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List of Working Papers

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2010.02 Bank productivity change and off-balance-sheet activities across different levels of economic development
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2012.01 Multicriteria decision aid models for the prediction of securities class actions: Evidence from the banking sector
V. Balla, C. Gaganis, F. Pasiouras, C. Zopounidis

Multicriteria decision aid models for the prediction of securities class actions: evidence from the banking sector

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Abstract

In recent years, there has been an increase in the number and value of securities class actions (SCAs), attracting the attention of various stakeholders such as investors, managers, policy makers, lawyers, etc. The present study extends the literature, by investigating for the first time the development of a classification model to forecast securities class actions filed against U.S. banks. Our results show that the proposed multicriteria decision aid model achieves a satisfactory accuracy, by classifying correct around 80% of the banks in an out-of-sample testing. We obtain similar results when we use a walk-forward approach, instead of a ten-fold cross validation technique, for the estimation and testing of the model. Further analysis indicates that the classification accuracies can improve further by the inclusion of a corporate governance indicator that relates to executive and director compensation and ownership.

Keywords: Banks, Classification, UTADIS, SCAs

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1. Introduction

A security class action (SCA) allows a representative stakeholder to initiate a legal suit against a corporation on behalf of a number of other stakeholders who are in similar situation. Apparently, SCAs can under certain circumstances influence in a material respect the reputation and the soundness of the enterprise and threaten the so-called going concern.

For instance, Pellegrina and Saraceno (2011) claim that the amount of the SCAs can be considered as a warning signal as far as the stability of the firm is concerned. There are at least three reasons for this. First, even the announcement of a filing of a SCA, might have a negative influence on the goodwill and reputation of the firm. Furthermore, when the settlement of the SCA case is very high, the firm may lose serious amounts of money. For example, data from Cornerstone Research reveal that the average settlement of court-approved SCAs since the passage of the Reform Act in 1995 through 2009 was $54.8 millions with the total amount of settlements reaching $61.5 billions. Second, SCA lawsuits affect stock returns, with negative stock price reactions (Bhagat et al., 1994; Gande et al. 2009). Further statistics from Cornerstone Research indicate that the mean total disclosure dollar loss over the period 1997-2009 was $133 billions with the mean total maximum dollar loss reaching $696 billions.[1] Third, SCAs may affect the cost of capital. The majority of companies rely on equity capital to expand their operations; however, due to the occurrence of a lawsuit filing, firms may find it difficult to raise new capital. Furthermore, corporate governance weakens, and an increase in information asymmetry between managers and investors takes place.

Therefore it is not surprising that a growing strand of the literature examines the phenomenon of securities class actions. Most of studies provide insights into the litigation process and analyze the effects of lawsuits on corporations (e.g. McTier and Wald, 2011). Others examine the factors the influence the probability of a SCA (e.g. Romano, 1991; Strahan, 1998). However, there are no studies focusing on the development of quantitative models to forecast SCAs in advance of their occurrence.

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[1] Cornerstone Research defines the two terms as follows. "Disclosure dollar loss" is the dollar value change in the market capitalization of the defendant firm between the trading day immediately preceding the end of the class period and the trading day immediately following the end of the class period. "Maximum dollar loss" is the dollar value change in the market capitalization of the defendant firm from the trading day during the class period when its market capitalization was the highest to the trading day immediately following the end of the class period.

This study attempts to close this gap by applying a multicriteria method, namely UTilités Additives DIScriminantes (UTADIS), to develop a classification model that discriminates between firms that face a SCA and those that do not. For the purposes of the present study, we concentrate on the banking industry for various reasons. First, banks have been traditionally subject to a number of SCAs. Second, banks are complex organizations with many divisions and multiple procedures that must be followed to comply with regulations. This differentiates them from firms operating in other sectors. Third, the recent financial crisis resulted in a number of credit-crisis cases filed since 2007. Thus, a number of financial institutions lost great amounts of money in credit-crisis related settlements, with the highest ones recorded in the case of the Countrywide Financial Corp. ($624 millions), Merrill Lynch & Co Inc. ($475 millions), New Century Financial Corp. ($124.8 millions), etc. (see Ryan and Simmons, 2011).

