Comparative Analysis of Liquidity Position of the European Banks

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Abstract
A forthcoming introduction of the new liquidity standards for banks (Basel III/CRD IV) imposes a need for evaluation of a degree of homogeneity across banks as regards the liquidity policies. The aim of this paper is therefore to classify the banking sectors from selected European Union countries according to their liquidity position. The sample, which is unbalanced, consists of 417 banks established in 21 European countries. The analysis envisions a 7-year time period from 2006 to 2012. The methods deployed in the study are principal component analysis (the PCA), Ward's clustering method and k-means clustering. The variables selected for the research are several balance sheet ratios reflecting the liquidity position of banks. The liquidity ratios are extracted from Bankscope. For the purpose of consistency of the results, standardized data is used and outliers are removed. The outcomes of the three different analyses are compared against each other in order to provide a relatively stable classification of the European banking sectors.

Keywords: bank liquidity, liquidity position, cluster analysis, principal component analysis
JEL codes: five, JEL codes, maximum

1. Introduction

Bank's liquidity has become an important concern for regulatory bodies in the European Union since 2007. The recent financial crisis has revealed poor liquidity management practices of banks, which led to a creation of new liquidity standards (LCR, NSFR). The standards were initially proposed by the Basel Committee in 2008 with the aim to strengthen banks' resilience through a common liquidity risk management framework (BCBS, 2008). The European Union incorporated the principles proposed by the BCBS through two legislative acts, known as Capital Requirements Regulation (CRR) (*Regulation*…) and Capital Requirements Directive (CRD IV) (*Directive*…). Technical aspects of the liquidity standards are still under development and can be found in the form of draft documents issued by the European Banking Authority (see: EBA, 2013a; EBA, 2013b; EBA 2013c; EBA, 2013d; EBA, 2013e). It is important to note that the new regulation is based on a single rulebook, which means that the institutions throughout the EU must respect these new harmonized prudential rules and that there is no room for divergences in national rules. On the one hand, it should promote a resilient, more transparent, and more efficient banking sector in the European Union. On the other hand, a threat remains that the banking sectors in less developed European Union countries might become exposed to a risk of financial instability in case of liquidity constraints in the other European Union countries. This is due to a fact that the regulation allows for liquidity transfers across the banking groups while there are banking sectors predominantly controlled by foreign investors, such as the Czech Republic, Bulgaria, Latvia, Lithuania, Romania, Slovakia, Croatia, Hungary, and Poland (Kruszka, 2011). The aim of the research is to assess homogeneity across banks in terms of their liquidity position by applying three different methods of classification to the banking sectors from selected EU countries during 2006-2012.

The paper is structured as follows. Firstly, it gives an overview of data and methodology used. Secondly, it provides a brief description of empirical results from three different multivariate analyses. Finally, certain conclusions are drawn from the study.

2. Data and methodology

Data used in the research had been extracted from Bankscope. The sample is unbalanced. It consists of 417 commercial banks established in 21 European Union countries, which are listed in the table 1. Outliers were removed from the data in order not to bias the results. The 7-year time-span data covers the period from 2006 to 2012.

Table 1: Countries selected for the study

Country	Code	Accession to the EU	Country	Code	Accession to the EU	Country	Code	Accession to the EU
Austria	AT	1995	France	FR	1957	Latvia	LV	2004
Belgium	BE	1957	Greece	GR	1981	Netherlands	NL	1957
Bulgaria	BG	2007	Croatia	HR	2013	Poland	PL	2004
Czech Rep.	CZ	2004	Hungary	HU	2004	Romania	RO	2007
Germany	DE	1957	Ireland	IE	1973	Sweden	SE	1995
Denmark	DK	1973	Italy	IT	1957	Slovenia	SI	2004
Spain	ES	1986	Lithuania	LT	2004	Slovakia	SK	2004

Source: own work

The liquidity position of banks was measured on an annual basis with several balance sheet ratios[1], such as the net loans/total assets ratio, the net loans/deposits and short term funding ratio[2], the net loans/total deposits and borrowings ratio, the liquid assets/deposits and short term funding ratio[3], or the liquid assets/total deposits and borrowings ratio. Should the ratios change over time, the means were calculated for each country during the entire period in order to provide an insight into a long-term liquidity position of banks.

The methodology used in this study is based on multivariate statistical analysis. Three different techniques were deployed to classify banks from the aforementioned countries according to their liquidity position during the years 2006-2012, namely: principal component analysis (PCA), cluster analysis and k-means method. These methods do not impose any a priori restrictions, so the dataset does not require the distinction between dependent and independent variables (Dardac and Boitan, 2009). Moreover, there is no prerequisite for normal multivariate distributions (Stanisz, 2007).

