The impact of reorganization filing and resolution on distressed-stock returns

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Abstract

This study presents the risky but significant lucrative investment opportunities available in the stocks of financially troubled firms. Our results suggest that an *ex ante* trading strategy of investing in distressed stocks with a 36.92% (50.77%) likelihood of being a winner generate $CAR_{\mathrm{F0\ to\ F+30}}$ ($CAR_{\mathrm{R0\ to\ R+30}}$) of +23.230% (+27.956%). We further analyze the possibilities of the neuro-fuzzy system and logit for constructing human skill-based distressed-stock trading models in order to mimic the behavior of investment winners by assigning them a set of continuous rules that explain the environment. In addition, this paper extends previous work by applying Receiver Operating Characteristic (ROC) curve analysis to compare the model performance of logit with that of a neuro-fuzzy system. The results show that trading decisions based on the neuro-fuzzy forecasts can achieve higher predictive accuracy than those based on logit.

Keywords: Corporate reorganization; Distressed stock investing; Logit; Neuro-fuzzy system; Receiver Operating Characteristic curve analysis

1. Introduction

When markets work, the cost of capital to a company is equal to the expected return on its stock. Investors provide capital for an expected return in exactly the way a lending bank provides capital in exchange for an expected interest rate (Miller & Modigliani, 1958). Explicitly, investing in stock is like lending money to a firm.

In normal circumstances a financially distressed firm would pay a higher interest rate than healthy firms in order to recompense the bank for its poorer earnings prospects and greater risk of default. The stock market similarly expects a higher return from a distressed firm than from a healthy firm. This induces investors to buy distressed stocks. If healthy firm had a higher expected return, or even the same expected return, nobody would buy distressed-firm stocks. Investors buy the distressed stocks because the market sets the discount rate so that these stocks have higher expected returns (Fama, 2000).

The more successful vulture investments became models to be emulated by the early and mid-1980s. In the 1980s, the investment opportunities for vultures grew for two reasons. First, severe downward spirals in sectors of the economy such as energy and steel sent many firms tumbling. Second, managers at struggling firms began to realize that the 1978 revision of the bankruptcy code encouraged bankrupt firms to reorganize, and they took advantage of the new system. By the late 1990s, the distressed securities market has turned from a cottage industry into a real marketplace. After the early 1990s — in what some now call the golden era of distressed investing — numerous new investors entered this niche field for high returns in a low-interest-rate economy.

Over the long term, investors in distressed-firm stocks are rewarded. Overall, the stocks of distressed firms have outperformed the stocks of healthy firms on average since such records began in the US, and also in other markets around the world. In diversified portfolios, distressed stocks are expected to outperform healthy stocks over the long run (Fama & French, 1992). Indro et al. (1999) report the potential substantial gains associated with investing in the equity securities of financially distressed firms. Altman (1998) also confirms that stocks emanating from Chapter 11 proceedings during the period 1980-1993 outperformed the relevant market indices by over 20% during their first 200 trading days. Moreover, prior research indicates that investment attention on distressed securities will not only continue but will increase in both supply and demand in the near-term future as well as the long run (*cf*. Hotchkiss & Mooradian, 1997; Altman, 1998; Chi & Tang, 2005).

Distressed-security investing is a journey to the distant frontiers of risk and return. A troubled outfit may be moving toward the scrap heap, but if it can stage a comeback, the returns may be enormous. However, there is a considerable risk that a favorable outcome will never materialize. In examining distressed firms, very simply, one must see the market as either verifying a trade or moving against the avoidable, that is a high stock price, a rickety balance sheet, and poor management. Most investors think interesting profitable firms have higher expected returns than besieged poorly-earning firms. A firm teetering on the brink of financial distress doesn't sound like a very good investment opportunity. But in many instances it can be significantly profitable for those who understand distressed-securities investing.

To shed some light on the intricacies involved in distressed-stock investing, this study dissects this little-known but increasingly common high-stakes investment vehicle; i.e., this study presents the risky but significant lucrative investment opportunities available in the stocks of financially troubled firms. The intent of the study is twofold: First, to investigate the impact of both the reorganization filing announcement and the reorganization resolution announcement on the distressed-stock return forecasting over a long horizon, from 30 trading days around the filing date to 30 trading days after the confirmation date of the reorganization plan. From this we are able to separate the investment winners (i.e., distressed firms whose investors experience at least +20% excess returns over a 30-day holding-period) from losers and identify the characteristics of winners and therefore develop effective *ex ante* trading strategies.

Our results show that losers significantly outnumber winners by 1.71 to 1 on day F0. For winners, the overall average excess monthly holding-period returns are +23.230%. For losers, $CAR_{\text{F0 to F+30}}$ are -61.915%. Over the event window (day R0, R+30), the proportion of winners in the total sample increases to 50.77%, which is more than half. The results reveal that this high-stakes investment vehicle is profitable. The cumulative returns for winners are significantly positive for all selected intervals. In contrast, none of the cumulative returns are positive for losers. $CAR_{\text{R0 to R+30}}$ are +27.956% (-21.591%) for winners (losers).

In the stock markets, the relationships between market variables are generally too complex to make tactical trading decisions and to gain stable returns using a conventional system theory approach. The existing evidence implies that human reasoning can be modeled as a neuro-fuzzy model (Jang, 1992; Kasabov, 1998, Wang, 2004). The second intent of this study is to analyze the possibilities of using a neuro-fuzzy system and an alternative approach, namely logit, that has commonly been used for this purpose, for constructing human skill-based distressed-stock trading models in order to mimic the behavior of investment winners by assigning them a set of continuous rules that explain the environment.

The area θ under the Receiver Operating Characteristic (ROC) curve is often used to evaluate the predictive power of different statistical models when the decision maker has no information, or has conflicting messages regarding the costs or severity of misclassification rates. In this study, we integrate ROC analysis into the context of prediction modeling and use area θ as the index for a model's prediction accuracy, an approach which has not previously been used for this purpose.

Our experiments confirm that the neuro-fuzzy system yields better results than logit with higher $\hat{\theta}$ values of 0.941 ± 0.022 and 0.929 ± 0.024 for training and testing subsamples, respectively, for Model 1. The plot depicted by the curve neuro-fuzzy system also lies above and to the left of the curve logit for Model 2. Again, these empirical results show that trading decisions based on the neuro-fuzzy forecasts can achieve higher predictive accuracy than those using logit.

Our paper is organized as follows. In Section 2, we describe the sampling procedure and empirical design. In Section 3, we present the empirical research design used in the analysis. We discuss our findings in Section 4. Section 5 offers a summary and conclusions.

2. Data and sample selection

In compiling the sample of firms that file petitions for reorganization, we use the Market Observation Post System from the Taiwan Stock Exchange Corporation (TSEC), which includes financial and reorganization information on traded firms that file for reorganization, or, if still in existence, from the firm itself. We identify the sample firms during the period 1980 through 2005, yielding an initial list of 123 filings. The distribution of filings over time is skewed toward more recent years; 50.77% of the reorganization petitions occur between 2000 and 2005. This list is then cross-checked with the Extemporary Newspaper Headline & Index Database to confirm the court related data and augment our sample outcomes accordingly.

The distressed investment information is obtained from the time period one year prior to filing through the final resolution of reorganization. Firms are included only once in the sample if the firm completes an out-of-court settlement but still files a reorganization petition in the next two years. We exclude firms in the financial sector because the accounting standards for income and profits for these firms are different from those in the other sectors. We also exclude firms for which data required for our empirical tests are missing. In addition, we restrict our selection to those firms whose shares remain trading on the exchange for at least 135 days past the plan confirmation. After applying these selection criteria, 65 firms are available for our empirical analysis.

Daily stock returns are obtained from the Taiwan Economic Journal (TEJ) for the period beginning 180 trading days prior to the reorganization filing announcements to 135 days after the filing announcements. The data on the financial characteristics of the sample firms are for the last fiscal year before the year of reorganization filing. They are gathered primarily from the TEJ, but when these data are not available we employ the annual reports, TSEC, and Compustat Global Data.

