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Developing Multicriteria Decision Aid Models for the Prediction of Share Repurchases

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Developing multicriteria decision aid models for the prediction of share repurchases

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Abstract

This study presents the first attempt to develop classification models for the prediction of share repurchases using multicriteria decision aid (MCDA) methods. The MCDA models are developed using two methods namely UTilités Additives DIScriminantes (UTADIS) and ELimination and Choice Expressing REality (ELECTRE) TRI, through a ten-fold cross-validation approach. The sample consists of 1060 firms from France, Germany and the UK. We find that both MCDA models achieve quite satisfactory classification accuracies in the validation sample and they outperform both logistic regression and chance predictions.

Keywords: Multicriteria, Share repurchases

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1. Introduction

The last two decades have witnessed a dramatic increase in the use of share repurchases. For example, as Grullon and Michaely (2002) highlight, expenditures on share repurchase programs (relative to total earnings) increased from 4.8% in 1980 to 41.8% in 2000, while more recent data from Standard and Poor's, show that share repurchases among companies that comprise the S&P 500 reached a record $172 billion during the third quarter of 2007. Given the growth in the importance and popularity of share repurchases, it is not surprising that this topic has attracted considerable attention in the literature. A number of studies have examined among others the short-and long-run valuation effects (e.g. Ikenberry, et al., 1995; McNally and Smith, 2007) as well as the determinants and motives of share repurchases (e.g. Grullon and Michaely, 2002; Baker et al., 2003).

The present study employs an alternative approach to extend the literature, by examining the possibility of developing multicriteria decision aid (MCDA) classification models for the prediction of firms' open market share repurchases announcements. The development of such models, although quite important has received limited attention compared to other financial decision making classification problems such as bankruptcy prediction and credit risk assessment where hundreds of papers have been published. This is surprising since there are a number of potential users of such models. First, existing empirical studies document large abnormal returns around the announcement day (Dann, 1981; Vermaelen, 1981; Comment and Jarrell, 1991) as well as in subsequent years (Ikenberry et al. 1995; Gong et al. 2008). Thus, from the perspective of a potential investor, the ability to identify share repurchases in advance, could result in the generation of a portfolio of stocks with abnormal returns. From the perspective of an existing stockholder, the ability to predict share repurchases could be useful in his decision on whether to hold or sell his share. Finally, from a managerial perspective, it may be useful to be in a position to predict in advance the decision of managers in peer firms.

To the best of our knowledge, up to date only Andriosopoulos (2010) has tested the out-of-sample prediction accuracy of his model using logistic regression. However, the MCDA methods proposed in the present study pose various advantages over traditional statistical and econometric methods such as discriminant analysis and logistic regression. For example, they do not make any assumptions about the normality of the variables or the group dispersion matrices, they are not sensitive to multicollinearity or outliers, they can easily incorporate qualitative data, and they are also very flexible in terms of incorporating any preferences of the decision maker. Furthermore, various finance and accounting applications from the field of bankruptcy prediction, credit risk assessment, acquisitions prediction, and auditing reveal that the MCDA methods tend to outperform traditional methodologies (e.g. Doumpos and Zopounidis, 2001; Pasiouras et al., 2007a; Ioannidis et al., 2010).

We use a sample of 530 open market share repurchases that were announced in France, Germany and the UK between 1997 and 2006 and an equally matched control group to develop two MCDA models for each country. For benchmarking purposes we compare the results of the MCDA models with the ones obtained by logistic regression. All the models are estimated and tested using a ten-fold cross-validation approach. Our results show that the MCDA models classify correctly around 70% of the firms in the validation sample, and they outperform logistic regression in all the cases.

The rest of the paper is as follows. Section 2 presents the data, variables and methodology. Section 3 discusses the empirical results. Section 4 concludes the study.

2. Data, Variables and Methodology

2.1. Data

The sample consists of 530 repurchasing firms and 530 non-repurchasing ones, operating in France, Germany and the UK. The sample was constructed as follows. First, we identified all the announcements of intention to repurchase ordinary shares in the open market, using news articles posted in Perfect Analysis and Factiva databases from 1st January 1997 until 31st December 2006.[1] Then, information on the share prices and accounting data were obtained from DataStream and Worldscope. Finally, repurchasing firms with available data were matched by country and year with a control sample of domestic non-repurchasing firms that have not announced a

[1] The study focuses on this period because it was not until 1998 that share repurchasing was allowed to take place more freely in both Germany and France. The Perfect Analysis and Factiva databases report any news announcements that were available in the press made by UK and European firms. Only firms that announced their intention to repurchase ordinary shares were included in the sample. The list of repurchasing firms that formed our starting basis was initially used in the study of Andriosopoulos (2010).

share repurchase announcement between 1997 and 2006. Table 1 presents information on the number of firms in the sample by year and country.

