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Abstract

Banking crises can be damaging for the economy, and as the recent experience has shown, nowadays they can spread rapidly across the globe with contagious effects. Therefore, the assessment of the stability of the banking sectors is important for regulators, depositors, investors and the general public. In the present study, we propose the development of classification models that assign the banking sectors in three classes, labelled "low stability", "medium stability", and "high stability". The models are developed using three multicriteria decision aid techniques, which are well-suited to ordinal problems. We use a sample of 114 banking sectors, and a set of criteria that includes indicators of the macroeconomic, institutional and regulatory environment, as well as basic characteristics of the banking and financial sector. The models are developed and tested using a 10-fold cross-validation approach and they are benchmarked against models developed with discriminant analyis and logistic regression.

Keywords: banking, multicriteria decision aid, risk, stability

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1. Introduction

Banking crises can be damaging for the economy, and as the recent experience has shown, nowadays they can spread rapidly across the globe with contagious effects. More detailed, after a relatively stable period between the Second World War and the early 1970s, several countries experienced a banking crisis over the last thirty years. Caprio and Klingebiel (2003) provide information on 117 systemic banking crises that occurred in 93 countries and 51 borderline and smaller banking crises in 45 countries since the late 1970s. Laeven and Valencia (2008) also provide details as well as management strategies for 42 systemic banking crises from 37 countries between 1970 and 2007. These crises have both direct and indirect costs for the economy. First, as documented in Caprio and Klingebiel (2003) the costs for restructuring and recapitalisation can reach 10-20% and occasionally 40-55% of GDP (e.g. Argentina, Indonesia). Second, the crises have adverse effects on the efficient operation of the market economy due to the central role of banks as financial intermediates. Such adverse developments result in reduction in investment and consumption, increases in unemployment, and disturb the flow of credit to individuals and firms causing an overall economic slowdown. This makes the assessment of the stability of the banking sectors of particular importance for regulators, depositors, investors and the general public.

Therefore, a number of studies examine the determinants of systemic banking crises or develop early warning models to predict the crises (e.g. Demirguc-Kunt and Detragiache, 1998; Davis and Karim, 2008; Moshirian and Wu, 2009). However, there are a number of problems associated with these studies. First, they focus on the 1980s and the 1990s, when we experienced the majority of banking crises, and their results may not be applicable to the current financial environment. Second, they concentrate on emerging market economies due to the higher frequency of crises in these economies in the past (Bell and Pain, 2000). Yet, the current crisis started from developed countries like the US and the UK. In addition, there are differences in the dates attributed to the banking crises (Bell and Pain, 2000), thus making their empirical modelling problematic. Third, dating is also problematic when there are successions of crises episodes as later crises can be extensions or re-emergences of previous financial distress rather than individual events (Caprio and Klingebiel, 1996; Davis and Karim, 2008). Fourth, the binary classification of the banking sectors, in the ones that experienced a crisis and those that did not experienced a crisis, reduces the usefulness of the models.

In contrast, in the present study we propose the classification of the banking sectors in three classes, labelled “low stability”, “medium stability”, and “high stability”. Furthermore, to avoid some of the aforementioned problems, we rely on the Economist Intelligent Unit (EIU) “Banking Sector Risk Ratings rather than banking crises. This approach can provide additional information, since it monitors the banking sectors as they deteriorate from the “high stability” to the “low stability” class. The models are developed using three multicriteria decision aid (MCDA) techniques, namely UTilities Additives DIScriminantes (UTADIS), Multi-group Hierarchical DIScrimination (MHDIS), and ELECTRE TRI. These methods are well-suited to ordinal problems, like the one that we examine. Furthermore, they are not making any statistical assumptions. We use a sample of 114 banking sectors and a set of criteria that includes indicators of the macroeconomic, institutional and regulatory environment, together with variables that consider the basic characteristics of the banking and financial sector. To ensure the proper estimation and validation of the models we follow a 10-fold cross-validation approach.

The rest of the paper is as follows. Section 2 discusses the sample and the variables used in the study, while Section 3 outlines the classification techniques. Section 4 discusses the empirical results, and Section 5 concludes the study.

2. Sample and variables

2.1. Sample

We start by considering the 120 banking sectors which were assigned an Economist Intelligent Unit (EIU) "Banking Sector Risk Rating" during 2008. The EIU ratings classify these sectors in 8 risk groups, ranging from C to AA. However, as our purpose is not to explain or replicate the ratings, but rather to use them as the basis for .the development of a general model, we group the banking sectors in three broad classes.[1] The first class includes banking sectors with ratings A and AA, the second class includes those banking sectors with ratings B, BB and BBB, and the third class consists of banking sectors with ratings C, CC, CCC. Thus, Class 1 includes "high stability" banking sectors, Class 2 includes "medium stability" banking sectors, and Class 3 includes "low stability" sectors.