Finally, classification and prediction are performed based on data from the last fiscal year before the year of filing and final resolution. Our full sample is used to predict the investment gain/loss at the first day after the filing. The sample is further partitioned into training and testing subsamples. The training subsample consists of 37 firms that file petition for reorganization from 1980 to 2000. The testing subsample consists of 29 firms that petition for reorganization from 2001 to 2005.

3. Methodology

3.1. Stock market's perception of reorganization filing

Standard event study methodology similar to Cochran et al. (1995) and Gupta et al. (1997) is used to compute distressed-stock daily abnormal returns (*AR*s) following two major event periods, *i.e.* the reorganization filing date (F0) and the resolution of plan confirmation date (R0). These *AR*s are averaged across sample firms in order to draw inferences about the impact of the reorganization filing. The daily *AR*s are then aggregated over various event windows to generate the cumulative abnormal returns (*CAR*s) and are subsequently examined for statistical significance.

The value-weighted market index for each distressed firm is drawn from the TSEC and TEJ daily returns file for the periods [t=F-180, t =F+135] and [t =R-180, t =R+135]. The two estimation periods for the market model are designated as [t=F-135, t =F+135] and [t =R-135, t =R+135], and the event periods as [t=F-30, t =F+30] and [t =R-30, t =R+30]. Since they are all financially distressed firms, a majority of the returns are expected to be generated by infrequent trading data. We therefore use the Scholes-Williams (1977) procedure to adjust for the nonsynchronous trading problem.

3.2. Variable selection

Data are collected for the years preceding the filing year (Y_F) and the final resolution year (Y_R) in order to facilitate isolation of the inputs contributing to the decision made in the subsequent year (*cf*. Daily, 1995; LoPucki & Whitford, 1993, for example). The dependent variable is the investment winner/loser, a dichotomous measure coded as 0 if the firm experiences at least +20% excess returns over a 30-day holding-period after the respective major event, and as 1 otherwise.

The input variables that we use in this study are firm size (the natural log of total assets), leverage (total liabilities/total assets), liquidity (cash and cash equivalents/total assets), profitability (net income/total assets), historical stock returns (the use of holding-period returns computed 180 days prior to the respective event days) (*cf*. Indro et al., 1999), and the Herfindahl-Hirschman Index (HHI), principally computed as the sum of the squared market shares of the distressed firms in a given industry, serves as a measure of the industry competition (Guadagni & Little, 1983). For an in-depth discussion of the model's input variables including their theoretical foundations, the reader is referred to Chi and Tang (2005).

3.3. Neuro-fuzzy model

The traditional fuzzy system is based on expert knowledge, and for this reason it is not very objective. In addition, it is difficult to acquire robust knowledge and find available human experts (Jang, 1992). A brief first introduction of the neuro-fuzzy approach is Kasabov (1998). The reason why fuzzy systems and neural networks make a successful fusion is that both technologies are highly complementary. Since the neuro-fuzzy classifier has the advantages of both the fuzzy system and neural networks, namely human-like thinking expressed as *IF-THEN* rules by fuzzy sets and learning of numerical data by neural networks, it appends the low-level learning and computational power of neural networks to the fuzzy system, and applies the high-level fuzzy reasoning of fuzzy systems to the neural networks (Wang, 2004).

In the market, the relationships between input variables are generally too complex to make accurate trading decisions and to generate stable profits using the traditional system theory approach. In contrast, many experts and practicians successfully trade stocks and generate substantial gains. A sophisticated method and tool for expert-knowledge extraction is the supervised learning methods, where human-expert behaviors are mapped using neuro-fuzzy system.

The neuro-fuzzy system is a straightforward implementation of a fuzzy inference system with a four-layered network structure that contains an input layer, a membership layer, a rule layer, and an output layer. Our six research inputs are uniformly partitioned into seven fuzzy linguistic spaces, that is, there are 42 term nodes in layer 2, and the number of rule nodes in layer 3 is 823,543 in the structure of our two neuro-fuzzy models.

3.3.1. Neuro-fuzzy model structure

Each node in layer 1 is used to directly transmit the numerical inputs to the next layer. Let x_i represent the differencing value of the i^{th} input signal of layer 1. Then the activation function can be expressed as follows:

$$o_i^1 = f_i^1(u_i^1) = u_i^1 \quad i = 1, \ldots, n,$$

Since the weights (w_i^1) at layer 1 are set equal to unity, both the input (u_i^1) and output (o_i^1) values at layer 1 can be rewritten as follows:

$$o_i^1 = u_i^1 = x_i^1$$

where o_i^1 and $u_i^1(u_i^1 = w_i^1 x_i^1)$ are the output and input values of the i^{th} node and x_i^1 is the input value of the i^{th} input value.

The function of layer 2 is to fuzzify the output values of layer 1 by utilizing membership function and to decide the membership degrees of the input variables. All links between layers 1 and 2 are set to unity. Trapezoidal membership function is adopted because its shape can correspond to fuzzify our data. The operation of the trapezoidal function is

$$o_j^2 = f_j^2(u_j^2) = u_j^2(x_{ij}^2) = \begin{cases} 0 & for\ x_{ij} \le a_j \\ \dfrac{x_{ij} - a_j}{b_j - a_j} & for\ a_j < x \le b_j \\ 1 & for\ x_{ij} > b_j \end{cases}$$

Each node of layer 3 represents the fuzzy rules that will combine the input variables using rules of the type *IF-THEN*. The w_{jk}^3 of the links are set to unity. The dynamic fuzzy reasoning is performed by the product of the input signals of the k^{th} rule node, which is represented as

$$o_k^3 = f_k^3(u_k^3) = \sum_{j=1}^{m} w_{jk}^3 x_{jk}^3 \qquad j = 1, \ldots, m, \quad k = 1, \ldots, p,$$

where $x_{jk}^3 = x_{jk}^3 z_j^3$

z_j^3 = 0.05 for j = 1, 2, 3, 4, 5, 6, 37, 38, 39, 40, 41, 42

z_j^3 = 0.1 for j = 7, 8, 9, 10, 11, 12, 31, 32, 33, 34, 35, 36

z_j^3 = 0.2 for j = 13,14,15,16,17,18, 25, 26, 27, 28, 29, 30

z_j^3 = 0.3 for j = 19, 20, 21, 22, 23, 24

w_{jk}^3 are the link weights between rule node k and membership node j. z_j^3 are weights on our model.

Since nodes 1, 7, 13, 19, 25, 31, 37 in layer 2 will be merged into node 1 of layer 3, for FS^3,

$$FS^3 = \sum_j w_j^1 x_j^1 \qquad j = 1, 7, 13, 19, 25, 31, 37$$

Similarly, $L1^3$, $L2^3$, P^3, HSR^3, and HHI^3 can be rewritten as

$$L1^3 = \sum_j w_j^2 x_j^2 \qquad j = 2, 8, 14, 20, 26, 32, 38$$

$$L2^3 = \sum_j w_j^3 x_j^3 \qquad j = 3, 9, 15, 21, 27, 33, 39$$

$$P^3 = \sum_j w_j^4 x_j^4 \qquad j = 4, 10, 16, 22, 28, 34, 40$$

$$HSR^3 = \sum_j w_j^5 x_j^5 \qquad j = 5, 11, 17, 23, 29, 35, 41$$

$$HHI^3 = \sum_j w_j^6 x_j^6 \qquad j = 6, 12, 18, 24, 30, 36, 42$$

where *FS*, *L1*, *L2*, *P*, *HSR*, and *HHI* are our input variables (*i.e*., firm size, leverage, liquidity, profitability, historical stock returns, and H-H Index, respectively).