[Insert Table 1 Around Here]

2.2. Variables

To select our variables we rely on theories that have been proposed to explain the potential motives for a share repurchase as well as empirical studies. In the discussion that follows we briefly outline those variables and the rationale for their inclusion in the present study.

Firms may decide to distribute their excess cash back to their shareholders via cash dividends or share repurchases in the open market. However, open market share repurchases can be considerably more flexible as a payout method compared to dividends, and existing evidence suggests that firms are more likely to repurchase their stock when they have high cash flows and low investment opportunities (Dittmar, 2000; Mitchell and Dharmawan, 2007). As in Dittmar (2000) and Andriosopoulos (2010) to proxy for excess cash we use the ratio of net operating income before taxes and depreciation to total assets at the year end prior to the repurchase announcement (CF).

Furthermore, for capturing both a firm's growth opportunities and excess cash flow, we follow Opler and Titman (1993) and Andriosopoulos (2010) and construct a dummy variable that takes the value of one for firms that have simultaneously low Tobin's *q* (lower than the median *q* of a firm's respective industry for each respective year) and high cash flow (higher than the median cash flow of the respective industry for each year) and the value of zero otherwise (DFCF).

For investigating the impact of undervaluation on the likelihood to announce an open market share repurchase, we follow Ikenberry et al. (1995), Ikenberry et al. (2000), Barth and Kasznik (1999), and Dittmar (2000), and we include as a proxy for potential undervaluation the market-to-book ratio at the year end prior to share repurchase announcement (MKBK).

The decision to distribute excess capital as a payout to shareholders through a share repurchase, reduces a firm's equity capital, which in turn increases its leverage ratio. Consequently, Bagwell and Shoven (1988) and Hovakimian et al. (2001) argue that a share repurchase programme, displays the managers' preference to employ debt instead of equity, so that they can approach their target leverage ratio. Indeed, a number of empirical studies report evidence that firms with low leverage are more likely to repurchase their shares (Hovakimian et al., 2001; Mitchell and Dharmawan, 2007; Dittmar, 2000). Therefore, to proxy for leverage we use the ratio of total debt to total assets at the year end prior to the repurchase announcement (*LVG).*

Vermaelen (1981) argues that smaller firms are more likely to have higher information asymmetries, since they get less scrutinised by analysts and the media. Consequently, smaller firms are more likely to be misvalued, which leads to a greater likelihood of repurchasing their shares. In line with this argument, are the findings of Mitchell and Dharmawan (2007) who find that firms which are small and announce their intention to repurchase a large fraction of their outstanding capital, have a significant signalling impact. In addition, Dittmar (2000), Grullon and Michaely (2002), and Ikenberry et al. (1995) report evidence that size has a positive relationship with the volume of share repurchases. Hence, size is a firm specific characteristic, which can have a significant impact on the likelihood to announce an open market share repurchase. To capture the impact of size on the repurchasing decision we use the natural logarithm of a firm's total assets at the year end prior to the share repurchase announcement (SIZE).

Typically, capital gains tax rate is lower than the respective personal income tax rate. Therefore, share repurchases can have a significant advantage over cash dividends, from a tax perspective. Therefore, the personal tax savings hypothesis, states that share repurchases can be more tax efficient and more beneficial to shareholders, compared to cash dividends (Grullon and Michaely, 2002). While Bagwell and Shoven (1989) and Dittmar (2000) find no evidence of taxation having a significant impact on corporate payouts, a number of research studies do find evidence of tax having a significant influence on firms' decision making on payouts, and of the market having a favourable reaction due to the tax impact (Masulis, 1980; Grullon and Michaely, 2002). Furthermore, open market share repurchases can have advantages relative to cash dividends such as tax differential and that they do not pose a commitment to the firm. Therefore, open market share repurchases can be considered to be substitutes to cash dividends (Grullon and Michaely, 2002). Therefore, we assume that a firm's payment of dividends can have a significant discriminatory ability that will help determine a firm's propensity to announce an open market share repurchase. We follow Dittmar (2000) and Jagannathan and Stephens (2003), and we employ the proxy variable *DIV/NI*, which is defined as the ratio of total regular cash dividends relative to net income. Finally, for incorporating the tax impact in our models, we follow McNally (1999) and we proxy for the average tax rate with the proxy variable *DIV_Y*, which is the dividend yield ratio.

