THE RECESSION RISK FOR THE EUROPEAN COUNTRIES

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Abstract: *Each economy among European countries is a cybernetic system, characterized by several properties: it has agents that action by established rules, there are relations between agents, there is a feedback in the system and a small action that affect the balance of the system might cause a severe imbalance. Therefore, analyzing the European economy as a whole, composed by countries' economies, we can identify the answer of the question raised in the past few years: "there are signs of a new European economic crisis?". The aim of this paper is to analyze and compare European countries economies for the past 5 years (between 2014 and 2018) using HCPC methodology, in order to identify what country/countries change the class and if there are signs for recession or depression. The factor analysis (FA) is preferred for reducing the number of variables, Ward's method to identify the best number of classes and k-means for allocate each country to a class. The analyses show that there are signs for the start of a new economic crisis in Europe because of the spreading of a high recession risk.*

Keywords: *economic crisis, HCPC, Europe, 2020, cluster, hierarchical*

JEL classification: E32, C38

1. Introduction and literature review

The answer for the question: there are any signs of a new European economic crisis? Is a new challenge for researchers, because a direct answer is difficult to provide. The number of economic indicators that show the signs for an economic crisis increased and caused the difficulty of choosing the most relevant indicators. However, the problem of working with high dimensionality is nowadays possible using methods of variables reducing that help express more information in few variables.

The latest research is about the last economic crisis that start in United States in 2007. So, the "struck the European economies" (Pottier, C. and Delette, G, 2019) is the "first signal forecasting the evolution of the crisis was the downgrading of

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Greece's sovereign debt at the end of 2009 from A to BBB+ by the rating agency Fitch" (Pottier, C. and Delette, G, 2019). Authors suggest that what happened in Greece was a "phenomenon with unclear information that allowed various policy entrepreneurs to promote different explanations for the crisis in accordance with their interests". Knowing the start and the austerity measures that were considered, it is important to focus on what were the consequences of the crisis for individuals, because "this crisis resulted in higher inequalities and put a lot of people at risk of poverty" (Novo-Corti, M Isabel et.all, 2019). The authors use regression analysis and cluster analysis. They demonstrate that "labor market is key in promoting economic policies in order to achieve social sustainability" (Novo-Corti, M Isabel et.all, 2019).
Starting from knowing the history and details about the economic crisis, the recent one being started in 2009, it is possible to learn from the past and think forward to the new economic crisis because the cyclicality of economy. It is considered that the new economic crisis in Europe, "the world's second-largest trading market, would have ripple effects on the world's economy"[3].

2. Methodologies

The main methodology used is HCPC (Hierarchical Clustering on Principal Components) that is a methodology composed by three data analysis methods: a dimensionality reducing method (principal components analysis, factor analysis or correspondence analysis), an hierarchical clustering method to determine the number of classes (usually Ward's method, because it provides the best results) and an algorithmic clustering method (k-means in general).
In this case, we choose the factor analysis (FA). This method is similar to principal components analysis, a variables dimensionality reducing method that extract the essential information from data. The main purpose of the method is to extract a small number of hidden factors from variables, factors that are responsible for correlations between variables. The factor analysis results should establish the number of factors necessary for explaining the patterns between variables, the nature of these factors and the amount of specific variance taken by the factors.
On the other side, the unsupervised learning techniques used in HCPC methodology are the Ward's hierarchical method and k-means algorithm. Both methods have close solutions, but Ward is used here in order to identify the best number of classes (by dendrogram), while the k-means algorithm provides the class for each country. Although the number of classes suggested by dendrogram is advisory, it remains one of the most used criteria in choosing the number of classes.

[3] https://www.barrons.com/articles/is-europe-ready-for-the-next-economic-crisis-51553901914

3. Datasets and results

The data selected represent 46 European countries and 17 macroeconomic indicators for the last five years: 2014-2018. For analysis, we did not keep all the countries because there are outliers' countries, so we had eliminated them. These countries are Azerbaijan, Bosnia and Herzegovina, Belarus, Cyprus, Ireland, Luxembourg, North Macedonia, Malta and Montenegro. The main source of data is the WorldBank website.