The rest of the paper is as follows. Section 2 discusses the variables and the dataset. Section 3 describes the UTADIS methodology. Section 4 discusses the results, and Section 5 concludes.

2. Variables and Dataset

Since there is no prior research on the prediction of SCAs, we select the variables for our study based on the CAMEL model, and the study of Pellegrina and Saraceno (2011) that focuses on the determinants of SCAs in banking.[2]

To account for capital strength we use the equity to total assets ratio. To control for asset quality we use the ratio of loan loss reserves to gross loans. Earnings are measured with the return on average assets that is the most commonly used indicator of profitability. The liquidity position of the banks is capture by the liquid assets to deposits and short term funding. We also control for loan activity, using the net loans to total assets, and for size using the logarithm of total assets. The inclusion

[2] CAMEL stands for Capital, Asset quality, Management, Earnings and Liquidity. The rationale for its use in the present study lies on the fact that investors, credit agencies, researchers, and bank regulators tend to evaluate banks along the dimensions of this model. Consistent with most of the previous studies, *Management* has not been included in the analysis due to its qualitative nature and the subjective analysis that is required. It would also be interesting to include variables related to corporate governance and internal control; however, such data were not available in our case. We hope that future research will improve upon this.

of the latter in the analysis is motivated by the findings of Pellegrina and Saraceno (2011) illustrating that SCAs target larger and "deep-pocketed" banks.

Following past studies on SCAs, we started the construction of a list of firms that faced a SCA by looking at the Standford Securities Class Action Clearinghouse Website. To be included in the sample, banks must have had information about the variables discussed above in the OSIRIS or BankScope databases of Bureau van Dijk. This gave us a sample of 120 SCA lawsuits that took place between 2002 and mid-2011.[3] Then, we matched the 120 SCAs to a control sample of 120 banks that never faced a SCA lawsuit in the past. Matching was performed on the basis of bank type and year.

3. UTilités Additives DIScriminantes (UTADIS*)*

The UTADIS approach develops an additive utility function of the following form:

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

where w_i is the weight of criterion (i.e. variable) g_i (the criteria weights sum up to 1) and $u_i'(g_i)$ is the corresponding marginal utility function normalized between 0 and 1.[4] The marginal utility functions provide a mechanism for decomposing the aggregate result (global utility) in terms of individual assessment to the criterion level. To avoid the estimation of both the criteria weights and the marginal utility 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 utility function is simplified to the following form which provides an aggregate score $U(x)$ for each bank along all criteria (i.e. variables):

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

[3]These 120 SCAs involve 87 banks. The number of fillings is higher because some banks faced more than one SCA during the period of our study.
[4] The use of the term "criterion" instead of "variable" originates from the multicriteria decision aid literature. We use the two terms interchangeably for the rest of the paper.

In the case of SCAs prediction, *U(x)* provides the basis for determining whether the bank could be classified in the group of non-SCA banks (C_1) or the SCA ones (C_2), using the following classification rule:

$$\left.\begin{array}{ll} U(x) \geq u_1 & \Rightarrow x \in C_1 \\ U(x) < u_1 & \Rightarrow x \in C_2 \end{array}\right\} \qquad (3)$$

The estimation of the additive value function and the cut-off threshold *(u_1)* 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 banks 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 banks in the training sample. Detailed description of the mathematical programming formulation can be found in the work of Doumpos and Zopounidis (2004).[5]

The model is developed and tested on the basis of a 10-fold cross validation approach. This allows the maximum use of the available data in the estimation stage, while ensuring the proper out-of-sample validation of the model. Thus, the total sample of 240 banks is initially 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. Thus, in each of the 10 replications, the training sample consists of 216 banks, whereas the validation (holdout) sample consists of not-the-same 24 banks. The average error rate over all the 10 replications is the cross-validated error rate.