Finally, we use the ratio of net income to total assets (ROA) to capture the potential impact that a firm's profitability and operating performance may have on the likelihood to announce an open market share repurchase (Grullon and Michaely, 2004).

2.3. Multicriteria classification methods

The problem considered in this study falls within the multicriteria classification problematic, which, in general involves, the assignment of a finite set of alternatives $\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n$ to a set of q ordered classes $C_1 \succ C_2 \succ \cdots \succ C_q$. Each alternative is described by m criteria (i.e. independent variables) and consequently it can be considered as a multivariate vector $\mathbf{x}_i = (x_{i1}, x_{i2}, ..., x_{im})$, where x_{ij} is the description of alternative i on criterion j.

In the present study, the alternatives involve the 1060 firms, the criteria correspond to the eight variables discussed in Section 2.2., and there are two classes. The two MCDA methods used in the present study, originate from different disciplines. The UTADIS method employs the framework of preference disaggregation analysis while the ELECTRE TRI method implements the outranking relations approach of multicriteria decision aiding (Roy and Bouyssou, 1993). [2]

[2] Preference disaggregation analysis (Jacquet–Lagreze & Siskos, 1982, 1983, 2001) refers to the analysis (disaggregation) of the global preferences (judgement policy) of the decision maker in order to identify the criteria aggregation model that underlies the preference result. Preference disaggregation analysis uses common utility decomposition forms to model the decision maker's preferences through regression-based techniques. More detailed, in preference disaggregation analysis the parameters of the utility decomposition model are estimated through the analysis of the decision maker's overall preference on some reference alternatives. The problem is then to estimate the utility function that is as consistent as possible with the known subjective preferences of the decision maker.

2.3.1. UTADIS

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

$$U(\mathbf{x}) = \sum_{j=1}^{m} w_j u'_j(x_j) \in [0,1]$$

where w_j is the weight of criterion j (the criteria weights sum up to 1) and $u'_j(x_j)$ 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 assessments on the criteria level. To avoid the estimation of both the criteria weights and the marginal value functions, it is possible to use the transformation $u_j(x_j) = w_i u'_j(x_j)$. Since $u'_j(x_j)$ is normalized between 0 and 1, it is obvious that $u_j(x_j)$ ranges in [0, w_i]. In this way, the additive value function is simplified to the following form, which provides an aggregate score $U(\mathbf{x})$ for each firm along all criteria:

$$U(\mathbf{x}) = \sum_{j=1}^{m} u_j(x_j) \in [0,1]$$

Comparing the value utilities with the cut-off thresholds, the classification of the firms is achieved as follows:

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

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 firms 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 observations in the training sample. Doumpos and

Zopounidis (2004) provide a detailed description of the mathematical programming formulation.

2.3.2. ELECTRE TRI

Within the context of classification problems, the outranking relation is used to estimate the outranking degree of an alternative $\mathbf{x}_i$ over a reference profile $\mathbf{r}_k$, which distinguishes the classes C_k and C_{k+1}. Each reference profile $\mathbf{r}_k$ is defined as a vector of individual profiles for each criterion, i.e., $\mathbf{r}_k=(r_{k1}, r_{k2}, \ldots r_{km})$.