The layer 4 executes the process of defuzzification. The node in this layer is the consequence with respect to the output variable from each rule. For the output node,

$$o_y^4 = f_y^4(u_y^4) = \sum_{k=1}^{t} w_{ky}^4 x_{ky}^4 \qquad y = 1$$

The link weight w_{ky}^4 that is the action strength of output associated with rule *k* can be fine-tuned by the supervised learning algorithm.

3.3.2. Learning algorithm of the neuro-fuzzy network

Step 1. Initialize learning rate (η) and network parameters (α , a_j, b_j)

$$\eta = 1 - \frac{n}{N}$$

defines the number of current training periods. η will decrease when training number (*n*) increases. Initially, the network parameters are set as 0.8, 20, and 35, respectively.

Step 2. Input a training sample and calculate a network output

Step 3. Calculate the propagated error term in layer 4

$$\delta_y^4 = -\frac{\partial E}{\partial u_y^4} = \frac{\partial E}{\partial f_y^4}\frac{\partial f_y^4}{\partial u_y^4} = d_y^4 - o_y^4 \qquad y=1$$

where o_y^4 is the output of the neuro-fuzzy system and d_y^4 *i*s the desired output for the t^{th} training sample.

Step 4. Adjust the link weight between layers 4 and 3

$$w_{ky}^4(t+1) = w_{ky}^4(t) + \eta \bullet \delta_y^4(t) \bullet x_{ky}^4(t) + \alpha \Delta w_{ky}^4(t)$$

where $\Delta w_{ky}^4(t) = w_{ky}^4(t) - w_{ky}^4(t-1)$

Step 5. Calculate the propagated error term in layer 3

$$\delta_k^3 = -\frac{\partial E}{\partial u_k^3} = -\frac{\partial E}{\partial f_k^3} \bullet \frac{\partial f_k^3}{\partial u_k^3} = \sum_y \delta_y^4 w_{ky}^4 \qquad k = 1\sim 6,\ y = 1$$

Step 6. Calculate the propagated error term in layer 2

$$\delta_j^2 = -\frac{\partial E}{\partial u_j^2} = -\frac{\partial E}{\partial f_j^2} \bullet \frac{\partial f_j^2}{\partial u_j^2} = -(\sum_k \frac{\partial E}{\partial u_k^3} \bullet \frac{\partial u_k^3}{\partial o_j^2}) \bullet \frac{f_j^2}{\partial u_j^2} = \sum_k \delta_k^3 \bullet z_j^3 \qquad j = 1\sim42,\ k = 1\sim6$$

Step 7. Adjust the membership function parameters

$$a_j(t+1) = a_j(t) + \eta\delta_j^2 \bullet \frac{x_{ij} - b_j}{(b_j - a_j)^2} + \alpha\,\Delta a_j(t)$$

$$b_j(t+1) = b_j(t) + \eta\delta_j^2 \bullet \frac{a_j - x_{ij}}{(b_j - a_j)^2} + \alpha\,\Delta b_j(t)$$

Step 8. Repeat step 2 to step 7 and calculate the energy function

Repeat step 2 to step 7 until all training samples are finished. In each period, the energy function (*E*) is computed by

$$E_n = \frac{1}{2}\sum_{t=1}^{T}(d_y^4(t) - o_y^4(t))^2$$

where d_t is the desired output for the t^{th} training sample and o_t is the output of the t^{th} training sample in our neuro-fuzzy model.

Step 9. Check if the stop condition is satisfied

Finally, if the energy function value decreases smoothly, a stop condition is reached. Otherwise, go to step 2.

3.4. Evaluation of model performance

For nonprobabilistic or categorical prediction, the contingency table provides a complete representation of performance for any number of classes, but it is difficult to display and interpret (Wilks, 1995). However, the two-class problem is unique in that the ability of a model can be demonstrated in a two-dimensional diagram.

The Receiver Operating Characteristic, or ROC, curve is a two dimensional measure of classification performance. The ROC curve plots diagnostic accuracy expressed in terms of the sensitivity or percentage of hits (e.g., true positives) of a model on the *x* axis against 1-specificity or percentage of false alarms (e.g., false positives) on the *y* axis. Their complements are the false negative rate (FNR) and the false positive rate (FPR) for functions. The result is a bowed curve rising from a 45-degree diagonal line to the upper left corner. Thus, the closer to the upper left corner and the sharper the curve, the better the model is.

The area under the ROC curve is often used to evaluate the predictive power of different statistical models when the decision maker has no information, or has conflicting messages regarding the costs or severity of misclassification rates. This measurement is also called AUC (Adams & Hand, 1999), the c-index or c-statistic (Harrell et al., 1984), and θ (Tang & Chi, 2005) and is equivalent to the Gini index (Thomas et al., 2002), the two independent samples Mann-Whitney nonparametric test statistic, and the Wilcoxon signed rank statistic (Hanley & McNeil, 1982).

In this study, we employ ROC analysis in the context of prediction modeling and use area θ as the index for a model's prediction accuracy. We, firstly, define the sensitivity and specificity of our model as follows:

$$^{n}TP = \sum_{t=1}^{W} predicted\,(winner_t)$$

$$^{n}FP = \sum_{t=1}^{L}\left[1 - predicted\,(loser_t)\right]$$

$$^{n}TN = \sum_{t=1}^{L} predicted\,(loser_t)$$

$$^{n}FN = \sum_{t=1}^{W}\left[1 - predicted\,(winner_t)\right]$$

$$Sensitivity = \frac{^{n}TP}{^{n}TP + {}^{n}FN}$$

$$Specificity = \frac{^{n}TN}{^{n}TN + {}^{n}FP}$$

where *predicted* is the probability of the occurrence of an event; $winner_t$ is the winner sample subset, and $loser_t$ is the loser sample subset.

Then, let *W* and *L* represent the measurements for the winner and loser sample, with low values suggesting a positive result and high values a negative result. The nonparametric approximation of $\hat{\theta}$ can be written as

$$\hat{\theta} = \frac{1}{N_W N_L} \sum_{(W,L)} \mu_{W,L}$$

where N_W, and N_L is the number of winner and loser stocks, respectively, and

$$\mu_{W,L} = \begin{cases} 1 & if \quad S_L \rangle S_W \\ \frac{1}{2} & if \quad S_L = S_W \\ 0 & if \quad S_L \langle S_W \end{cases}$$

with S_W, and S_L being the current output score of a winner and a loser subject, respectively.

4. Empirical findings

4.1. The price reaction to reorganization filing

The average *AR*s and *CAR*s surrounding filing day (F0) are reported in Tables 1 and 2. For these firms, the market seems to have recognized the financial distress and reacted negatively long before the filing. As expected, our whole sample experience significantly negative returns for the entire 21-event date and the selected intervals. The proportion of losers to the total sample is 63.08%; losers significantly outnumber winners by 1.71 to 1 with a generalized sign *z*-statistic of -3.059. Figures 1 and 2 clearly suggest that investments in filing firm stocks are unprofitable.

While returns on 12 of the 21 days in the entire 21-event day, which range from -1.637% to +2.495%, are positive for winners, only the excess on day F+10 is statistically significant. Our loser group experience larger and more significant decreases in stock prices than winners. The *AR*s for losers deteriorate sharply after the filing announcement, and ranged from -2.481% on day F+10 to -4.248% on day F+4.

Furthermore, the gains and losses between winners and losers differ in magnitude, and the differences are statistically significant. For winners, the overall average excess monthly holding-period returns are +23.230%. For losers, $CAR_{\text{F0 to F+30}}$ are -61.915%. A Wilcoxon rank-sum test shows that differences in mean $CAR_{\text{F0 to F+30}}$ (85.146%) across these two groups are significant at the 0.01 levels with the large value of z-statistics of -3.464, indicating they are all different from zero.

The nonparametric generalized sign test in column 5 of Table 2 confirms the evidence in column 4 that the significant shift which occurs in the ratio of positive to negative cumulative return observations in the period immediately following the reorganization filing results is equal to the ratio in the estimation period. That is, the proportion of positive to negative returns is not equal to the ratio in the estimation period.