Data for end-2007 for the macroeconomic and institutional environment, as well as basic characteristics of the banking sector, all at the country/sector level, were collected from the following sources: (i) the deposit insurance database developed by Demirguc-Kunt et al. (2005), (ii) the financial structure database developed by Beck

[1] We are not interested in replicating all the ratings of EIU for two reasons. First, the classification of the banking sectors in three general classes allows to avoid potential problems that could arise during the estimation and validation of the models due to the small number of sectors falling in a few of the original EIU groups. Second, this approach allows us to avoid (at least to some extent) problems associated with the timely adjustment of ratings. For instance, a delay in a downgrade from AA to A or from BBB to B would have no impact in assessing the overall stability of a banking sector as we do. Furthermore small errors of judgment in the assignment of ratings such as rating an A banking sector as AA would also had no impact on our model. Obviously, large errors of judgment could make a difference but we have no reason to believe that EIU would classify let us say a *B* banking sector as *A* and *visa versa*.

et al. (2000, 2007), (iii) Heritage Foundation, and (iv) World Development Indicators (WDI).

After excluding 6 banking sectors due to missing data for the selected criteria, the final sample consists of 114 banking sectors. The distribution in the three classes is as follows: 20 (Class 1), 79 (Class 2), and 15 (Class 3). Table 1 presents the within-stability class geographical percentage composition of the sample. More detailed, the figures in Table 1 show that 5% of the banking sectors in sample that are classified as "high stability" come from Africa, 55% of them are from Northern and Western Europe, and so on.

[Insert Table 1 Around Here]

2.2. Criteria of banking stability

We use a total of 11 criteria falling in four general categories: (i) regulations, (ii) other banking and financial sector attributes, (iii) institutional environment, and (iv) macroeconomic conditions. These criteria and the corresponding sources of information are presented in Table 2 and discussed below.

[Insert Table 2 Around Here]

2.2.1. Regulations

Theoretical and empirical evidence suggests that banking regulations such as entry into the banking industry, restrictions on activities, etc., as well as state ownership of banks can influence the stability of the banking sector (see Barth et al., 2004). As in Demirguc-Kunt et al. (2004) and Pasiouras et al. (2007a) we use an overall indicator of the relative openness of each country's banking and financial system (BFREG), taken by Heritage Foundation. This index indicates the extent of restrictions on financial services, central bank independence, government ownership of banks, the difficulty of opening and operating domestic and foreign financial firms and government influence on the allocation of credit. Higher scores indicate higher freedom (i.e. less restrictions) in the banking and financial sector.

Deposit insurance is another regulatory tool used in many countries as a way to avoid bank runs. However, deposit insurance schemes may encourage excessive risk-taking behaviour (Demirguc-Kunt and Detragiache, 2002). The main reason is that depositors will have no incentives to monitor bank managers, who can take on riskier investments under the assumption that depositors are protected in the event of a failure. Demirguc-Kunt and Detragiache (2002) provide evidence that an explicit deposit insurance scheme, in the absence of strong banking regulations tends to increase the probability of banking crises. Barth et al. (2004) also report a positive relationship between deposit insurance "generosity" and the likelihood of a crisis. Therefore, we use a dummy variable indicating whether an explicit deposit insurance scheme has been adopted (DEPINS = 1) or not (DEPINS = 0).

2.2.2. Other Banking and financial sector attributes

As the recent crisis revealed, liquidity can become a very important problem for banks especially when there is reluctance for interbank borrowings and depositors demand a higher rate for their savings. To assess the liquidity of the banking sector we use the average ratio of bank credit to bank deposits (BLIQ) that shows the percentage of deposits that is tied up in loans. Therefore, higher ratios may indicate that the banking sector has fewer funds available to meet a sudden recall of its funding.

The literature suggests that increased competition decreases bank charter value and induces bank managers to increase risk (Keeley, 1990). Cross-country evidence by De Nicolo et al. (2004) shows that highly concentrated banking markets faced levels of systemic risk potentially higher than less concentrated markets during the 1993-2000 period, and this relationship strengthened between 1997 and 2000. In contrast, Beck et al. (2006) report that more concentrated national systems are subject to a lower probability of systemic banking crises. As a rough measure of competition, we use the percentage of assets held by the three largest commercial banks relative to the total assets of the commercial banking sector within the country (BCONC).

Results from bank-level studies indicate that profitability is negatively related to the probability of failure (e.g. Wheelock and Wilson, 2000; Lanine and Vander Vennet, 2006). Therefore, we use the average return on assets in the banking industry (BROA) under the assumption that higher ROA will result in a more stable sector.