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

Once the outranking relation is developed, the classification of the alternatives is performed through heuristic assignment procedures. For example, ELECTRE TRI employs two assignment procedures, the pessimistic and the optimistic one. Under the pessimistic assignment, in a classification problem with q classes, each alternative $\mathbf{x}_i$ is compared successively to the profiles $\mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_{q-1}$. Let $\mathbf{r}_k$ be the first profile such that $\sigma(\mathbf{x}_i, \mathbf{r}_k)\geq\lambda$. Then, $\mathbf{x}_i$ is assigned to group C_k (if there is no profile such that $\sigma(\mathbf{x}_i, \mathbf{r}_k)\geq\lambda$, then $\mathbf{x}_i$ is assigned to group C_q). In the case of the optimistic assignment each alternative $\mathbf{x}_i$ is compared successively to the profiles $\mathbf{r}_{q-1}, \mathbf{r}_{q-2}, \ldots, \mathbf{r}_1$. Let $\mathbf{r}_k$ be the first profile such that $\mathbf{r}_k$ P $\mathbf{x}_i$. Then, $\mathbf{x}_i$ is assigned to group C_{k+1} (if the there is no profile satisfying the above condition, then $\mathbf{x}_i$ is assigned to group C_1). The differences between the two procedures appear in the presence of the incomparability relation. For instance, in a two-group case an alternative that is incomparable to the profile $\mathbf{r}_1$ will be assigned to group C_1 with the optimistic procedure and to group C_2 with the pessimistic procedure. Consequently, the differences between the two rules facilitate the identification of alternatives with special attributes, which make the comparison of the alternatives to the profiles difficult.

In the present study we use the pessimistic assignment procedure while all the parameters of the ELECTRE TRI model (e.g. weights of the criteria, thresholds, etc.) are estimated using the evolutionary optimization approach that was proposed by Doumpos et al. (2009).

3. Empirical Results

Table 2 presents descriptive statistics (median and standard deviation) along with the results of Kruskal-Wallis test of medians' differences between the two groups. The latter shows that in several cases the significance of the medians' differences varies across countries. For example, consistent with our expectations CF and ROA are higher for repurchasing firms in Germany and the UK; however, the medians are not significantly different in the case of France. In the case of DFCF, the medians differ significantly in France and the UK, but not in Germany. We observe similar differences in the case of DIV/NI and MKBK across countries. However, we also observe similarities across countries with the differences between the medians being statistically significant in all three countries in the case of DIV_Y, LVG, and SIZE.

[Insert Table 2 Around Here]

The results obtained from the two MCDA methods are analyzed both in terms of the criteria (i.e., independent variables) weights and the classification accuracy of the models. At this point it should be mentioned that an important issue of concern in evaluating the classification ability of a model is to ensure that it does not over-fit to the training (estimation) data set, and that its out-of-sample generalization ability is adequately assessed. In the present study, we adopt a 10-fold cross validation approach to develop and evaluate the models. Under this approach, the total sample of

1060 firms 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 954 firms, whereas the validation (holdout) sample consists of not-the-same 106 firms. The average error rate over all the 10 replications is the cross-validated error rate.

Table 3 illustrates the contribution of the 8 criteria in each one of the country-specific models. The presented results correspond to the average weights (in percentage) over the 10 replications of the model development process. We observe both similarities and differences between the two MCDA methods and across the three countries. For example, consistent with the univariate results, SIZE appears to be the most important variable in the three models developed through the ELECTRE TRI method as well as in the UTADIS-UK model, while at the same time it is one of the most important variables in the UTADIS models developed for Germany and France. Similarly, the total cash dividend payout to net income (DIV/NI) is the most important variable in the case of the UTADIS-Germany and UTADIS-France models, and one of the most important variables in the remaining cases. MKBK appears to have a moderate impact in most models, whereas other variables such as CF, LVG and DFCF are in general the least important ones. Turning to some differences, it appears that ROA is quite important in the UTADIS-UK model (weight of 35.86%), while it is considerably less important in the remaining models. One of the most important variables in the case of Germany is the dividend yield ratio (DIV_Y) which carries weights equal to 24.73% (UTADIS) and 21.17% (ELECTRE TRI).

The differences across the country-specific models developed with a given technique (e.g. UTADIS) could be attributed to country-specific characteristics (e.g. shareholder protection, ownership concentration) which shape managerial attitudes towards shareholder value and the choice of firm payout decisions. For example, French firms tend to be more family owned, and German firms have higher levels of ownership concentration compared to the UK. Furthermore, as discussed in Brounen et al. (2004), UK firms consider shareholder wealth maximization as one of the most prominent priorities, which is not the case in France and Germany.

While there is no particular reason for the differences between the two MCDA models developed for a given country (e.g. UK), such differences among alternative classification methods have been observed in past classification studies in finance (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 firms as possible, they consider different ways of processing the same information in the dataset. For instance, while the weights in the value functions developed with UTADIS 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.