Table 3. Key macroeconomic indicators

Indicator name[4]	**Indicator code**
"GDP growth (annual %)"[3]	V1
"GDP per capita growth (annual %)"[3]	V2
"Inflation, consumer prices (annual %)"[3]	V3
"Services, value added (annual % growth)"[3]	V4
"Industry (including construction), value added (annual % growth)"[3]	V5
"Agriculture, forestry, and fishing, value added (annual % growth)"[3]	V6
"Foreign direct investment, net inflows (% of GDP)"[3]	V7
"Foreign direct investment, net outflows (% of GDP)"[3]	V8
"Employers, total (% of total employment)"[3]	V9
"Claims on central government, etc. (% GDP)"[3]	V10
"Commercial bank branches (per 100,000 adults)"[3]	V11
"Domestic credit provided by financial sector (% of GDP)"[3]	V12
"Domestic credit to private sector by banks (% of GDP)"[3]	V13
"Unemployment, total (% of total labor force)"[3]	V14
"External balance on goods and services (% of GDP)"[3]	V15
"Manufacturing, value added (% of GDP)"[3]	V16
"Trade (% of GDP)"[3]	V17

Analyzing the possibility of a new economic crisis in Europe, the choice of indicators is the most challenging issue. The increase or the decrease of a several key indicators might show the phase of the economic cycle, so the macroeconomic variables will considered for several years. Table 1 presents the most relevant indicators that show, by their fluctuation, the state of the economy. While the growth of GDP indicated directly the economic cycle phase, the consumer prices

[4] https://www.worldbank.org/

reflect in general the purchasing power of individuals and is very sensitive to any change of the economic system.

The added value of each GDP component considered in annual percentage growth is the first indicator of a potential economic crisis. Each industry is strongly correlated with all other industries, so that a small change of a component will imbalance the entire system. In this respect, it is possible to identify the component of the system that imbalanced the entire system and started the new crisis.

On the other side, the foreign direct investment (both inflows and outflows) as well as trade are variables that are highly correlated with the interest shown by external individuals for each economy as a whole. The variable V11 show the trust that banks have in economic and political system of a country, so that a small number of bank branches per 100000 adults demonstrate the lack of this trust. Either the domestic credit provided by financial sector or banks as percent of GDP also indicate a trust of creditors into the economic system and an eligibility of clients for credits.

```
> kmo
        [,1]    [,2]    [,3]   [,4]   [,5]
[1,] 0.50857 0.43817 0.44125 0.5205 0.5462
> b
       [,1]   [,2]   [,3]   [,4]   [,5]
[1,] 405.99 433.56 465.95 447.75 391.96
> qchisq(0.05,136,lower.tail=F)
[1] 164.22
```

Figure 1. KMO indicator and Bartlett's test statistic

The figure from above show the results for Bartlett test of sphericity and KMO indicator for all five datasets. The KMO indicator is computed as the sum of correlation indicators divided by the sum of correlation indicators added with the sum of partial correlation indicators and show the utility of factor analysis on each dataset. Because the values of KMO indicator are high, the utility of FA is confirmed.

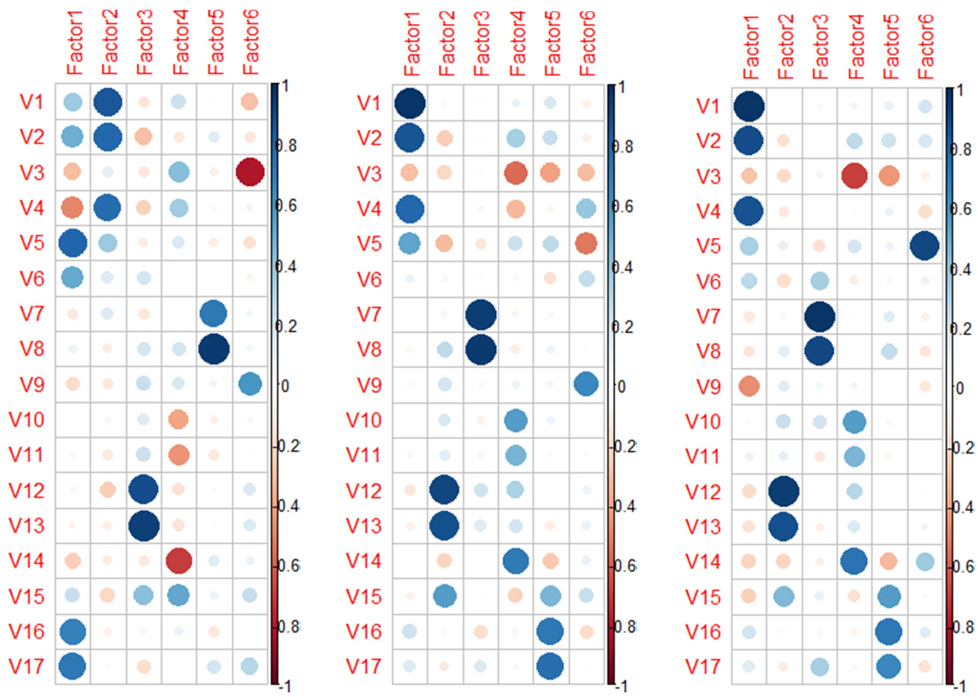
On the other side, the Bartlett test computed statistic is above 164.22 (the critical value) for all five datasets and show the rejection of null hypothesis that states that the variables in datasets are orthogonal, so the extraction of common factors is not justified.