Principal component analysis serves as a tool for reduction of the number of dimensions of the observations by forming new variables (the PCs) as linear combinations of the original multivariate set, without much loss of information (Härdle and Simar, 2003). The PCA may also serve as a classification method. The first principal component explains the largest possible variance, whereas the second component is computed under the constraint of being orthogonal to the first component and extracts the largest proportion of the remaining variance. The other components are computed in the same manner until all the variance is extracted. It is worth noting that the principal components are uncorrelated (Abdi and Williams, 2010; Cu et al., 2009).

Cluster analysis enables diagnosis of complex relations among national characteristics and international linkages (Sørrensen and Gutiérrez, 2006). It might be then perceived as a useful method to examine the degree of homogeneity of the banking sector in the European Union countries in terms of the liquidity position. There are plenty of techniques to perform cluster analyses and k-means is one of them. The k-means aims to minimize the sum of squared Euclidean distances between all points and the cluster centre (Ray and Turi, 1999; Likas et al., 2003). The first step of the procedure requires selection of the number of clusters. In order to indicate the number of clusters Pietrzykowski and Kobus (2008) applied Ward's method, which deploys the analysis of variance approach to determine the distances between clusters. The same approach was used in this study. It should be noted that clustering is very sensitive to outliers and collinearity issues. What is more, if there are different types

[1] The liquidity ratios were extracted from Bankscope. The higher the ratios, which use the net loans as denominator, the less liquid bank, whereas the higher the remaining ratios, the more liquid reserves bank holds.
[2] The deposits and short term funding include: total deposits, money market and short term funding.
[3] The liquid assets include: trading securities and at FV through income, loans and advances to banks, reserve repos and cash collateral, cash and due from banks (including mandatory reserves).

of scales and different kinds of measurement of the attributes, the data ought to be standardized (Arai and Barakbah, 2007). Although it is not the case in this study, standardized data is used in order to assure consistency in the results.

3. Findings

3.1 Principal component analysis

In order to assess the structure of the dataset, correlation matrix was computed. It can be clearly seen from the table 2 that the variables are strongly correlated (>0,7). The least correlated variables are the net loans/deposits & short term funding ratio and the liquid assets/deposits & short term funding ratio. From the correlation matrix it can be assumed that there exists a structure, which might affect the principal components.

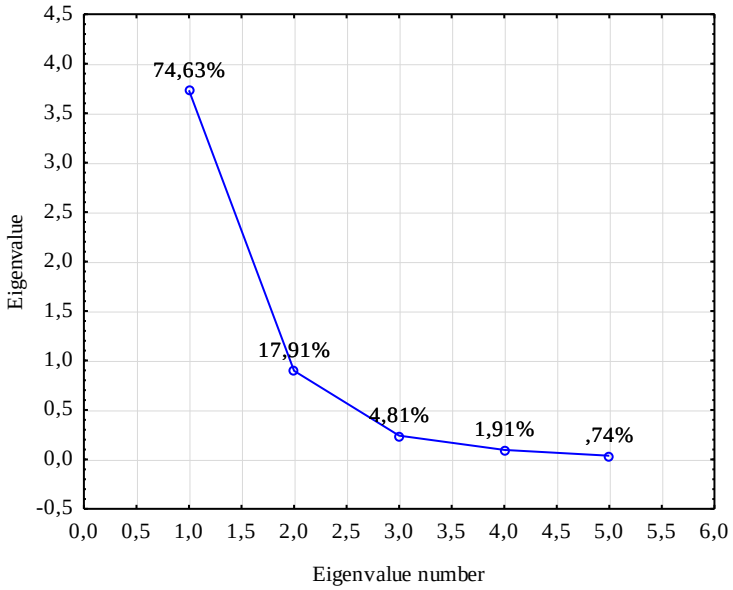
Table 2: Correlation matrix

	Net Loans / Tot Assets	Net Loans / Dep & ST Funding	Net Loans / Tot Dep & Bor	Liquid Assets / Dep & ST Funding	Liquid Assets / Tot Dep & Bor
Net Loans / Tot Assets	1,000000	0,784618	0,961727	-0,598227	-0,673471
Net Loans / Dep & ST Funding	0,784618	1,000000	0,795999	-0,360721	-0,512812
Net Loans / Tot Dep & Bor	0,961727	0,795999	1,000000	-0,562204	-0,646366
Liquid Assets / Dep & ST Funding	-0,598227	-0,360721	-0,562204	1,000000	0,885399
Liquid Assets / Tot Dep & Bor	-0,673471	-0,512812	-0,646366	0,885399	1,000000

Source: own computation

In order to assess the number of principal components the scree test was proposed. From the plot of eigenvalues (see figure 1) it can be assumed that 2 factors should be retained in the analysis. The first two PCs explain 92,5% of the variance.