As discussed in Demirguc-Kunt and Detragiache (1998) financial liberalization may increase banking sector fragility due to increased opportunities for excessive risk-taking and fraud. Therefore, following, Demirguc-Kunt and Detragiache (1998) and Davis and Karim (2008) among others, we use the ratio of domestic credit to private sector over GDP (CRGDP) to proxy for financial liberalization.

2.2.3. Institutional environment

The stability of the banking sector may also be affected by the country's institutional environment which can also mitigate the adverse effects of deposit insurance. For example, Barth et al. (2004) find that better-developed private property rights and greater political openness mitigate the negative association of moral hazard and bank fragility. Demirguc-Kunt and Detragiache (2002) and Demirguc-Kunt and Kane (2002) also conclude that a sound legal system with proper enforcement of rules reduces the adverse effects of deposit insurance on bank risk-taking.

In the present study, we use three indicators of the level of the development of institutional environment. The first is an index of the protection of property rights (PRIGHTS) taken by Heritage Foundation. This index indicates the ability to accumulate private property, secured by clear laws that are fully enforced by the stage, and it can take values between 0 (i.e. private property is outlawed and all property belongs to the state) and 100 (i.e. private property is guaranteed by the government). The second is the Heritage index of corruption (CORRUPT) that reveals the degree of corruption in the business environment, including levels of governmental legal, judicial, and administrative corruption. It takes values between 0 and 100, with higher figures indicating lower corruption. Finally, as in past studies we use the GDP per capita as a general indicator of institutional development (e.g. Demirguc-Kunt et al., 2004).

2.2.4. Macroeconomic conditions

Several studies document a relationship between real GDP growth and the probability or hazard rate of banking crisis (e.g. Demirguc-Kunt and Detragiache, 1998; Noy, 2004; Davis and Karim, 2008; Evrensel, 2008). As Davis and Karim (2008) mention, GDP growth cannot only reduce non-performing loans it can also delay banking crises due to pro-cyclicality. Following these studies, we use the real GDP growth (GDPGR) as an overall indicator of economic growth. Finally, we use the annual inflation rate (INFL) since past studies show that it can impact the stability of the banking sector (e.g. Demirguc-Kunt and Detragiache, 1998; Davis and Karim, 2008).

Table 3 presents descriptive statistics for the above criteria while distinguishing between the three stability classes. The Kruskal-Wallis non-parametric test indicates that there are statistically significant differences between the means of the three groups in all the cases.

[Insert Table 3 Around Here]

3. Multicriteria classification techniques

The problem considered in this case study falls within the multicriteria classification problematic, which, in general involves, the assignment of a finite set of alternatives $X = \{x_1, x_2, ..., x_n\}$, each one described along a set of m criteria g_1, g_2, …, g_m, to a set of q ordered classes $C_1 \succ C_2 \succ \cdots \succ C_q$. In the present study, the alternatives involve the 114 banking sectors, the criteria correspond to the 11 variables discussed in Section 2.2., and there are three ordered classes.

3.1. UTilités Additives DIScriminantes (UTADIS)

The UTADIS method develops an additive value function, which is used to score the banking sectors and decide upon their classification. The value function has the following general form:

$$U(x) = \sum_{i=1}^{m} w_i u_i'(g_i) \in [0,1]$$

where w_i is the weight of criterion g_i (the criteria weights sum up to 1) and $u_i'(g_i)$ is the corresponding marginal value function normalized between 0 and 1. The marginal value functions provide a mechanism for decomposing the aggregate result (global value) in terms of individual assessment to the criterion level. To avoid the estimation of both the criteria weights and the marginal value functions, it is possible to use the transformation $u_i(g_i) = w_i u'_i(g_i)$. Since $u'_i(g_i)$ is normalized between 0 and 1, it becomes obvious that $u_i(g_i)$ ranges in the interval [0, w_i]. In this way, the additive value function is simplified to the following form which provides an aggregate score $U(x)$ for each banking sector along all criteria:

$$U(x) = \sum_{i=1}^{m} u_i(g_i) \in [0,1]$$

To classify the banking sectors it is necessary to estimate the thresholds $0 \le t_{q-1} < \cdots < t_2 < t_1 \le 1$ that distinguish the class. Comparing the value utilities with the thresholds, the classification is achieved as follows:

$$\left.\begin{array}{cc} U(x) \ge t_1 & \Rightarrow x \in C_1 \\ \cdots & \cdots \\ t_k \le U(x) < t_{k-1} & \Rightarrow x \in C_k \\ \cdots & \cdots \\ U(x) < t_{q-1} & \Rightarrow x \in C_q \end{array}\right\}$$

The estimation of the additive value function and the cut-off thresholds is performed through linear programming techniques. The objective of the method is to develop the additive value model so that the above classification rules can reproduce the predetermined grouping of the banking sectors as accurately as possible. Therefore, a linear programming formulation is employed to minimize the sum of all violations of the above classification rules for all the banking sectors in the training sample. Detailed description of the mathematical programming formulation can be found in the work of Doumpos and Zopounidis (2004).