4.2. The price reaction to final resolution

Tables 3 and 4 report the results of event study surrounding the date of the final resolution (R0). Since all the bad news has already been revealed, we find that a price rebound occurs after post-filing. The ratio of positive to negative *AR*s is 29 to 36, indicating that 44.62% firms have positive *AR*s on day R+1 and R+2, respectively. Moreover, 31 of 65 firms (47.65%) have positive *CAR*s on the traditional 3-day window (R-1, R+1). Over the event window (day R0, R+30), the proportion of winners in the total sample increases to 50.77%, which is more than half. The results reveal that this high-stakes investment vehicle is profitable.

Fig. 3 shows an interesting phenomenon relating to the plan confirmation announcement. Over the 4 days preceding the event period *(i.e.*, from days R-7 to R-4), the distressed firms, on average, still experience significantly negative returns. However, from day R-3, the market gains knowledge of the confirmation of the plan prior to the announcement, and from days R-3 to R+4, the stock prices increase significantly.

The cumulative returns for winners are significantly positive for all selected intervals. In contrast, none of the cumulative returns are positive for losers. $CAR_{\text{R0 to R+30}}$ are +27.956% (-21.591%) for winners (losers). The differences in mean $CAR_{\text{R0 to R+30}}$ (49.551%) across these two groups are significant at the 0.01 levels with the large value of z-statistics of -3.261 by using Wilcoxon rank-sum test, indicating they are all different from zero.

Lastly, note from column 4 in Table 4 that using the excess monthly holding-period returns criteria to classify firms into groups of winners and losers explains 50.77% and 49.23% of the result, respectively. Furthermore, the significant generalized sign test show that a shift occurs in the nature of the plan confirmation reaction distribution for the winner and loser groups, that is, the proportion of positive to negative returns is different from the ratio in the estimation period.

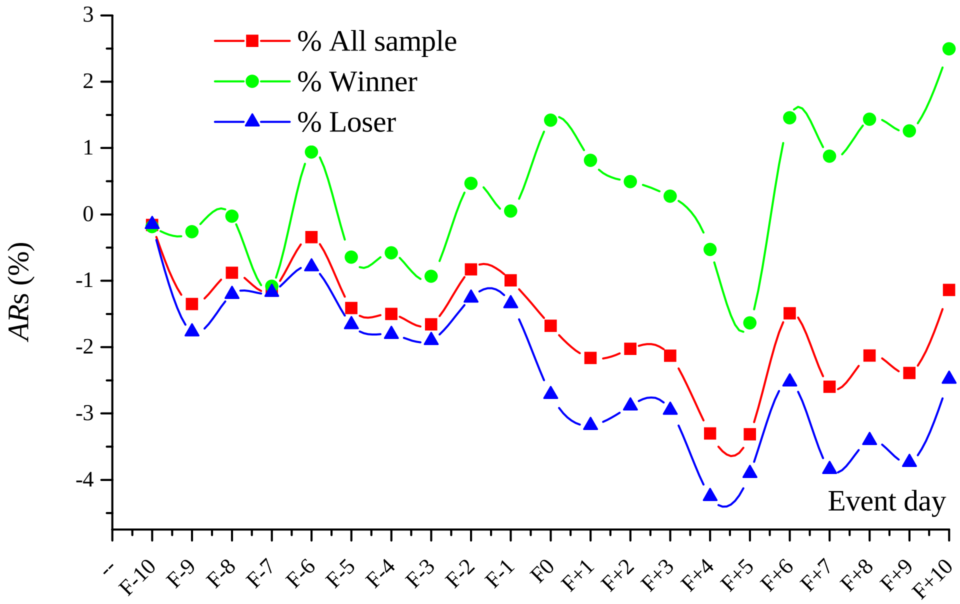

Figure 1 *AR*s surrounding day F0

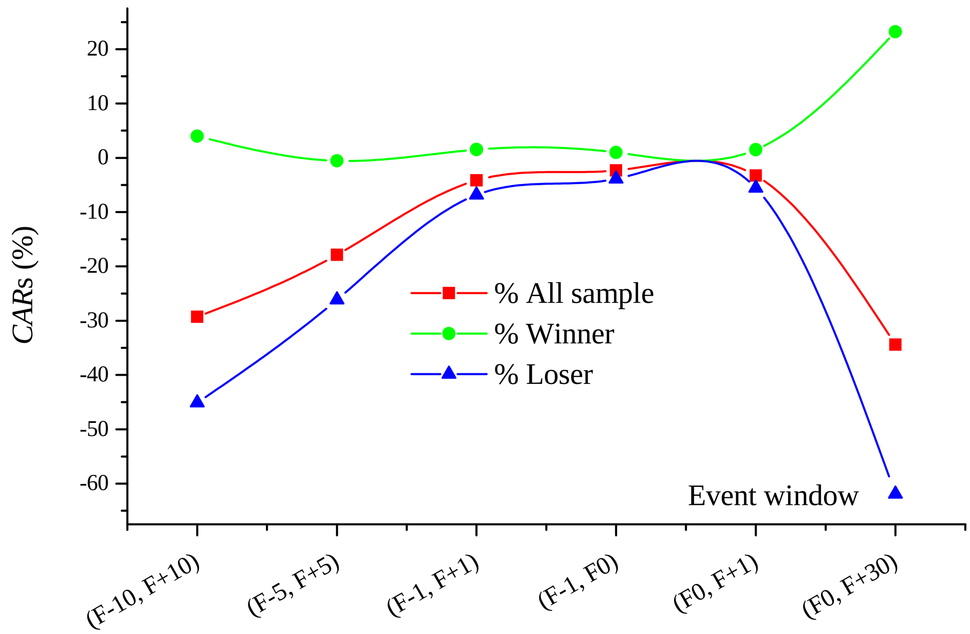

Figure 2 *CAR*s surrounding day F0

Table 1

ARs surrounding the reorganization filing date (day F0)