Figure 1: Eigenvalues of covariance matrix



Source: own work

From the table 3 it can be seen that the PC1 explains 88,3% of the net loans/total assets ratio's variance (0,939611^2). The sign of the coefficient is positive, which means that the higher the ratio (and hence illiquidity), the higher the value of the first principal component. The PC2 explains 34,8% of the liquid assets/deposits and short term funding ratio's variance. The sign of the coefficient is negative, which indicates that the higher the ratio (and hence liquidity), the lower the value of the second principal component.

Table 3: Factor coordinates of the variables, based on correlations

Variables	PC 1	PC 2
Net Loans / Tot Assets	0,939611	-0,225955
Net Loans / Dep & ST Funding	0,804067	-0,471650
Net Loans / Tot Dep & Bor	0,928200	-0,271161
Liquid Assets / Dep & ST Funding	-0,780301	-0,590256
Liquid Assets / Tot Dep & Bor	-0,855262	-0,447422

Source: own computation

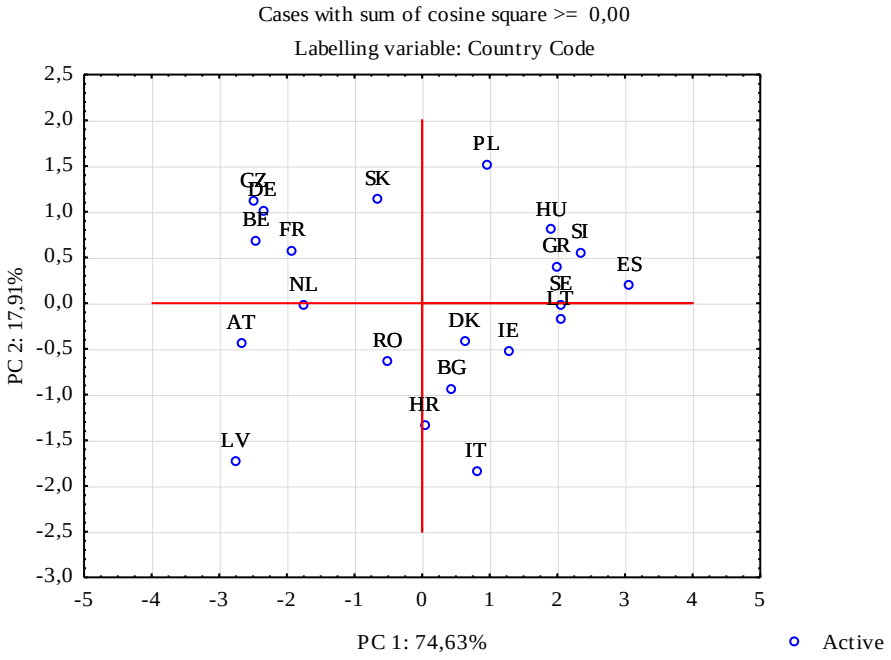
By using the case factor coordinates plot it is possible to classify the banking sectors from the selected EU's countries according to their average liquidity position during 2006-2012. As presented in figure 2, the examined banking sectors might be assigned to one of the three following groups.

Group 1: RO, HR, IT, BG, DK, IE – the banking sectors characterized by a relatively low level of liquidity as measured by the net loans/total assets ratio and a relatively high liquidity buffer as measured by the liquid assets/deposits and short term funding ratio.

Group 2: LT, SE, ES, GR, SI, HU, PL – the banking sectors characterized by a relatively low level of liquidity as measured by the net loans/total assets ratio and a relatively low liquidity buffer as measured by the liquid assets/deposits and short term funding ratio.

Group 3: AT, NL, FR, BE, DE, CZ, SK – the banking sectors characterized by a relatively high level of liquidity as measured by the net loans/total assets ratio and a relatively low liquidity buffer as measured by the liquid assets/deposits and short term funding ratio.