Table 4. FA results

Dataset	Cumulative Var.						p-value
	F1	F2	F3	F4	F5	F6	
2014	0.16	0.29	0.43	0.52	0.61	**0.69**	0.401
2015	0.16	0.30	0.41	0.52	0.62	**0.68**	0.0632
2016	0.19	0.31	0.44	0.54	0.64	**0.70**	0.00956
2017	0.20	0.35	0.46	0.57	0.66	**0.69**	0.0672
2018	0.16	0.28	0.39	0.49	0.57	**0.65**	0.613

The table from above show the cumulative variance explained by all six factors and the statistic test that show if the selected number of factors for each dataset is sufficient. Tests were performed for a lower number of factors (starting from 2) until the p-value statistic associated to each test is higher than 0.05. In this respect, the null hypothesis is accepted and there is a perfect fit of factors.

The only exception is for 2016 dataset, the p-value is lower than 0.05, but not significantly lower. Still, for 2016, there were selected six factors, in order to compare the results with all other datasets. The total amount of variance explained by factors in each model is between 0.65 and 0.7.



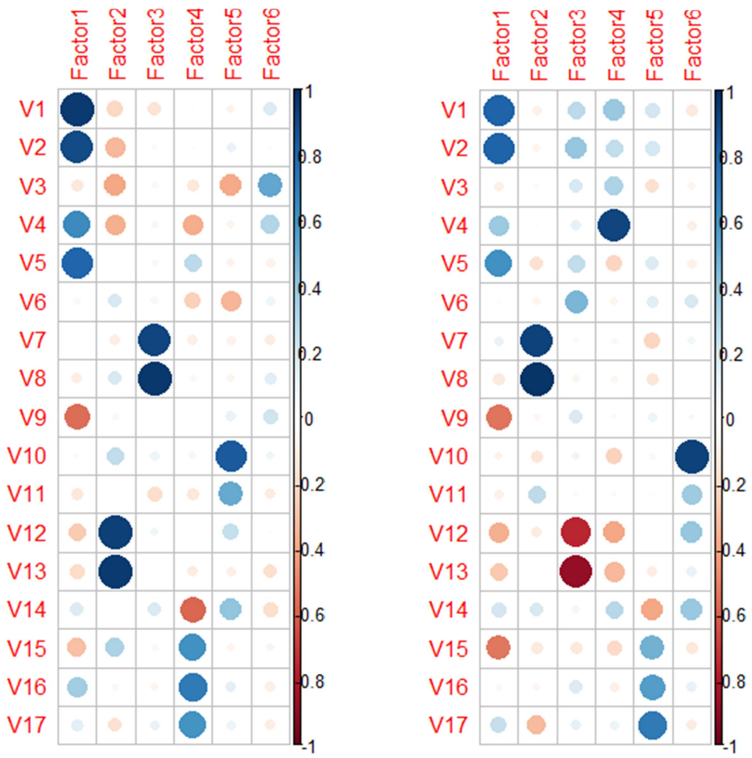


Figure 2. Factors correlations with original variables

The correlations between factors and the original variables (for all datasets: 2014 to 2018 from left to right) are presented in the figure from above. Using the correlations we observe that each factor is highly correlated with one or several variables and its signification may be determined through these correlations.