Event day	All sample				Winners				Losers				Difference (%)	Wilcoxon rank-sum test
	AR_t (%)	t (AR_t)	+ / -	Generalized sign test	AR_t (%)	t (AR_t)	+ / -	Generalized sign test	AR_t (%)	t (AR_t)	+ / -	Generalized sign test		
F-10	-0.160	-0.293	27 / 38	-4.541[c]	-0.184	-0.171	8 / 16	-1.604[a]	-0.151	-0.235	19 / 22	-2.934[b]	-0.033	-0.982
F-9	-1.352	-2.413[b]	24 / 41	-4.286[c]	-0.260	-0.223	9 / 15	-1.604[a]	-1.768	-2.806	15 / 26	-3.408[c]	1.508	-0.982
F-8	-0.881	-1.136	29 / 36	-4.703[c]	-0.028	-0.029	9 / 15	-1.604[a]	-1.206	-1.198	20 / 21	-3.408[c]	1.178	-2.947[b]
F-7	-1.149	-2.01[b]	23 / 42	-4.197[c]	-1.085	-1.085	7 / 17	-1.826[a]	-1.173	-1.682[a]	16 / 25	-3.920[c]	0.088	-3.309[c]
F-6	-0.342	-0.596	26 / 39	-4.457[c]	0.938	1.059	9 / 15	-1.342	-0.789	-1.121	17 / 24	-3.920[c]	1.727	-2.385[b]
F-5	-1.411	-2.097[b]	20 / 45	-3.920[c]	-0.645	-0.487	5 / 19	-1.342	-1.660	-2.113[b]	15 / 26	-3.823[c]	1.016	-3.292[c]
F-4	-1.501	-2.483[b]	19 / 46	-3.823[c]	-0.578	-0.414	7 / 17	-1.342	-1.808	-2.733[b]	12 / 29	-3.180[c]	1.230	-3.292[c]
F-3	-1.657	-2.506[b]	22 / 43	-4.107[c]	-0.933	-0.743	7 / 17	-1.342	-1.898	-2.431[b]	15 / 26	-3.180[c]	0.965	-3.296[c]
F-2	-0.829	-1.321	26 / 39	-4.457[c]	0.466	0.384	9 / 15	-1.604[a]	-1.260	-1.730[a]	17 / 24	-3.408[c]	1.726	-3.295[c]
F-1	-0.996	-1.472	25 / 40	-4.372[c]	0.050	0.045	7 / 17	-1.604[a]	-1.344	-1.633[a]	18 / 23	-3.516[c]	1.393	-3.293[c]
F0	-1.679	-2.578[b]	18 / 47	-3.724[c]	1.419	1.168	8 / 16	-1.826[a]	-2.712	-3.840[c]	10 / 31	-2.934[b]	4.131	-3.296[c]
F+1	-2.163	-3.479[c]	14 / 51	-3.233[c]	0.813	0.803	8 / 16	-2.201[b]	-3.179	-4.565[c]	6 / 35	-2.023[b]	3.991	-1.915[a]
F+2	-2.026	-3.127[b]	21 / 44	-4.015[c]	0.494	0.501	10 / 14	-2.366[b]	-2.886	-3.792[c]	11 / 30	-2.521[b]	3.380	-3.296[c]
F+3	-2.129	-3.258[b]	17 / 48	-3.621[c]	0.274	0.243	8 / 16	-1.826[a]	-2.950	-3.922[c]	9 / 32	-1.826[a]	3.224	-1.664[a]
F+4	-3.302	-4.855[c]	13 / 52	-3.296[c]	-0.529	-0.449	6 / 18	-1.342	-4.248	-5.504[c]	7 / 34	-1.604[a]	3.719	-1.915[a]
F+5	-3.315	-4.992[c]	11 / 54	-2.934[b]	-1.637	-1.446	5 / 19	-1.342	-3.902	-4.935[c]	6 / 35	-1.826[a]	2.265	-2.919[b]
F+6	-1.491	-2.189[b]	21 / 44	-4.015[c]	1.456	1.398	9 / 15	-1.342	-2.523	-3.204[b]	12 / 29	-2.366[b]	3.979	-3.292[c]
F+7	-2.596	-3.759[c]	16 / 49	-2.366[b]	0.877	0.785	7 / 17	-1.342	-3.842	-5.052[c]	9 / 32	-1.826[a]	4.719	-3.293[c]
F+8	-2.128	-3.725[c]	13 / 52	-3.180[c]	1.435	1.374	7 / 17	-1.342	-3.407	-6.120[c]	6 / 35	-1.342	4.842	-3.296[c]
F+9	-2.391	-3.720[c]	18 / 47	-3.724[c]	1.258	1.268	10 / 14	-1.342	-3.736	-5.448[c]	8 / 33	-1.826[a]	4.994	-3.292[c]
F+10	-1.141	-1.629[a]	24 / 41	-4.286[c]	2.495	3.208[b]	12 / 12	-1.342	-2.481	-3.036[b]	12 / 29	-1.826[a]	4.976	-3.296[c]

a, b, c Significant at the 0.1, 0.05, and 0.01 levels, respectively

Table 2

CARs surrounding the reorganization filing date (day F0)

Event window	All sample				Winners				Losers					
	CAR_t (%)	t (CAR_t)	+ / -	Generalized sign test	CAR_t (%)	t (CAR_t)	+ / -	Generalized sign test	CAR_t (%)	t (CAR_t)	+ / -	Generalized sign test	Difference (%)	Wilcoxon rank-sum test
(-10,+10)	-29.270	-5.415^{c}	15 / 50	-3.408^{c}	3.959	-0.285	8 / 16	-2.521^{b}	-45.129	-7.349^{c}	7 / 34	-2.201^{b}	49.088	-1.965^{b}
(-5,+5)	-17.869	-5.159^{c}	12 / 53	-2.366^{b}	0.538	-0.107	6 / 18	-2.201^{b}	-26.141	-6.163^{c}	6 / 35	-2.023^{b}	26.679	-1.036
(-1,+1)	-4.134	-3.188^{b}	18 / 47	-3.724^{c}	1.521	0.95	8 / 16	-2.201^{b}	-6.833	-4.164^{c}	10 / 31	-2.666^{b}	8.354	-2.605^{b}
(-1,0)	-2.304	-2.363^{b}	20 / 45	-3.296^{c}	0.979	0.879	7 / 17	-2.366^{b}	-3.871	-3.015^{b}	13 / 28	-3.059^{b}	4.850	-3.233^{c}
(0,+1)	-3.276	-3.617^{c}	13 / 52	-3.180^{c}	1.488	1.354	7 / 17	-2.366^{b}	-5.550	-5.027^{c}	6 / 35	-1.826^{a}	7.038	-0.408
(0,+30)	-34.407	-2.762^{b}	13 / 52	-3.059^{b}	23.230	1.151	13 / 11	-1.604^{a}	-61.915	-7.089^{c}	0 / 41	-1.604^{a}	85.146	-3.464^{c}

a, b, c Significant at the 0.1, 0.05, and 0.01 levels, respectively

Table 3

ARs surrounding the final resolution date (day R0)

Event day	All sample AR_t (%)	All sample $t(AR_t)$	All sample + / -	Generalized sign test	Winners AR_t (%)	Winners $t(AR_t)$	Winners + / -	Generalized sign test	Losers AR_t (%)	Losers $t(AR_t)$	Losers + / -	Generalized sign test	Difference (%)	Wilcoxon rank-sum test
R-10	-0.107	-0.131	24 / 41	-4.286^{c}	-1.174	-1.027	10 / 23/	-2.803^{b}	0.916	-0.235	14 / 18	-2.934^{b}	-2.090	-4.286^{c}
R-9	0.078	0.111	26/ 39	-4.197^{c}	1.034	1.008	16 / 17	-2.521^{b}	-0.840	-2.806^{b}	10 / 22	-2.803^{b}	1.874	-3.714^{c}
R-8	0.253	0.387	23 / 42	-4.197^{c}	0.403	0.460	11 / 22	-2.934^{b}	0.109	-1.198	12 / 20	-3.059^{b}	0.294	-0.714
R-7	-0.946	-1.354	19 / 46	-3.823^{c}	-1.188	-1.162	9 / 24	-2.666^{b}	-0.714	-1.682^{a}	10 / 22	-2.803^{b}	-0.474	-2.429^{b}
R-6	-1.508	-2.235^{b}	18 / 47	-3.724^{c}	-2.574	-2.724^{b}	6 / 27	-2.201^{b}	-0.486	-1.121	12 / 20	-3.059^{b}	-2.088	-4.257^{c}
R-5	-1.113	-1.797^{a}	17 / 48	-3.621^{c}	-2.533	-2.934^{b}	5 / 28	-2.023^{b}	0.307	-2.113^{b}	12 / 20	-3.059^{b}	-2.840	-4.319^{c}
R-4	-1.327	-2.208^{b}	21 / 44	-4.015^{c}	-1.430	-1.480	11 / 22	-2.934^{b}	-1.224	-2.733^{b}	10 / 22	-2.803^{b}	-0.206	-0.498
R-3	0.244	0.349	25 / 40	-4.372^{c}	0.914	0.907	14 / 19	-2.934^{b}	-0.426	-2.431^{b}	11 / 21	-2.934^{b}	1.341	-3.619^{c}
R-2	0.111	0.173	27 / 38	-4.107^{c}	0.153	0.160	15 / 18	-2.803^{b}	0.066	-1.730^{a}	12 / 20	-3.059^{b}	0.087	-2.086^{b}
R-1	0.621	0.799	26 / 39	-4.197^{c}	-0.247	-0.216	12 / 21	-3.059^{b}	1.526	-1.633^{a}	14 / 18	-2.803^{b}	-1.773	-3.971^{c}
R0	0.699	1.073	26 / 39	-4.107^{c}	3.163	3.874^{c}	21 / 12	-2.023^{b}	-1.979	-3.840^{c}	5 / 27	-2.023^{b}	5.143	-4.197^{c}
R+1	1.356	2.093^{b}	29 / 36	-3.920^{c}	3.408	4.032^{c}	19 / 14	-2.201^{b}	-0.781	-4.565^{c}	10 / 22	-2.803^{b}	4.189	-4.286^{c}
R+2	0.982	1.415	29 / 36	-3.920^{c}	3.235	4.338^{c}	20 / 13	-2.023^{b}	-1.365	-3.792^{c}	9 / 23	-2.666^{b}	4.600	-4.200^{c}
R+3	0.984	1.26	28 / 37	-4.015^{c}	3.569	3.795^{c}	20 / 13	-2.023^{b}	-1.709	-3.922^{c}	8 / 24	-2.521^{b}	5.278	-4.286^{c}
R+4	0.010	0.013	24 / 41	-4.286^{c}	3.436	4.695^{c}	19 / 14	-2.201^{b}	-3.559	-5.504^{c}	5 / 27	-2.023^{b}	6.995	-4.257^{c}
R+5	-0.147	-0.203	25 / 40	-4.286^{c}	1.599	1.586^{c}	15 / 18	-2.803^{b}	-1.966	-4.935^{c}	10 / 22	-2.803^{b}	3.565	-4.286^{c}
R+6	-0.556	-0.781	23 / 42	-4.197^{c}	0.496	0.490	14 / 19	-2.934^{b}	-1.653	-3.204^{b}	9 / 23	-2.666^{b}	2.149	-4.286^{c}
R+7	0.010	0.015	26 / 39	-4.197^{c}	0.846	0.890	15 / 18	-2.803^{b}	-0.861	-5.052^{c}	11 / 21	-2.934^{b}	1.708	-4.286^{c}
R+8	-0.032	-0.044	18 / 47	-3.724^{c}	1.374	1.232	12 / 21	-3.059^{b}	-1.498	-6.120^{c}	6 / 26	-2.201^{b}	2.873	-4.286^{c}
R+9	1.280	1.817^{a}	27 / 38	-4.107^{c}	2.793	3.335^{b}	16 / 17	-2.666^{b}	-0.295	-5.448^{c}	11 / 21	-2.934^{b}	3.088	-4.286^{c}
R+10	1.454	2.246^{b}	30 / 35	-3.823^{c}	2.160	2.494^{b}	16 / 17	-2.666^{b}	0.718	-3.036^{a}	14 / 18	-2.666^{b}	1.442	-4.200^{c}