3.2. Multi -group Hierarchical DIScrimination (MHDIS)

In contrast to UTADIS, MHDIS distinguishes the classes progressively, starting by discriminating the first class from all the others, and then proceeds to the discrimination between the alternatives belonging into the other classes. To accomplish this task, instead of developing a single additive value function that describes all alternatives (as in UTADIS), two additive value functions are developed in each one of the $q-1$ steps, where q is the number of classes. The first function $U_k(x)$ describes the alternatives of class C_1, while the second function $U_{\sim k}(x)$ describes the remaining alternatives that are classified in lower classes $C_{k+1},\ldots,C_q$.

$$U_k(x)=\sum_{i=1}^{m} w_{ki}u_{ki}(g_i) \text{ and } U_{\sim k}(x)=\sum_{i=1}^{m} w_{\sim ki}u_{\sim ki}(g_i),\ k=1,2,...,q-1$$

The corresponding marginal value functions for each criterion g_i are denoted as $u_{ki}(g_i)$ and $u_{\sim ki}(g_i)$ which are normalized between 0 and 1, while the criterion weights w_{ki} and $w_{\sim ki}$ sum up to 1. As mentioned above, the model is developed in $q-1$ steps. In the first step, the method develops a pair of additive value functions $U_1(x)$ and $U_{\sim 1}(x)$ to discriminate between the alternatives of class C_1 and the alternatives of the other classes $C_2,\ldots,C_q$. On the basis of the above function forms the rule to decide upon the classification of any alternative has the following form:

If $U_1(x)\geq U_{\sim 1}(x)$ then x belongs in C_1

else if $U_1(x)\leq U_{\sim 1}(x)$ then x belongs in $\{C_2,\ldots,C_q\}$

The alternatives that are found to belong into class C_1 (correctly or incorrectly) are excluded from further analysis. In the next step, another pair of value functions $U_2(x)$ and $U_{\sim 2}(x)$ is developed to discriminate between the alternatives of class C_2

and the alternatives of the classes $C_3, \ldots, C_q$. Similarly to step 1, the alternatives that are found to belong in class C_2 are excluded from further analysis. This procedure is repeated up to the last stage ($q-1$), where all classes have been considered.

The estimation of the weights of the criteria in the value functions as well as the marginal value functions is accomplished through mathematical programming techniques. More specifically, at each stage of the hierarchical discrimination procedure, two linear programs and a mixed-integer one are solved to estimate optimally the two required functions and minimize the classification error. Further details of the mathematical programming formulations used in MHDIS can be found in Zopounidis and Doumpos (2002).

3.3. ELECTRE TRI

The ELECTRE TRI method implements the outranking relations approach of multicriteria decision aiding (Roy and Bouyssou, 1993). The outranking relation is a binary relation that enables the assessment of the outranking degree of an alternative x_i over an alternative x_j. The outranking relation allows to conclude that x_i outranks x_j if there are enough arguments to confirm that x_i is at least as good as x_j (concordance), while there is no essential reason to refute this statement (discordance).

Within the context of classification/sorting problems the outranking relation is used to estimate the outranking degree of an alternative x_i over a reference profile r_k that distinguish the classes C_k and C_{k+1}. Each reference profile r_k is defined as a vector of individual profiles for each criterion $g_1, g_2, \ldots, g_m$: $r_k=(r_{k1}, r_{k2}, \ldots r_{km})$.

In order to determine whether an alternative x_i outranks a reference profile r_k, all paired comparisons (g_{ij}, r_{kj}) and (r_{kj}, g_{ij}) should be performed for each criterion g_j. The former comparison enables the assessment of the strength $\sigma(x_i, r_k)$ of the affirmation "alternative x_i is at least as good as profile r_k", while the latter comparison leads to the assessment of the strength $\sigma(r_k, x_i)$ of the affirmation "profile r_k is at least as good as alternative x_i". Typically, an alternative x_i is preferred to a profile r_k (x_i P r_k) if $\sigma(x_i, r_k)\geq\lambda$ and $\sigma(r_k, x_i)<\lambda$ (λ is a pre-specified cut-off point). If $\sigma(x_i, r_k)\geq\lambda$ and $\sigma(r_k, x_i)\geq\lambda$, then x_i and r_k are considered as indifferent (x_i I r_k). Finally, if $\sigma(x_i, r_k)<\lambda$ and $\sigma(r_k, x_i)<\lambda$ then x_i and r_k are considered incomparable (x_i R r_k). The estimation of the credibility index $\sigma(x_i, r_k)$ is performed in two stages. The first stage involves the concordance test, which considers the criteria for which x_i is at least as good as r_k. The second stage considers the veto conditions, which may arise if x_i is significantly worse than r_k in some criteria. The details of this process can be found in Roy and Bouyssou (1993).