4. Results

4.1. Base Results

Table 1 presents descriptive statistics of the variables, while distinguishing between the two groups of banks. The results of a Kruskal-Wallis test shows that the univariate differences are statistically significant in all the cases.

[5] To the best of our knowledge, UTADIS has been successfully applied in a number of studies in the field of banking, accounting and finance (e.g. Pasiouras et al., 2007, 2010; Ioannidis et al, 2010) but not in the prediction of SCAs.

[Insert Table 1 Around Here]

The results in Table 2 show the average weights of the six criteria over the ten replications of the cross-fold validation approach. Clearly, size appears to be the most important criterion in the UTADIS model, in discriminating between banks that face an SCA and those that does not, with an average weight equal to 42.48%. This is consistent with the findings of Pellegrina and Saraceno (2011) confirming that investors suit larger and potentially “deep-pocketed” banks. Asset quality and profitability also appear to be quite important criteria with loan loss reserves (% gross loans) and profits (% average assets) accounting together for another 44.35%. Capital strength (equity to assets ratio) also plays a moderate role with an average weight over the ten replications equal to 11.38%. In contrast, liquidity, and loan activity do not appear to contribute in the model, despite their univariate significance.

[Insert Table 2 Around Here]

Table 3 presents the classification accuracies. For benchmarking purposes, at this stage we construct two additional models using two traditional techniques, namely discriminant analysis (DA) and ordinary logistic regression (OLR). Although there are important differences in the underlying philosophies of UTADIS, DA and OLR, the comparison of these techniques in a common set of data is well documented, since they can all be applied to discriminate between SCAs and non-SCAs banks. The models generated through DA and OLR, are developed and tested following exactly the same methodology that was used in the development of the classification model through UTADIS. The overall correct classifications at the training stage range between 77.05% (DA) and 79.59% (UTADIS). Thus, all three methods are able to provide a satisfactory distinction between SCAs and non-SCAs, with UTADIS achieving slightly better classification results. However, these results refer to the same banks that were used to develop the models, and the potential upwards bias should be kept in mind.

Thus, we turn to the results in the validation datasets (Panel B) that provide a more accurate assessment of the performance of the classification models. We observe two things. First, all three models are quite robust in terms of the achieved classification accuracies (compared to the training sample). However, UTADIS records the lowest decrease, with the overall classification accuracy falling by just 0.10%. At the same time the accuracy of DA decreases by 1.76% and that of OLR by 1.44%. Second, UTADIS outperforms DA and OLR in both group-specific accuracies, classifying correctly 83.71% of banks in Group 1 (i.e. SCAs) and 75.47% of banks in Group 2 (non-SCAs). The corresponding figures are 79.72% and 73.40% in the case of OLR, and 79.64% and 70.94% in the case of DA.

Finally, it is worthwhile mentioning that apart from the observed differences in the classification accuracies, another advantage of the UTADIS method is that it is not making any assumptions, as the traditional statistical and econometric techniques, about the normality of the variables or the group dispersion matrices (e.g., discriminant analysis) and is not so sensitive to multicollinearity or outliers (e.g., logit analysis).

[Insert Table 3 Around Here]

4.2. Further Analysis

In this section, we present the results of further analysis. First, we re-estimate our base model using a walk-forward approach rather than cross-validation. Second, we re-estimate our base model by incorporating bank corporate governance characteristics in the analysis.