All six factors considered for each dataset have almost the same signification (with slightly different composition) though datasets (even if the factor name is different) as:

- One factor is highly correlated with variables V1, V2, V4 (even V5) - GDP growth
- One factor correlated with V7 and V8 - direct investments
- One factor correlated with V15, V16, V17 - trade
- One factor correlated with V12 and V13 - domestic credit. For 2018, dataset has a negatively correlation.
- One factor is correlated with V14 and V3 (for some datasets) - unemployment, prices
- One factor correlated with V10 and V11 - banks and claims on central government.

There are also variables that have a high uniqueness value, so that factors cannot take much information from these variables. Even so, the interpretation for all six factors are almost the same in all five datasets, so classes in cluster analysis could have the same interpretation.

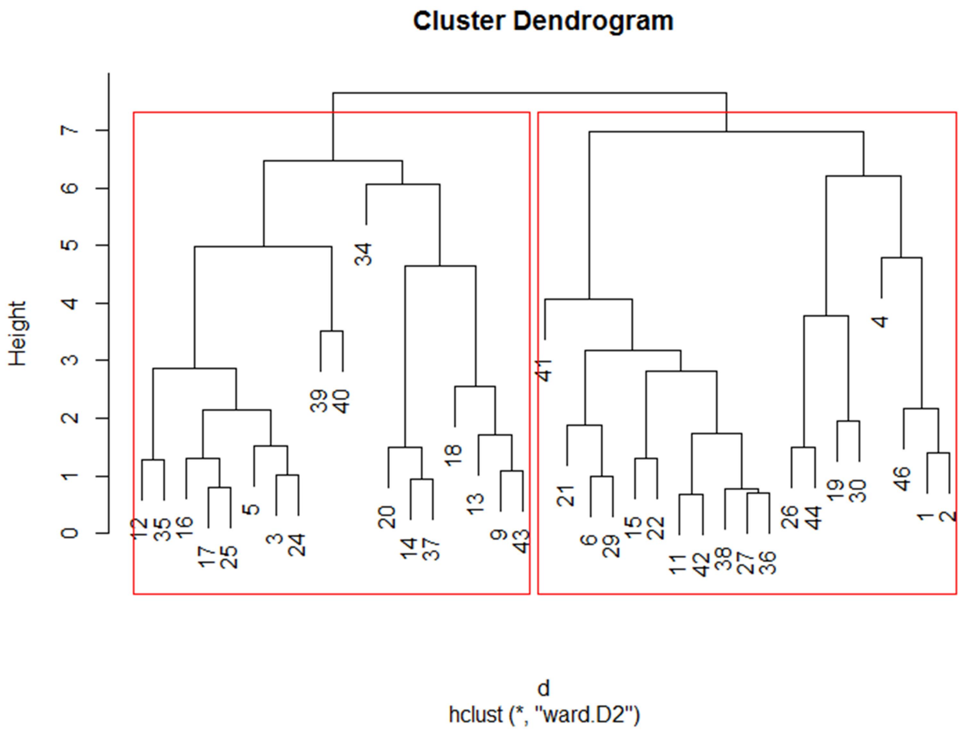


Figure 3. Ward's cluster method dedrogram - 2014 dataset

The factors extracted and interpreted above are used as new variables in Ward's hierarchical unsupervised cluster method in order to identify the best number of classes. For 2014 dataset, the dendrogram presented above shows that the best number of classes is two (it could be selected even three classes). In order to maintain the comparability between all five years, it selected only two classes. These two classes describes better the situation from factors point of view.

```
> k2014$size
[1] 16 21
> k2015$size
[1] 22 15
> k2016$size
[1] 16 21
> k2017$size
[1] 16 21
> k2018$size
[1] 18 19
```

```
> round(k2014$centers,4)
       F1      F2      F3      F4      F5      F6
1  0.6295  0.2128 -0.2545  0.3672  0.3594 -0.4860
2 -0.4797 -0.1622  0.1939 -0.2798 -0.2738  0.3703
> round(k2015$centers,4)
       F1      F2      F3      F4      F5      F6
1  0.0578  0.1349  0.0472 -0.5678  0.3249 -0.0196
2 -0.0848 -0.1978 -0.0692  0.8327 -0.4765  0.0287
> round(k2016$centers,4)
       F1      F2      F3      F4      F5      F6
1  0.1367 -0.1727 -0.2215 -0.2918  0.1732  0.8914
2 -0.1041  0.1316  0.1688  0.2223 -0.1320 -0.6791
> round(k2017$centers,4)
       F1      F2      F3      F4      F5      F6
1 -0.4499  0.8998 -0.1509 -0.0135  0.2064 -0.0314
2  0.3427 -0.6856  0.1150  0.0103 -0.1572  0.0239
> round(k2018$centers,4)
       F1      F2      F3      F4      F5      F6
1  0.7287  0.0279  0.3655  0.3218  0.2000 -0.1749
2 -0.6904 -0.0264 -0.3463 -0.3049 -0.1895  0.1657
```