Once the outranking relation is constructed, its exploitation to sort the alternatives in X is performed through several heuristic assignment procedures. For instance, ELECTRE TRI employs two assignment procedures, the pessimistic and the optimistic one. Assuming a classification problem with q classes, in the pessimistic assignment, each alternative x_i is compared successively to the profiles $r_1, r_2, \ldots, r_{q-1}$. Let r_k be the first profile such that $\sigma(x_i, r_k)\geq\lambda$. Then, x_i is assigned to group C_k (if there is no profile such that $\sigma(x_i, r_k)\geq\lambda$, then x_i is assigned to group C_q). In the optimistic assignment each alternative x_i is compared successively to the profiles $r_{q-1}, r_{q-2}, \ldots, r_1$. Let r_k be the first profile such that $\sigma(r_k, x_i) \geq \lambda$ and $\sigma(x_i, r_k) < \lambda$. Then, x_i is assigned to group C_{k+1} (if the there is no profile satisfying the above condition, then x_i is assigned to group C_1).

The differences between the two procedures arise in the presence of the incomparability relation. For example, in a two-group case an alternative that is incomparable to the profile r_1 will be assigned to group C_1 with the optimistic procedure and to group C_2 with the pessimistic procedure. Thus, the differences between the two assignment rules facilitate the identification of alternatives with special characteristics, which make the comparison of the alternatives to the profiles difficult.

In this study we employ the pessimistic assignment procedures and all the parameters of the ELECTRE TRI model (weights of the criteria, preference, indifference and veto thresholds, as well as the λ cut-off point) are estimated using the evolutionary optimization approach, which has been recently proposed by Doumpos et al. (2009).

4. Results

Table 4 presents the average weights (in %) of the criteria along all replications over the 10-fold cross-validation analysis.[2] The banking-financial regulatory environment (BFREG) and corruption (CORRUPT) are the two most important criteria in the UTADIS model, accounting together for around 40%. Property rights (PRIGHTS) and liquidity (BLIQ) are of medium importance with weights around 12% each, while the weights of the rest of the criteria range between 0.21% (DEPINS) and 9.78% (INFL). Turning to the ELECTRE TRI model we observe that the weights of the criteria are quite more balanced ranging between 3.54% (DEPINS) and 15.88% (GDPCAP). The interpretation of the weights is more complicated in the case of MHDIS due to the multiple functions that are developed. The most important criteria in the first set of

[2] As mentioned earlier, we adopt a 10-fold cross validation approach to develop and evaluate the models. The full sample of the 114 banking sectors is randomly split into 10 mutually exclusive sub-samples (i.e. non-overlapping folds of approximately equal size). Then, 10 models are developed in turn, using nine folds for training and leaving one fold out each time for validation. The average error rate over all the 10 replications is the cross-validated error rate.

the utility functions U_1 (i.e. “high stability”) and $U_{\sim 1}$ (i.e. “medium” and “low” stability) are the domestic credit to private sector over GDP (CRGDP), GDP per capita (GDPCAP), and corruption (CORRUPT). However, in the second set of utility functions other criteria become important. In particular, in U_2 which characterizes the “medium stability” banking sectors and $U_{\sim 2}$ which characterizes the “low stability” banking sectors the four most important criteria are: bank concentration (BCONC), banking-financial regulatory environment (BFREG), domestic credit to private sector over GDP (CRGDP), and GDP growth (GDPGR).

[Insert Table 4 Around Here]

Overall, it appears that deposit insurance is the less important criterion in all models, while the institutional environment is a good predictor (on an aggregate basis) of the stability of the banking sectors. Yet, there is no general agreement in the models as for the importance of the criteria. While there is no particular reason for that, such differences have been observed in past studies as well (e.g. Espahbodi and Espahbodi, 2003; Barnes, 2000; Pasiouras et al., 2007b). One possible explanation is that although all methods attempt to classify correctly as many observations as possible, they consider different ways of processing the same information in the dataset. Another explanation is that, while UTADIS and ELECTRE develop only one function characterizing all banking sectors, MHDIS develops four functions that correspond to difference classes. It should also be noted, while the weights in the value functions developed with UTADIS and MHDIS represent tradeoffs, the weights in ELECTRE TRI represented the strength of the criteria in a weighted voted process. As discussed in Pasiouras et al. (2007b), whether the weights attributed by one method are intuitively more appealing than those selected by another method is a matter of subjective judgment.