a, b, c Significant at the 0.1, 0.05, and 0.01 levels, respectively

Table 4

CARs surrounding the final resolution date (day R0)

Event window	All sample				Winners				Losers					
	CAR_t (%)	t (CAR_t)	+ / -	Generalized sign test	CAR_t (%)	t (CAR_t)	+ / -	Generalized sign test	CAR_t (%)	t (CAR_t)	+ / -	Generalized sign test	Difference (%)	Wilcoxon rank-sum test
(-10,+10)	1.722	0.344	26 / 39	-4.286[c]	16.878	2.690[b]	19 / 14	-1.604	-10.487	-2.560[b]	7 / 25	-2.521[b]	27.365	-2.273[b]
(-5,+5)	1.780	0.424	27 / 38	-4.197[c]	13.162	3.481[b]	19 / 14	-2.201[b]	-11.393	-2.515[b]	8 / 24	-2.934[b]	24.555	-1.088
(-1,+1)	2.007	2.001[a]	31 / 34	-3.724[c]	2.514	3.494[b]	20 / 13	-2.023[b]	-0.247	-0.661	11 / 21	-3.059[b]	2.762	-1.743[b]
(-1,0)	0.985	1.291	28 / 37	-4.015[c]	5.665	2.041[b]	16 / 17	-2.666[b]	-1.785	-0.224	12 / 20	-2.521[b]	7.451	-3.620[c]
(0,+1)	1.539	1.830[a]	26 / 39	-4.197[c]	18.969	4.467[c]	18 / 15	-2.366[b]	-20.255	-2.512[b]	8 / 24	-1.826[a]	39.224	-0.359
(0,+30)	1.255	0.583	28 / 37	-4.197[c]	27.956	4.238[c]	23 / 10	-1.604	-21.591	-4.228[c]	4 / 28	-1.826[a]	49.551	-3.261[c]

a, b, c Significant at the 0.1, 0.05, and 0.01 levels, respectively

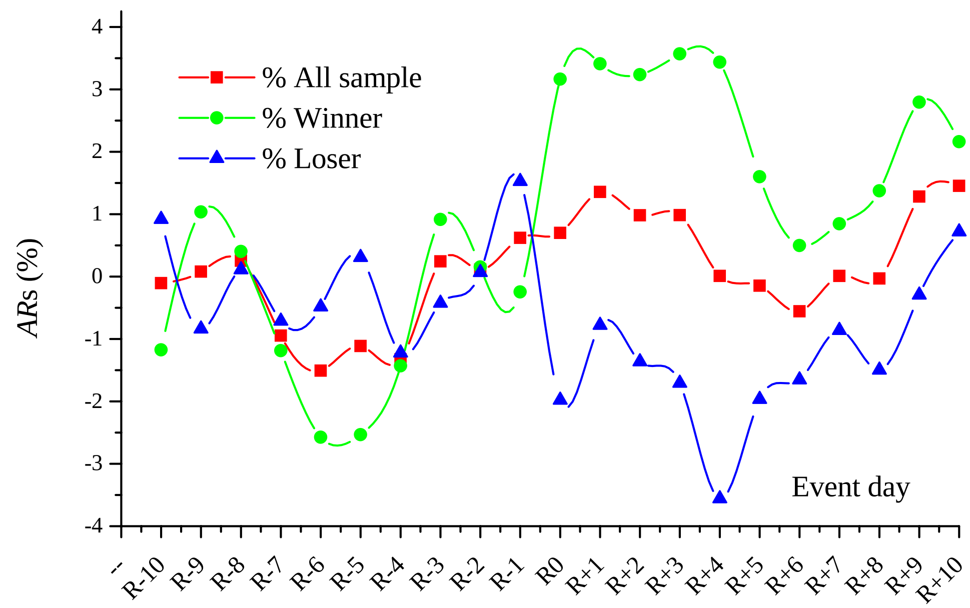

Figure 3 *AR*s surrounding day R0

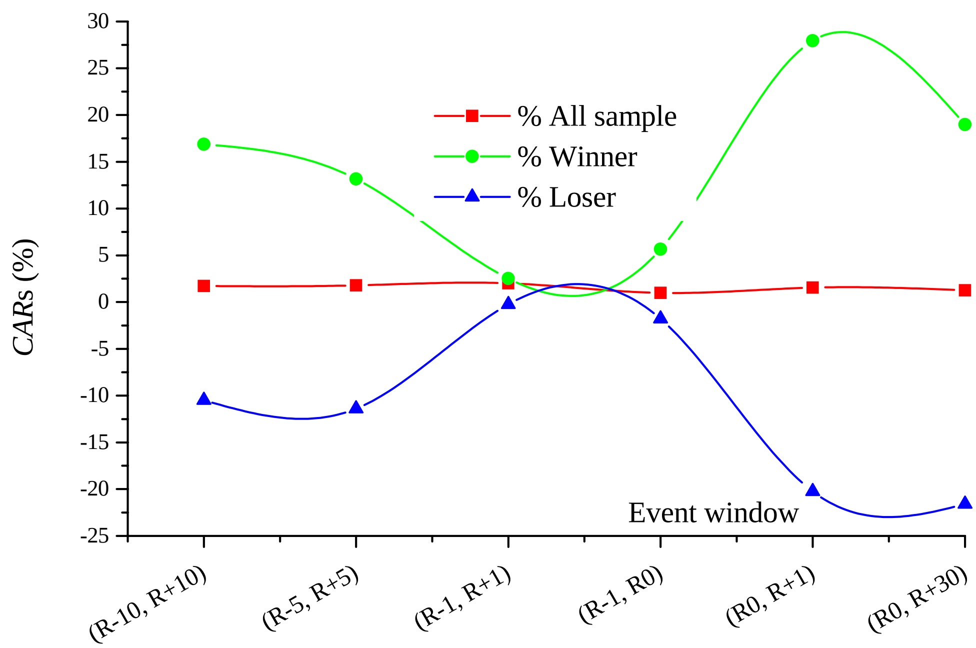

Figure 4 *CAR*s surrounding day R0

4.3. Sensitivity analysis results

To assess the relative importance of the input variables, we built a Multilayer Perceptrons model using six variables as inputs, and submitted them to sensitivity analysis. Sensitivity analysis is effective in identifying key variables, allowing an important form of knowledge extraction to be applied to our subsequent model construction.