4.2.1 Walk-forward approach

As mentioned earlier, the main advantage of the cross-validation technique is that it allows the estimation of the model with the maximum use of the available data, while performing an out-of-sample validation of the model. This is of particular importance when one uses a moderate sample size like the one of the present study. However, one drawback of such re-sampling techniques is that they do not provide an out-of-time evaluation, and thus they do not account for the case of a "drifting" population. Therefore, to test the stability of the model over time, we adopt a walk-forward technique, similar to the one used in Pasiouras et al. (2007), among others. For the purposes of the present study, the first model was developed with data from years 2002 to 2007 and was then tested on data from the year 2008. As such, the outputs of the first model for 2008 are out-of-time for banks existing in previous years (i.e. 2002-2007), and out-of sample for banks whose data become available after 2007 (i.e. in 2008). Then, we re-estimate the model using data from 2002-2008, and test it in 2009, and so on. We use the 2002-2007 time period for the estimation of the first model, due to the small number of observations that were available from each year. Furthermore, this cut-off point corresponds with the beginning of the crisis.[6] Obviously, this is a very strong test for our model since it is estimated in the pre-crisis period and validated during the crisis.

The results in Table 4 show that the classification accuracy of the models developed through UTADIS ranges between 66.67% (2011) and 84.52% (2008) in the validation sample, with the average over the entire period being equal to 76.03%.[7] Thus, the performance of the UTADIS model appears to be quite robust over time.[8]

[Insert Table 4 Around Here]

4.2.2 Corporate governance and classification accuracy

Theory predicts that SCAs should be related to corporate governance due to managerial agency problems, while the reasons for which SCAs are filed (e.g. stock price manipulation, insider trading of directors, misstatements in financial statements, compensation disclosures, etc.) appear to confirm the existence of weak corporate governance and internal control systems. Thus, in this part of the analysis we examine whether the inclusion of corporate governance related characteristics improves the classification accuracy of the models.

We use the Corporate Governance Quotient (CGQ) that is calculated by RiskMetrics.[9] This index quantifies the quality of a firm's governance practices in relation to other firms from the same sector, and it is calculated on the basis of approximately sixty variables falling in the following four broad groups: (i) board of

[6] Many colleagues and market participants argue that the crisis started in mid-2007. Thus, it is not clear whether 2007 should be part of the pre-crisis or the crisis period. For the purposes of the present study, we include it in the pre-crisis period to ensure that we have a sufficient number of observations for the estimation of the model.

[7] The relatively low classification accuracy in 2011 can be attributed to the very small validation sample in 2011 that consist of 6 banks, only.

[8] Furthermore, in all the cases, the models developed through UTADIS outperform the ones developed with DA and OLR using the same walk-forward approach. To conserve space these results are not presented, but they are available from the authors upon request.

[9] RiskMetrics is used frequently as a source of information in studies related to corporate governance (see e.g. Bruno and Claessens, 2010; Aggarwal et al., 2011).

directors, (ii) executive and director compensation and ownership, (iii) audit, and (iv) takeover defense. In all the cases, the scores are calculated in such a way that higher values indicate better governance mechanisms. The subscores for the four categories range between one and five. A score of five (one) reveals that the firm is in the top (low) quintile in a governance area. Theoretically, the CGQ index may take values between zero and one hundred, with higher values indicating better governance.

The category "board of directors" (BOARD) includes various board aspects such as: board composition, nominating committee's composition, compensation committee's composition, governance committee, board size, changes in board size, cumulating voting, boards served on by the CEO, former CEOs on the board, Chairman/CEO separation, board attendance, related-party transactions involving officers and directors, majority voting, etc. The category executive and director compensation and ownership (COMP_OWNER) includes indicators related to: (i) ownership (e.g. director stock ownership, executive and director stock ownership guidelines, officer and director stock ownership levels, etc.), (ii) executive and director compensation (e.g. cost of option plans, compensation committee interlocks, director compensation, performance-based compensation, option expensing, etc.), (iii) progressive practices (e.g. board performance review, individual director performance reviews, meetings of outside directors, etc.), and (iv) director education (i.e. directors' participation in education programs). The third group (ANTITAKE) considers: (i) the Charter/Bylaws (e.g. poison pill adoption, poison pill-shareholder approval, review of the vote requirement to amend the charter/bylaws and to approve mergers, review of whether shareholders may call special meetings, review of capital structure, etc.), and (ii) the stage of incorporation (e.g. state of incorporation antitakeover provisions, control share acquisition, control share cashout, freezeout, stake endorsement of poison pills). The fourth group (AUDIT) considers the independence of the members of the audit committee, audit fees, auditor ratification, the financial expert composition of the audit committee, financial results restatements during the past 24 months, etc.