Table 5 presents the average classification results obtained over the 10 replications. Since the classification accuracies in the training sample can be upward biased, we focus on the ones achieved in the validation sample. Panel B shows that these accuracies are quite satisfactory being 79.81% (ELECTRE TRI), 78.83% (UTADIS), and 75.60% (MHDIS). Of particular importance is that ELECTRE TRI and UTADIS perform very well in identifying banking sectors that belong in Class 3, which bear the highest risk. MHDIS on the other hand achieves the highest accuracy in classifying banking sectors in Class 2. This is also a difficult task since the characteristics of these banking sectors may overlap with the ones belonging in the lower band of Class 1 and/or the upper band of Class 3.

[Insert Table 5 Around Here]

As a benchmark to the three MCDA methods, we also develop two models using discriminant analysis (DA) and logistic regression (LR). The average classification accuracies of DA and LR are considerably lower than the ones of the three MCDA methods. Despite being quite similar on average (i.e. DA: 67.38%; LR: 67.02%), these accuracies are achieved in a different way. While the performance of DA is balanced among the three classes, LR classifies very poorly banking sectors belonging in class 3, with an accuracy as low as 22.22%.

A closer look at the two models with the lowest misclassification errors in the validation sample indicate the following. First, 62% of the misclassification errors of UTADIS involve downgrades. More detailed, Greece, Portugal, and Botswana are downgraded from the class of high stability to the one of medium stability. Countries downgraded from medium to low stability come mostly from Asia (India, Bangladesh, Indonesia, etc.), Africa (Algeria, Egypt, Nigeria, etc.), Latin-Southern America (Guatemala, Paraguay, Bolivia) and Eastern Europe (Russia, Romania). Only 38% of the errors involve upgrades. Most of them refer to upgrades of banking sectors from the medium stability class to the high stability one[3] ,while there are also three misclassifications involving upgrades from the low stability class to the medium stability one (i.e. Sudan, Jamaica, Syria).

We observe a similar picture in the case of ELECTRE TRI, with downgrades accounting for 70% of the misclassification errors. More detailed, the model downgrades four banking sectors from the high stability class to the medium stability one (Germany, USA, Singapore and Switzerland). As it concerns downgrades from the medium to the low stability class, they mostly involve countries from Western Asia (Azerbaijan, United Arab Emirates, Turkey), South-Eastern Asia (Indonesia, Malaysia), Eastern Europe (Moldova, Slovakia), Africa (Tunisia, Gabon, Equatorial Guinea), and Central – South America (Guatemala, Argentina, Uruguay). The misclassification errors of the model that are due to upgrades account for 30%, involving one upgrade from the medium to high stability class (Tanzania) and seven upgrades from low to medium stability class (Kenya, Honduras, Sudan, Uzbekistan, Nicaragua, Syria, and Vietnam).

5. Conclusions

The recent financial crisis that started in the US and the UK and spread across the globe, highlighted the importance of early warning models to assess the stability of the banking sector. Using a sample of 114 banking sectors, and a set of eleven

[3] These are mostly countries from Oceania (New Zealand, Australia), Europe (Spain, UK, Slovenia, Czech Republic), Israel, and South-eastern Asia (Korea, Malaysia).

variables we developed three multicriteria decision aid models to classify banking sectors as “high stability”, “medium stability,” and “low stability”. These models were capable in classifying correctly between 75.60% and 79.81% in the validation sample. Models developed with discriminant analysis and logistic regression for benchmarking purposes achieved accuracies around 67%. The models developed in the present study could be useful in assessing the soundness of the banking sectors and monitor them as their stability deteriorates from the group of “high stability” to the one of “low stability”.

References

Barnes P., (2000), The identification of U.K. takeover targets using published historical cost accounting data. Some empirical evidence comparing logit with linear discriminant analysis and raw financial ratios with industry-relative ratios, International Review of Financial Analysis, 9(2), 147−162.

Barth, J.R., Caprio G. Jr, Levine, R., (2004), Bank regulation and supervision: what works best? Journal of Financial Intermediation, 13, 205-248.

Beck T., Demirguç-Kunt A., Levine R., (2000), A New Database on Financial Development and Structure, World Bank Economic Review, 14, 597-605.

Beck T., Demirguç-Kunt A., Levine R., (2007), A New Database on Financial Development and Structure (1960-2007), September 2007 update, World Bank.

Beck T., Dermirguc-Kunt A., Levine R., (2006), Bank concentration, competition and crises: First results. Journal of Banking and Finance, 30, 1581-1603.