Table 5 summarizes the sensitivity of the variables in discriminating between winners and losers surrounding the reorganization filing (Model 1): the errors compare with a baseline error of 0.275. Column 2 of Table 5 reveals that the order of importance (i.e., order of descending error) of each input variable is firm size (0.418), HHI (0.229), leverage (0.178), profitability (0.095), historical returns (0.059), and liquidity (0.021). The error (ratio) respectively of our six variables is 1.068 (38.807) for firm size, 0.619 (22.470) for leverage, 0.532 (19.336) for liquidity, 0.599 (21.769) for profitability, 0.599 (21.761) for historical returns, and 0.667 (24.244) for HHI. It can be seen that all variables are rated as of high sensitivity and should therefore be retained in subsequent analyses.

As to the discrimination between winners and losers surrounding the filing resolution (Model 2), the results of the sensitivity analysis are presented in Table 6. The relative importance of our six variables for Model 2 is firm size (0.373), historical returns (0.330), leverage (0.137), liquidity (0.086), profitability (0.057), and HHI (0.016), in descending order. The ratios between the errors and the baseline error (0.355) are all over one, that is, all six variables appear to reflect the higher dimensionality of our Model 2.

Table 5
Sensitivity analysis of input variables for Model 1

Variables	Rank	Error when omitted	Ratio	Importance of Inputs
Firm size	1	1.068	38.807	0.418
Leverage	3	0.619	22.470	0.178
Liquidity	6	0.532	19.336	0.021
Profitability	4	0.599	21.769	0.095
Historical returns	5	0.599	21.761	0.059
HHI	2	0.667	24.244	0.229

Table 6
Sensitivity analysis of input variables for Model 2

Variables	Rank	Error when omitted	Ratio	Importance of Inputs
Firm size	1	1.300	3.663	0.373

Leverage	3	1.109	3.125	0.137
Liquidity	4	1.106	3.115	0.086
Profitability	5	0.988	2.782	0.057
Historical returns	2	1.136	3.201	0.330
HHI	6	0.912	2.570	0.016

4.4. Performance measures

Logistic regression (logit) is a multivariate model which has frequently been compared with Artificial Intelligence. Trigueiros and Taffler (1996) indicate that logit has been the most commonly used technique in recent literature for binary events research. In this study, we present a trading decision that compares the classification and generalizability of the logit and hybrid neuro-fuzzy approach.

4.4.1. Performance of logit and neuro-fuzzy approaches in Model 1

Using logit, 76.00% of the troubled firms are identified corresponding to 50.00% of winners and 88.24% of losers. The performance of the neuro-fuzzy system achieves a sensitivity of 1 at a specificity of 0.933. The use of the logit approach results in 50.00% being shown as true positive (TP), 88.24% as true negative (TN), 11.76% as false positive (FP), and 50.00% as false negative (FN) samples. The neuro-fuzzy system results in 100% TP, 92.86% TN, 0.071% FP, and 0 FN cases. The $\hat{\theta}$ value of the neuro-fuzzy system is 0.941 ± 0.022; range, 0.919 to 0.963.

The predictive performance of the two constructed models is evaluated using the untouched testing data (second period sets). The use of the ROC curve of the logit (neuro-fuzzy) model in Table 8 results in 0.750 (1) sensitivity, 0.800 (0.882) specificity, 0.200 (0.118) FPR, and 0.250 (0) FNR. The $\hat{\theta}$ area under the ROC curve for logit is 0.739 ± 0.025; range, 0.714 to 0.764, and that for the neuro-fuzzy approach is 0.929 ± 0.024 (0.905, 0.953), suggesting that the neuro-fuzzy system is more suitable. More importantly, we find that logit’s power is quite accurate in the discrimination of losers, whereas the neuro-fuzzy model is superior in classifying winners.

4.4.2. Performance of logit and neuro-fuzzy approaches in Model 2

The percentage of our training sample surrounding day R0 classified by the logit approach is 70.00% of winners and 84.62% of the losers with an ROC area of 0.741 ± 0.025; range, 0.716 to 0.766. The performance of the neuro-fuzzy system at the sensitivity level 0.950 is 0.813 specificity. The use of logit results in 70.00% TP, 84.62% TN, 30.00% FN, and 15.38% FP cases; the neuro-fuzzy system results in 95.00% TP, 81.25% TN, 5.00% FN and 18.75% FP cases. The $\hat{\theta}$ value of the neuro-fuzzy model is 0.922 ± 0.027 (0.895, 0.949).

In order to further understand the prediction accuracy of models built on different data sets from the same process, our testing sample is examined. Table 10 provides the comparative result of two types of models for ROC curve analysis. The sensitivity improves to 0.750 at the specificity level of 0.692 for the logit model. The summary statistics are 0.846 sensitivity, 0.895 specificity, 0.105 FPR, and 0.154 FNR for the neuro-fuzzy model. By overlaying the ROC curves for each of the tests on the same graph in Figure 8, the plot depicted by the curve of the neuro-fuzzy system lies above and to the left of the logit curve. Again, these empirical results show that the trading predictions based on the neuro-fuzzy forecasts can be more accurate than those based on logit model.

Table 7
Testing summary on the training set for Model 1

Sensitivity	Specificity	FPR	FNR	$\hat{\theta}$	$\hat{\sigma}_{\hat{\theta}}$	p	95% Confidence Interval
Panel A: Logit analysis							
0.500	0.882	0.118	0.500	0.734	0.025	.000	[0.695, 0.794]
Panel B: Neuro-fuzzy system							
1	0.929	0.071	0	0.941	0.022	.000	[0.938, 1.025]

Table 8
Testing summary on the testing set for Model 1

Sensitivity	Specificity	FPR	FNR	$\hat{\theta}$	$\hat{\sigma}_{\hat{\theta}}$	p	95% Confidence Interval
Panel A: Logit analysis							
0.750	0.800	0.200	0.250	0.739	0.025	.000	[0.700, 0.798]
Panel B: Neuro-fuzzy system							
1	0.882	0.118	0	0.929	0.024	.000	[0.931, 1.027]

Table 9
Testing summary on the training set for Model 2

Sensitivity	Specificity	FPR	FNR	$\hat{\theta}$	$\hat{\sigma}_{\hat{\theta}}$	p	95% Confidence Interval
Panel A: Logit analysis							
0.700	0.846	0.153	0.300	0.741	0.025	.000	[0.702, 0.799]
Panel B: Neuro-fuzzy system							
0.950	0.813	0.187	0.050	0.922	0.027	.000	[0.909, 1.016]

Table 10

Testing summary on the testing set for Model 2

Sensitivity	Specificity	FPR	FNR	$\hat{\theta}$	$\hat{\sigma}_{\hat{\theta}}$	p	95% Confidence Interval
Panel A: Logit analysis							
0.750	0.692	0.308	0.250	0.727	0.026	.000	[0.686, 0.787]
Panel B: Neuro-fuzzy system							
0.846	0.895	0.105	0.154	0.897	0.045	.000	[0.839, 1.014]