Figure 4. K-Means results

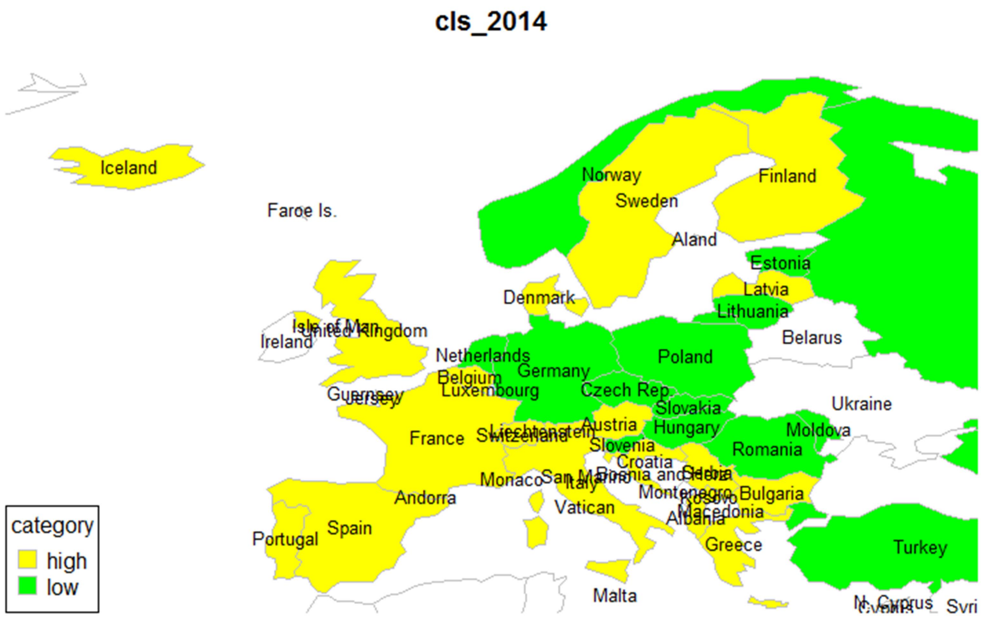
Figure from above presents the results for the third method of HCPC. The number of observations in each class is presented in the left side, while the classes' centers are in the right side. Interpreting the centroids of each class and dataset by taking into account the six factors, each class can have a low or a high risk of recession.

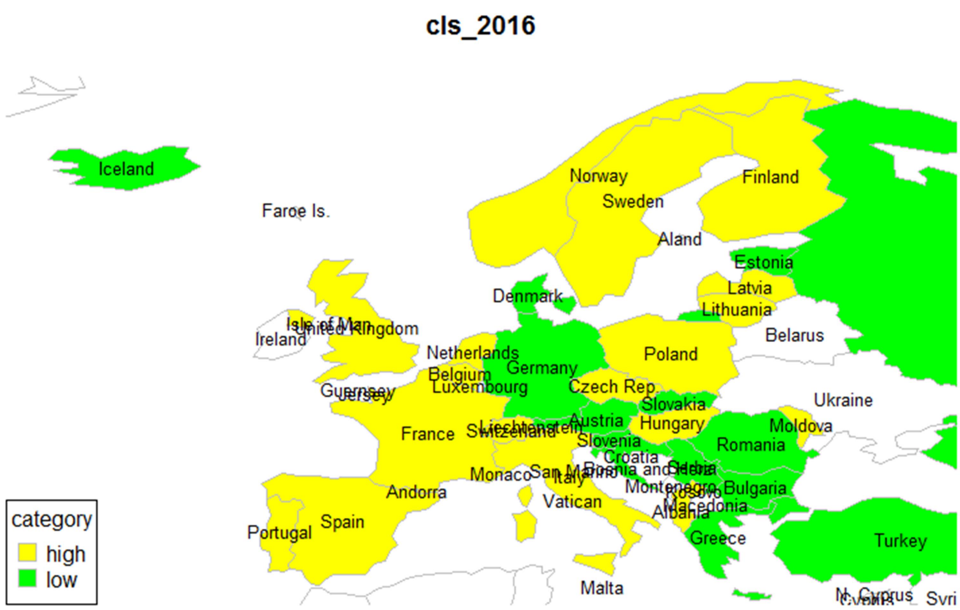
Therefore, the characteristics of each classes are:

- One class have positive values for the average values of factors, so that represents high values for original positive correlated variables (except F3 in 2018, that is negatively correlated with variables V12 and V13). This class have a low recession risk, with low inflation, low domestic credits, high GDP growth and is class1 in 2014, 2015, 2016 and 2018 datasets (except that in 2018, the credits start to grow) and class2 in 2017 dataset.

- Another class have the opposite description than class1: high domestic credits, low GDP growth (maybe negative values for GDP growth), high inflation, low trade. This class have a high recession risk.

The dynamic of classes components in time show that there are countries that "changed" their class membership and that something in that economy lead to an economic imbalance. In addition, if we consider a new categorical variable provided by WorldBank and named Income Group, we notice the difference between the evolution in time of the obtained classes and the current income class.


cls_2014
category
high
low
Iceland
Faroe Is.
Norway
Sweden
Finland
Aland
Estonia
Latvia
Lithuania
Denmark
Ireland
Netherlands
Belgium
Luxembourg
Germany
Poland
Belarus
Czech Rep.
Slovakia
Ukraine
Austria
Hungary
Moldova
Slovenia
Romania
Croatia
France
Andorra
Monaco
Italy
Vatican
Bulgaria
Macedonia
Albania
Greece
Turkey
Portugal
Spain
Malta
Syri


cls_2016
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Iceland
Faroe Is.
Norway
Sweden
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Aland
Estonia
Latvia
Lithuania
Denmark
Ireland
Netherlands
Belgium
Luxembourg
Germany
Poland
Belarus
Czech Rep.
Slovakia
Ukraine
Austria
Hungary
Moldova
Slovenia
Romania
Croatia
France
Andorra
Monaco
Italy
Vatican
Bulgaria
Macedonia
Albania
Greece
Turkey
Portugal
Spain
Malta
Syri