Bell J., Pain D., (2000), Leading indicator models of banking crises – a critical review, Financial Stability Review, December, 113-129.

Caprio G., Jr., Klingebiel D., (1996), Bank Insolvencies: Cross-country Experience, World Bank Policy Research Working Paper 1620, July.

Caprio G., Klingebiel D., (2003), Episodes of Systemic and Borderline Financial Crises, January, World Bank, available at http://go.worldbank.org/5DYGICS7B0

Davis E.P., Karim D., (2008), Comparing early warning systems for banking crises, Journal of Financial Stability, 4, 89-120.

De Nicolo G., Bartholomew P., Zaman J., Zephirin M., (2004), Bank consolidation, internationalization, and conglomeration: Trends and implications for financial risk. Financial Markets, Institutions & Instruments, 13, 173-217.

Demirguc-Kunt A., Detragiache E., (1998), The Determinants of Banking Crises in Developing and Developed Countries, IMF Staff Papers, 45, 81-109.

Demirguc-Kunt A., Detragiache E., (2002), Does deposit insurance increase banking system stability? An empirical investigation. Journal of Monetary Economics 49, 1373-1406.

Demirguc-Kunt A., Kane E.J., (2002) Deposit insurance around the world: Where does it work? Journal of Economic Perspectives 16, 175-195.

Demirguc-Kunt A., Karacaovali B., Laeven L., (2005), Deposit Insurance around the World: A Comprehensive Database, World Bank Policy Research Working Paper 3628, June.

Demirguc-Kunt A., Laeven L., Levine R., (2004), Regulations, Market Structure, Institutions and the Cost of Financial Intermediation, Journal of Money, Credit and Banking, 36, 593-622.

Doumpos M., Marinakis Y., Marinaki M., Zopounidis C. (2009), An evolutionary approach to construction of outranking models for multicriteria classification: The case of the ELECTRE TRI method, European Journal of Operational Research (in press).

Doumpos M., Zopounidis C., (2004), Developing sorting models using preference disaggregation analysis: An experimental investigation, European Journal of Operational Research, 154, 585-598.

Espahbodi H., Espahbodi P., (2003), Binary choice models for corporate takeover, Journal of Banking and Finance, 27, 549−574.

Evrensel A.Y., (2008), Banking crisis and financial structure: A survival-time analysis, International Review of Economics and Finance, 17, 589-602.

Keeley M.C., 1990. Deposit insurance, risk, and market power in banking. American Economic Review 5, 1183-1200.

Laeven L., Valencia F., (2008), Systemic Banking Crises: A New Database, IMF Working Paper 08/224, October.

Lanine G., Vander Vennet R., (2006), Failure prediction in the Russian bank sector with logit and trait recognition models, Expert Systems with Applications, 30, 463-478.

Moshirian F., Wu Q., (2009), Banking industry volatility and banking crises, International Financial Markets, Institutions and Money, In press.

Noy I., (2004), Financial liberalization, prudential supervision, and the onset of banking crises, Emerging Markets Review, 5, 341-359.

Pasiouras F., Gaganis C., Doumpos M., (2007a), A multicriteria discrimination approach for the credit ratings of Asian banks, Annals of Finance, 3, 351- 367.

Pasiouras F., Tanna S., Zopounidis C., (2007), The identification of acquisition targets in the EU banking industry: An application of multicriteria approaches, International Review of Financial Analysis, 16, 262-281.

Roy, B., and Bouyssou, D. (1993), *Aide Multicritère à la Décision: Méthodes et Cas*, Economica, Paris.

Wheelock D.C., Wilson P.W., (2000), Why do banks disappear? The determinants of U.S. bank failures and acquisitions, The Review of Economics and Statistics 82, 127-138.

Zopounidis C., Doumpos M., (2002), Multi-group discrimination using multi-criteria analysis: Illustrations from the field of finance, European Journal of Operational Research, 139, 371-389.

Table 1– Within-stability group geographical composition (%) of the sample

	High Stability	Medium Stability	Low Stability	Overall
Africa	5.0	25.3	33.3	22.8
Northern & Western Europe	55.0	5.1	0.0	13.2
Western Asia & Middle East	0.0	15.2	6.7	11.4
South-eastern Asia & Oceania	15.0	8.9	13.3	10.5
Central America	0.0	10.1	20.0	9.6
Southern America	5.0	8.9	13.3	8.8
Eastern Europe	0.0	11.4	0.0	7.9
Southern Europe	10.0	8.9	0.0	7.9
Central Asia	0.0	6.3	13.3	6.1
North America	10.0	0.0	0.0	1.8
All sample	100	100	100	100