[Insert Table 3 Around Here]

Table 4 presents the classification results. Panel A corresponds to the training sample, while Panel B corresponds to the validation sample. At this stage we also perform a comparative analysis with the corresponding results obtained through logistic regression. Since the classification accuracies in the training sample are usually upwards biased we focus on the ones obtained in the validation sample.

[Insert Table 4 Around Here]

Our results can be summarized as follows. First, the models are quite stable, with the classification accuracies in the validation sample being only slightly lower than the ones obtained in the training sample. Second, while there is no clear winner between UTADIS and ELECTRE TRI they both outperform logistic regression in all the cases in the validation sample. The best model is developed with UTADIS achieving a quite satisfactory overall accuracy that is equal to 76.96%. Third, it appears that the models developed for France are capable of classifying correctly a higher percentage of firms that then corresponding models developed for Germany and the UK. Actually, the results do indicate a fair amount of misclassification in the case of Germany which is around 33% to 37%. Fourth, with the exception of the LR-UK model, we observe that the models are capable in classifying better firms belonging in Group 1 (non-share repurchasing firms) rather than in Group 2 (share repurchasing firms). However, all the models are capable of achieving quite balanced accuracies, with the differences between the two groups being in general quite small.

As Barnes (1999) notes perfect prediction models are difficult to develop even in the bankruptcy prediction literature, where failing firms have definitely inferior or abnormal performance compared to healthy firms. The problem with the identification of firms that announce share repurchases is that are potentially many reasons for their decision, while at the same time managers do not always act in a manner which maximizes shareholder returns. It is more reasonable, therefore, to compare the performance of the models with chance assignments. Since we have equally matched samples, a naïve model based on random assignments would assign correctly 50% of the firms on average. Thus, we can conclude that all the developed models perform considerably better than chance.

4. Conclusions

In this study we developed, to the best of our knowledge for the first time in the literature, multicriteria decision aid classification models for the identification of firms announcing share repurchases. The sample consisted of 1060 firms operating in France, Germany and the UK, out of which 530 announced a share repurchase between 1997 and 2006. The models were developed using UTADIS and ELECTRE TRI, through a ten-fold cross-validation approach. Logistic regression was also employed for benchmarking purposes. To account for differences across countries we developed country specific models. Thus, a total of 9 models were developed.

Our results indicate that the characteristics that can be useful in discriminating between the two groups of firms may differ across the methods used to develop the models. However, this is not surprising and it has been the case in past studies from other disciplines as well (e.g. prediction of acquisitions, bankruptcy prediction, etc). We also find that the firm characteristics vary among countries which may be related to country-specific attributes that influence the managerial decisions with regards to share repurchases. As it concerns the classification ability of the models, the average results over the 10 replications in the validation set showed that all models achieve quite balanced accuracies between the two groups and they performed better than a naïve model based on random assignment to outcomes based on prior probabilities (i.e. 50% in an equal sample).

Future research could extend the present study towards various directions such as the testing of the usefulness of the models in other countries, the employment of and comparison with alternative methods (i.e. support vector machines, neural networks, etc), and the combination of MCDA and other methods into integrated models.

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Table 1- Sample distribution by country and year

	United Kingdom	France	Germany	Total
1997	16	2	0	18
1998	38	28	0	66
1999	28	32	16	76
2000	26	52	36	114
2001	42	26	60	128
2002	62	50	46	158
2003	48	44	26	118
2004	60	40	28	128
2005	60	18	46	124
2006	54	38	38	130
Total	434	330	296	1060

Table 2 – Descriptive Statistics & Kurskal-Wallis test

United Kingdom	Non-share repurchasing		Share repurchasing		
	Median	Std. Dev.	Median	Std. Dev.	Kruskal – Wallis (p-value)
CF	0.067	1.257	0.107	0.106	0.000***
DFCF	0.000	0.392	0.000	0.474	0.000***
DIV/NI	0.000	15.077	0.000	870.860	0.442
DIV_Y	1.016	2.280	3.009	2.691	0.000***
LVG	0.122	0.391	0.203	0.179	0.016**
MKBK	1.590	8.500	1.570	31.762	0.564
SIZE	11.322	2.494	14.130	2.506	0.000***
ROA	0.015	0.687	0.044	0.156	0.000***