Owning to missing data for the CGQ index, our sample now includes 46 SCAs and 46 non-SCAs. This decrease in the sample size by approximately 50% does not allow us to compare these results with the ones obtained in our base analysis. Thus, we also re-estimate the model that incorporates only the financial variables, to use it as a benchmark. For the same reason (i.e. reduction in sample), we rely on the use of the cross-validation approach rather than the walk-forward approach. After all, the analysis in 4.2.1 illustrates the robustness of the results.

The CGQ index obtains a small weight in the UTADIS model that is equal to 3.22%. The results in Table 5 show that the classification accuracy in the training sample improves slightly compared to the model that contains the financial ratios only (i.e. 87.54% versus 86.82%). However, this is no longer the case, when assessing the performance of the model in the validation sample, with the classification accuracy being 80.20% (financial ratios) and 77.29% (CGQ and financial ratios). Thus, it appears that the CGQ index makes only a marginal contribution (in terms of the variable’s weight), and it decreases the out-of sample classification accuracy of the UTADIS model.

[Insert Table 5 Around Here]

To investigate this issue further, we replace the CGQ index by the various subscores, by including them in the analysis one-by-one. Thus, the first model includes the subscore BOARD and the financial ratios. The second includes the subscore COMP_OWNER and the financial ratios, and so on. The contribution of these variables (in terms of weights) ranges between 0% (AUDIT) and 12.30% (COMP_OWNER). The inclusion of the BOARD and ANTITAKE variables worsens slightly the performance of the model, with the average accuracy being 79.37% and 78.54%, respectively. The model that includes the variable AUDIT yields exactly the same results as the one that includes only the financial variables. This also explains why the weight of the AUDIT variable equals 0%.

The picture changes when we consider the model that includes the COMP_OWNER variable. In this case, the accuracy of the model improves by 8.67% in the case of the non-SCA group, and by 5.33% in the case of the SCA group. As a result, the average accuracy of this model stands at 87.20% that is a considerable improvement compared to the model that includes only the financial ratios (i.e. 80.20%). Potential explanations for the contribution of the COMP_OWNER variable are among others that stock ownership by directors may align their interests with those of shareholders, it can prevent fraud, and it can result to excess accounting returns and stock price returns. Furthermore, the proper construction of compensation-performance schemes may result in less dissatisfied shareholders, decreasing the probability of security class actions.

The opposing results that we obtain when using the four subscores of governance explain why the inclusion of the CGQ index in the analysis does not improve the accuracy of the base model with the financial ratios.

5. Conclusions

Banking institutions have been traditionally subject to securities class actions, a phenomenon that was accelerated with the financial crisis. Thus, a number of financial institutions lost great amounts of money in credit-crisis related settlements, and they also observed a fall in their share price. The present study examines the potential development of a quantitative model that predicts securities class actions filed against U.S. banks. Such a model could be of use to bank managers, investors, and policy makers.

We use a sample of 120 SCA cases matched by an equal number of non-SCA cases, a multicriteria decision aid technique, and a ten-fold cross-validation technique. We find that the proposed model achieves a satisfactory accuracy, by classifying correct around 80% of the banks in an out-of-sample testing. This model performs better than traditional techniques like discriminant and logit analyses used for benchmarking purposes. In further analysis, we use a walk-forward approach instead of ten-fold cross-validation technique. The results are comparable, illustrating the stability of the model in out-of-time and out-of-sample prediction. Then, we incorporate corporate governance characteristics in the analysis. Initially, we use an aggregate index that controls for board quality, directors' compensation and ownership, auditing, and antitakeover. We also consider these indicators on an individual basis. The results show that directors' compensation and ownership is the only governance characteristic that improves the classification accuracy of the model with the financial variables.