Table 2 –Definition and Sources of Criteria

	Calculation-Description	Source
Regulations		
BFREG	Index of Banking and Financial Regulatory Freedom. Higher scores indicate higher freedom	Heritage Foundation
DEPINS	Dummy variable taking the value of 1 if there is an explicit deposit insurance scheme and 0 otherwise	Demirguc-Kunt et al. (2005)
Other Banking and Financial Industry Attributes		
BLIQ	Average ratio of bank credit to bank deposits in the banking sector	Beck et al. (2000, 2007)
BCONC	Concentration in the banking industry (% of assets held by 3 largest banks)	Beck et al. (2000, 2007)
BROA	Average return on assets in the banking industry	Beck et al. (2000, 2007)
CRGDP	Domestic credit to private sector /GDP	World Development Indicators
Institutional environment		
PRIGHTS	Index of Property Rights. Higher figures indicate more secured property rights	Heritage Foundation
CORRUPT	Index of Corruption Higher figures indicate lower corruption	Heritage Foundation
GDPCAP	GDP per capita ($US) in constant prices	World Development Indicators
Macroeconomic conditions		
GDPGR	GDP growth (%)	World Development Indicators
INFL	Inflation rate (%)	World Development Indicators

Table 3– Descriptive Statistics

	High Stability			Medium stability			Low Stability			Kruskal – Wallis
	Mean	**Median**	Std. Dev.	**Mean**	**Median**	Std. Dev.	**Mean**	**Median**	Std. Dev.	
Deposit insurance	0.85	1.00	0.49	0.62	1.00	0.49	0.53	1.00	0.52	4.67*
Credit to private sector / GDP	133.26	129.84	45.27	54.30	40.40	45.27	31.11	25.67	21.33	33.90***
GDP growth	3.55	3.25	3.30	6.54	6.20	3.30	6.00	6.90	4.41	19.29***
GDP per capita	26971.63	27732.77	6500.55	5796.14	2867.75	6500.55	1375.54	783.03	1482.34	48.90***
Inflation	2.13	2.01	6.63	7.34	5.58	6.63	25.04	8.24	59.18	25.65***
Banking & financial index	68.00	70.00	16.55	53.42	50.00	16.55	38.46	38.46	19.58	19.47***
Property rights index	83.50	90.00	18.31	44.43	40.00	18.31	27.69	30.00	10.79	51.12***
Corruption index	79.55	82.50	16.42	38.97	34.00	16.42	26.08	26.00	4.22	50.35***
Bank credit / Bank deposits	1.30	1.20	0.44	0.98	0.91	0.44	0.82	0.83	0.25	7.35**
Bank concentration	75.65	0.78	0.18	66.85	0.66	0.18	75.66	0.79	0.19	5.79*
ROA	1.14	0.01	0.02	1.72	0.01	0.02	2.33	0.02	0.04	5.63*

The Kruskal-Wallis test indicates whether there are statistically significant differences between the three groups. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 4– Weights of Criteria (averages over 10 replications, in %)

			MHDIS			
	UTADIS	ELECTRE TRI	U_1	$U_{\sim 1}$	U_2	$U_{\sim 2}$
DEPINS	0.21	3.54	0.00	0.00	1.26	0.68
CRGDP	2.37	6.33	20.47	26.87	14.98	13.61
GDPGR	6.91	11.46	3.85	0.36	13.36	17.41
GDPCAP	4.78	15.88	18.32	16.67	5.78	8.07
INFL	9.78	11.66	9.77	13.43	5.75	7.36
BFREG	20.27	8.30	0.01	0.01	18.67	17.43
PRIGHTS	12.61	11.47	8.75	6.34	6.77	3.08
CORRUPT	20.17	9.36	19.35	20.91	7.28	9.46
BLIQ	12.36	5.66	10.63	7.76	7.27	5.86
BCONC	5.19	8.33	1.90	2.29	16.23	12.20
BROA	5.34	8.02	6.95	5.36	2.63	4.83

Table 5 – Classification results (averages over 10-fold cross-validation)

	High Stability	**Medium Stability**	**Low Stability**	**Average**
Panel A: Estimation				
ELECTRE TRI	93.83%	78.56%	98.35%	90.25%
UTADIS	95.53%	65.26%	97.08%	85.96%
MHDIS	100.00%	99.86%	100.00%	99.95%
DA	90.51%	63.47%	81.81%	78.60%
LR	80.93%	95.90%	26.31%	67.71%
Panel B: validation				
ELECTRE TRI	82.41%	73.69%	83.33%	79.81%
UTADIS	87.96%	65.21%	83.33%	78.83%
MHDIS	78.70%	79.34%	68.75%	75.60%
DA	76.67%	62.98%	62.50%	67.38%
LR	85.19%	93.64%	22.22%	67.02%