different, more extensive periods, and the systematization may or may not retain the panel character. At the same time, other methodologies may be approached, for a better deciphering of the realities of the field. In this regard, futures steps take into account the shortcomings or limitations of the present study.

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