The current research could be extended towards several directions. First of all, alternative classification techniques, such as neural networks and support vector machines could be employed and compared with the developed models. Furthermore, the results of the different methods could be combined in an integrated model, an approach that has resulted in promising outcomes in applications in other disciplines. Third, the development of multicriteria decision support systems could be particular useful for investors and managers interesting in discriminating between banks that could face an SCA and those that are not likely SCA targets. We hope that future research will improve upon these issues. Until then, our study presents a first effort to construct a classification model for the prediction of banks' SCAs.

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Table 1 – Descriptive statistics

	Non-SCA		SCA		
	Mean	**Std. Deviation**	**Mean**	**Std. Deviation**	Kruskal–Wallis (p-value)
Equity / Total assets	12.54	8.64	8.26	7.56	0.000
Loan loss reserves / Gross loans	2.44	2.65	1.66	2.13	0.000
Return on average assets	0.93	2.16	0.25	1.99	0.000
Liquid assets/ Deposits & short term funding	20.49	44.37	70.94	115.09	0.000
Net loans / Total assets (-)	62.28	19.06	39.40	26.84	0.000
Logarithm of total assets (-)	6.91	1.08	8.04	0.97	0.000

Table 2 –Weights of criteria (variables) in the UTADIS model (average over 10 replications)

Equity / Total assets	11.38%
Loan loss reserves / Gross loans	24.64%
Return on average assets	19.71%
Liquid assets/ Deposits & short term funding	1.79%
Net loans / Total assets	0.00%
Logarithm of total assets	42.48%

Table 3 – Classification results (average over 10 replications)

	Group		
	Non-SCA	SCA	Overall
Panel A: Training			
UTADIS	83.71%	75.47%	79.59%
OLR	80.26%	75.74%	78.00%
DA	81.50%	72.61%	77.05%
Panel B: Validation			
UTADIS	82.89%	76.10%	79.49%
OLR	79.72%	73.40%	76.56%
DA	79.64%	70.94%	75.29%

Notes: UTADIS: UTilités Additives DIScriminantes, OLR: Ordinary Logistic Regression, DA: Discriminant Analysis

Table 4 – Classification results – UTADIS model
(Walk forward approach)

	Estimation				Validation			
		Non-SCA	SCA	Average		Non-SCA	SCA	Average
Model 1	2002-2007	88.10%	80.95%	84.52%	2008	88.10%	80.95%	84.52%
Model 2	2002-2008	87.84%	79.73%	83.78%	2009	82.61%	78.26%	80.43%
Model 3	2002-2009	86.60%	75.26%	80.93%	2010	75.00%	70.00%	72.50%
Model 4	2002-2010	83.76%	77.78%	80.77%	2011	100.00%	33.33%	66.67%
Average		86.57%	78.43%	82.50%		86.43%	65.64%	76.03%

Table 5 – Classification results – UTADIS model
(Corporate Governance and financial variables)

	Training			**Validation**		
Model	Non-SCA	SCA	Average	Non-SCA	SCA	Average
Financial Variables only	87.44%	86.20%	86.82%	80.33%	80.07%	80.20%
Financial variables + CGQ	86.72%	88.37%	87.54%	76.17%	78.40%	77.29%
Financial variables + BOARD	88.90%	87.16%	88.03%	78.67%	80.07%	79.37%
Financial variables + COMP_OWNER	91.07%	89.84%	90.45%	89.00%	85.40%	87.20%
Financial variables + ANTITAKE	87.94%	85.73%	86.83%	80.33%	76.74%	78.54%
Financial variables + AUDIT	87.44%	86.20%	86.82%	80.33%	80.07%	80.20%

Notes: CGQ: RiskMetrics Corporate Governance Quotient aggregate index; BOARD: index for board quality; COMP_OWNER: index for executive and director compensation and ownership; ANTITAKE: antitakeover index; AUDIT: index for auditing quality