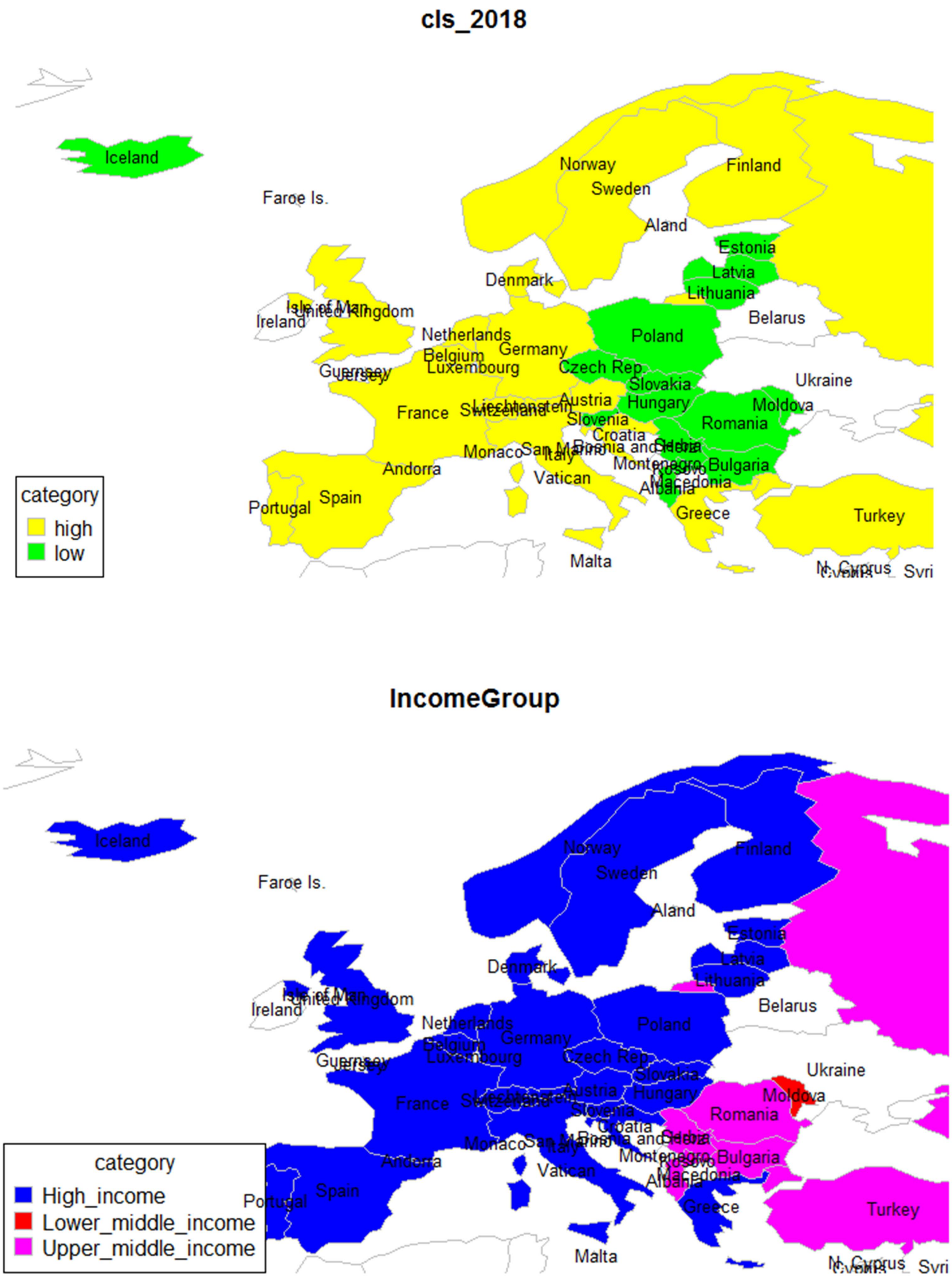

Figure 5. Risk of recession in Europe

The figure from above show the situation of the European countries selected for analysis (and not removed as a result as outliers' analysis for many variables). The first three maps present the class distribution for 2014, 2016 and 2018, while the last map present the income group. It is visible that the yellow area (corresponding to high recession risk class) is spreading from one map to another for large countries, considered as high income countries.

There are some several conclusions here:
- There are countries that passed (from 2014 to 2018 or from 2016 to 2018) from high recession risk to low recession risk, like Albania, Armenia, Bulgaria, Czech Republic, Hungary, Lithuania, Latvia, Moldova, Poland or Serbia. Most of these countries have an increase of GDP growth, an increase of inflation (except for Moldova and Serbia), a decrease of number of banks branches and an increase of trade.
- there is a group of countries (Austria, Germany, Denmark, Greece, Croatia, Netherlands, Norway, Russia, Turkey), most of them with high income, strong economies in Europe that change the class from low to high risk of recession (from 2014 to 2016 or from 2016 to 2018). Most of these countries have a decrease of GDP per capita growth, an increase of inflation, trade and decrease of unemployment.

4. Conclusions and discussions

The HCPC methodology is used here in order to identify a possible answer to the question: there are signs of a future European economic crisis. The FA performed to extract a smaller number of aggregate variables and reduce the dimensionality of datasets. Ward's method used to confirm that the number of two classes is a good choice, while k-means algorithm was applied to allocate each observation to a class.

The interpretation of classes through factors and the evolution of classes suggest that in the future, starting with 2020, a new economic crisis in Europe might be possible. However, in order to stop the potential crisis, politics (economically, monetary, socially) should be implemented.

The further research should be represented by analyzing each European country that "changed" the class among years and identify the cause and the factors (economy, politics, social) that lead to the change for each case.

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