France	Non-share repurchasing		Share repurchasing		
	Median	Std. Dev.	Median	Std. Dev.	Kruskal –Wallis (p-value)
CF	0.107	0.189	0.101	0.074	0.152
DFCF	0.000	0.371	0.000	0.487	0.000***
DIV/NI	0.000	2.787	0.151	310.592	0.003***
DIV_Y	1.304	2.040	1.591	1.601	0.021**
LVG	0.183	0.177	0.209	0.144	0.099*
MKBK	1.865	26.092	2.110	3.212	0.078*
SIZE	10.988	1.803	14.209	2.292	0.000***
ROA	0.031	0.141	0.029	0.092	0.226

Germany	Non-share repurchasing		Share repurchasing		
	Median	Std. Dev.	Median	Std. Dev.	Kruskal – Wallis (p-value)
CF	0.099	0.231	0.119	0.113	0.063*
DFCF	0.000	0.467	0.000	0.472	0.804
DIV/NI	0.000	1.549	0.000	11.412	0.007***
DIV_Y	0.338	1.879	1.289	1.714	0.008***
LVG	0.163	0.190	0.099	0.139	0.020**
MKBK	1.850	2.910	2.210	2.907	0.005***
SIZE	11.291	1.871	12.689	2.381	0.000***
ROA	0.015	0.260	0.032	0.127	0.003***

Notes: *** Statistically Significant at the 1 level, ** Statistically Significant at the 5 level, * Statistically Significant at the 10 level; CF = net operating income before taxes and depreciation to total assets, DFCF = dummy variable that takes the value of one for firms that have simultaneously low Tobin's *q* (lower than the median *q* of a firm's respective industry for each respective year) and high cash flow (higher than the median cash flow of the respective industry for each year), *DIV/NI* = total regular cash dividends relative to net income, *DIV_Y* = dividend yield ratio, MKBK = market-to-book ratio, LEG = total debt to total assets, SIZE = natural logarithm of a firm's total assets, ROA = net income to total assets.

Table 3– Weights of criteria (averages over 10 replications, in %)

	United Kingdom		France		Germany	
	UTADIS	ELECTRE TRI	UTADIS	ELECTRE TRI	UTADIS	ELECTRE TRI
CF	0.00	6.22	9.56	7.13	1.17	8.92
DFCF	0.00	0.03	0.00	1.93	1.47	9.58
DIV/NI	12.04	29.20	62.80	13.34	41.79	17.23
DIV_Y	1.70	1.70	0.99	3.27	24.73	21.17
LVG	0.00	8.66	0.05	8.06	0.00	1.91
MKBK	1.06	13.78	10.78	12.07	7.24	9.08
SIZE	49.33	36.07	15.23	48.50	23.53	25.69
ROA	35.86	4.33	0.60	5.69	0.08	6.41

Notes: CF = net operating income before taxes and depreciation to total assets, DFCF = dummy variable that takes the value of one for firms that have simultaneously low Tobin's *q* (lower than the median *q* of a firm's respective industry for each respective year) and high cash flow (higher than the median cash flow of the respective industry for each year), *DIV/NI* = total regular cash dividends relative to net income, *DIV_Y* = dividend yield ratio, LEG = total debt to total assets, MKBK = market-to-book ratio, SIZE = natural logarithm of a firm's total assets, ROA = net income to total assets.

Table 4 - Table – Classification accuracies over 10 replications (in %)

	United Kingdom			France			Germany		
Panel A: Training sample									
	Group 1	Group 2	Overall	Group 1	Group 2	Overall	Group 1	Group 2	Overall
UTADIS	74.03	72.28	73.16	80.54	73.34	76.95	72.18	63.16	67.68
ELECTRE TRI	79.78	69.92	74.85	81.17	74.86	78.02	67.09	65.24	66.17
LR	69.96	74.84	72.40	78.96	73.53	77.15	69.46	66.23	67.84
Panel B: Validation Sample									
	Group 1	Group 2	Overall	Group 1	Group 2	Overall	Group 1	Group 2	Overall
UTADIS	73.63	71.99	72.81	79.74	74.18	76.96	68.92	63.35	66.14
ELECTRE TRI	78.29	68.93	73.61	77.26	71.57	74.42	67.09	65.24	66.16
LR	67.73	75.76	71.74	76.6	70.68	73.64	64.71	61.92	63.31

Notes: UTADIS = UTilités Additives DIScriminantes, ELECTRE = ELimination and Choice Expressing Reality, LR = Logistic Regression; Group 1= Non-share repurchasing; Group 2 = Share repurchasing