Figure 2: Projection of the cases on the factor-plane



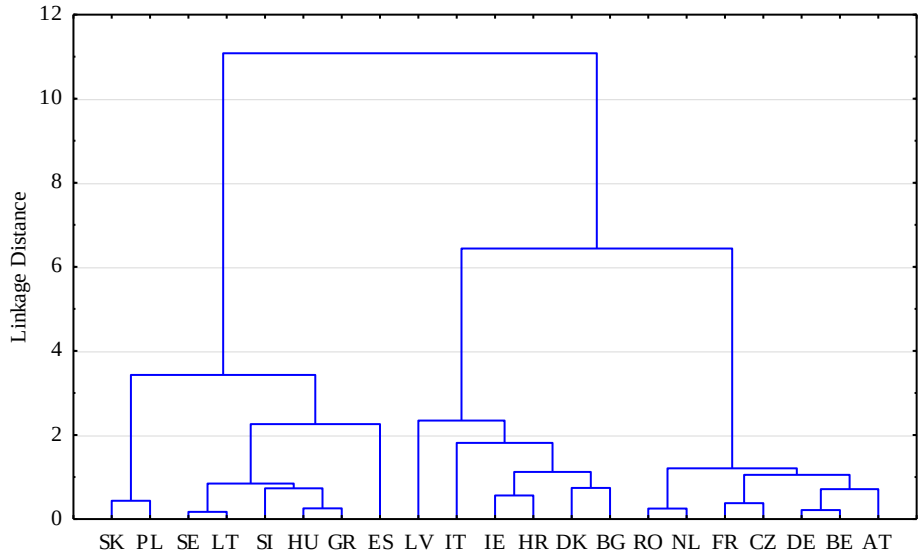
Source: own work

The liquidity position of the Latvian banking sector is somewhat outstanding. It cannot be classified to any of the identified groups because it is characterized by a relatively high level of liquidity as measured by the net loans/total assets ratio and a relatively high liquidity buffer as measured by the liquid assets/deposits and short term funding ratio.

3.2 Ward's method

As can be seen in the table 1 the variables are highly correlated. Due to this fact, the least correlated variables were taken into consideration while performing the clustering, namely the net loans/deposits and short term funding ratio and the liquid assets/deposits and short term funding ratio. The Ward's classification is presented in the form of a dendogram in the figure 3.

Figure 3: The Ward's classification (Euclidean distances)



Source: own work

Based on the observation of the dendogram, three clusters can be identified. It is worth noting that the Wards' classification is similar to the one obtained through the PCA, with certain exceptions.

3.3 K-means clustering

The PCA and the Ward's method both indicate the number of clusters equal to three. The variables used for k-means clustering are the same as for the Ward's method. The results of the analysis are presented in table 4.

Table 4: The k-means clustering

Cluster 1		**Cluster 2**		**Cluster 3**	
Members	Distance*	Members	Distance*	Members	Distance*
HR	0,373689	DK	0,672665	AT	0,424849
IE	0,238218	ES	1,218039	BE	0,209602
IT	0,484030	GR	0,089138	BG	0,614664
* The distances are measured from respective cluster centres		HU	0,265107	CZ	0,564046
		LT	0,134021	DE	0,360332
		PL	0,819133	FR	0,426781
		SE	0,251902	LV	0,952211
		SI	0,464006	NL	0,138381
		SK	0,833058	RO	0,247926

Source: own computation

As can be seen from the table 4 clusters no. 2 and 3 consist of nine banking sectors each, whereas there are only three banking sectors included in cluster 1. It is worth to note that the cluster 2 consists mostly of the banking sectors of the new EU's countries. The longest distances from the cluster centre can be assigned to the banking sectors of Spain (ES), Slovakia (SK), and Poland (PL). In contrast, the cluster 3 consists mostly of the banking sectors of the old EU's countries and the longest distances from the cluster centre can be observed for Bulgaria (BG), the Czech Republic (CZ), and Latvia (LV). The distances between the three clusters (see table 5) indicate that the cluster no. 2 and cluster no. 3 are most distant from each other.

Table 5: Euclidean distances between clusters
(distances below diagonal; squared distances above diagonal)

Cluster number	No. 1	No. 2	No. 3
No. 1	0,000000	1,675364	1,980346
No. 2	1,294359	0,000000	2,326444
No. 3	1,407248	1,525268	0,000000

Source: own computation

An analysis of variance (see table 6) allows for a conclusion that both variables - the net loans/deposits and short term funding ratio and the liquid assets/deposits and short term funding ratio significantly explain the k-means classification with p-levels equal to 0,000501 and 0,000001 respectively.

Table 6: Analysis of variance

	Between SS	df	Within SS	df	F	signif. p
Net loans / Dep & ST Funding	11,40281	2	8,597194	18	11,93706	0,000501
Liquid assets / Dep & ST Funding	15,94444	2	4,055557	18	35,38354	0,000001

Source: own computation

4. Conclusion

The banking sector in the European Union seems rather heterogeneous in terms of the average liquidity position during the years 2006-2012. This finding may support the introduction of the new liquidity standards, which should lead to a greater homogeneity across banks as regards their liquidity policies. The results of the three different methods of classification applied in the study (the principal component analysis, the Ward's method, and the k-means clustering) differ slightly, however certain patterns in the data structure can be observed. There exists a clear distinction between the banking sectors of the Czech Republic, Austria, Belgium, Germany, France, Netherlands and the remaining European countries. No matter of the clustering method used in the research, the aforementioned banking sectors can be jointly classified to a single group. Moreover, the banking sectors of Croatia, Ireland and Italy form rather a consistent group. The results of classification of the banking sectors of Poland, Slovakia, Latvia, and Spain are inconsistent. These banking sectors cannot be assigned to any cluster with a sufficient degree of certainty.

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