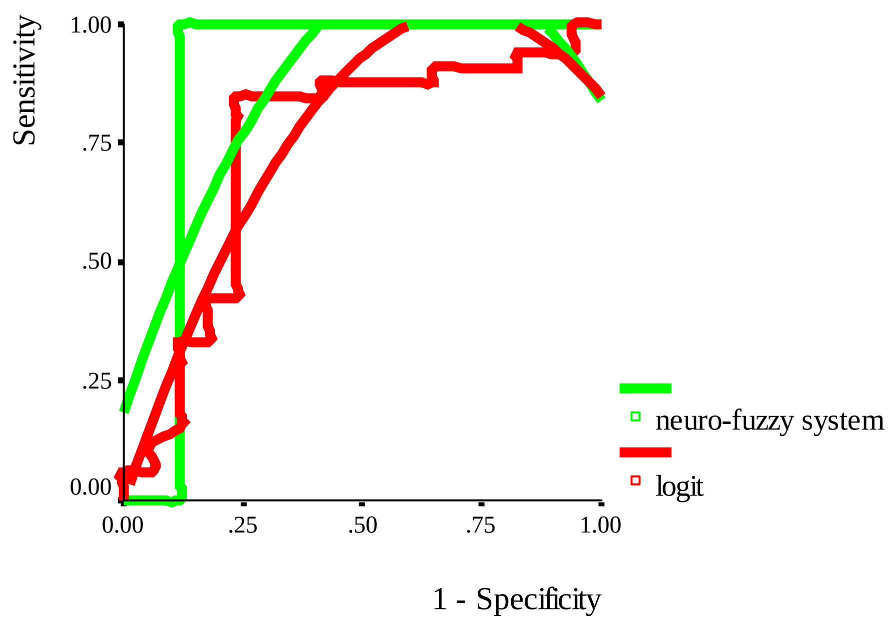

Figure 5 ROC Curves for Model 1 (Training sample)

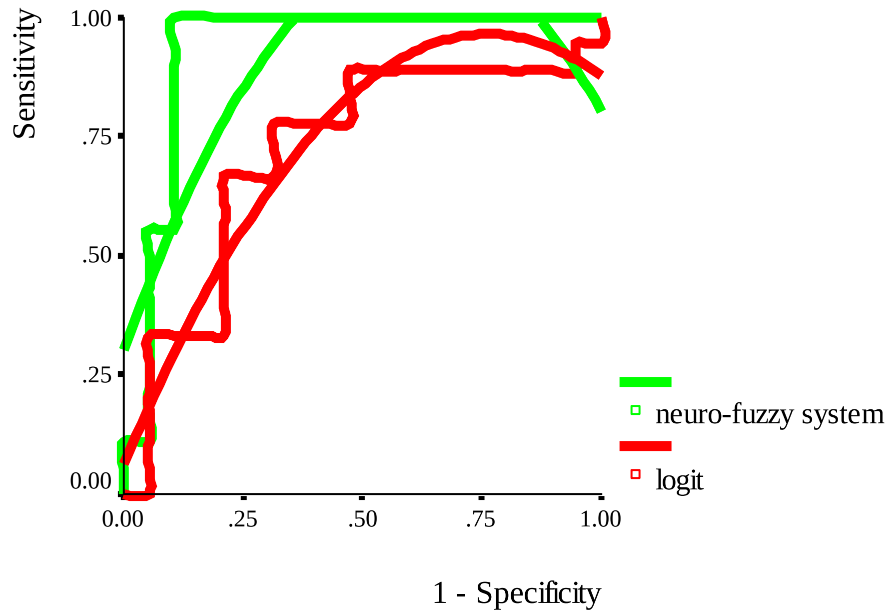

Figure 6 ROC Curves for Model 1 (Testing sample)

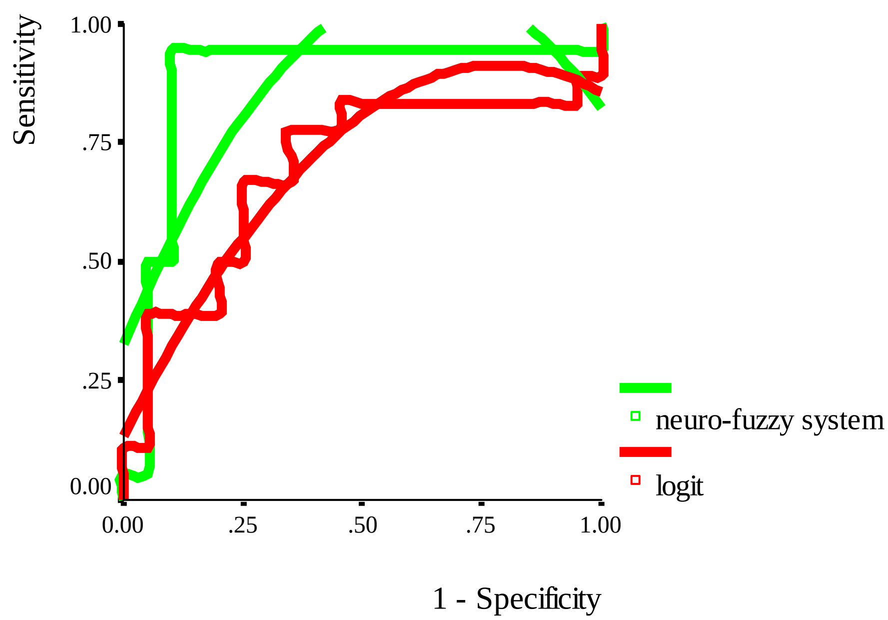

Figure 7 ROC Curves for Model 2 (Training sample)

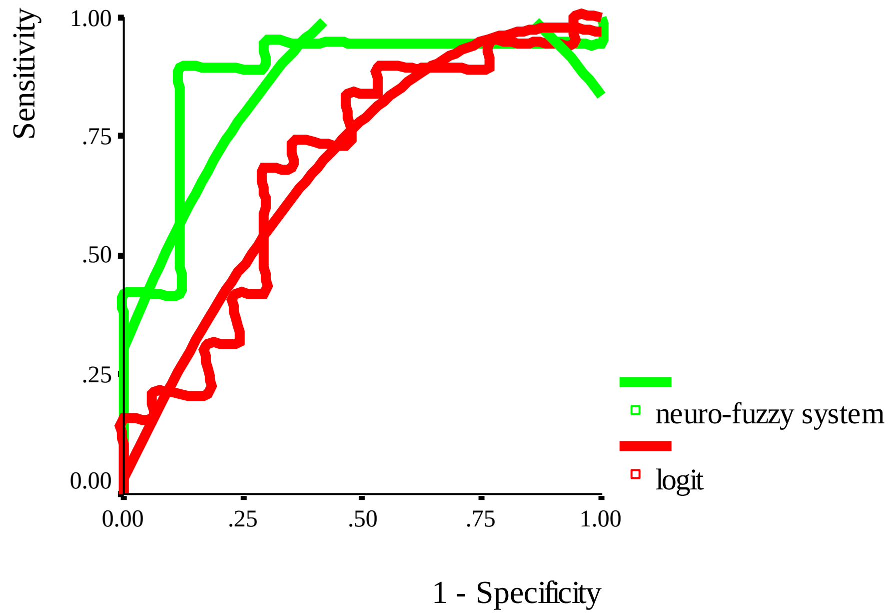

Figure 8 ROC Curves for Model 2 (Testing sample)

5. Conclusions

This study documents the effect of the information released by a reorganization announcement on investors in distressed stock. Substantial adverse stock price reaction to the filing announcement is presented. More interestingly, the results show that the winners and losers react differently to the information revealed by the filing announcement. The winners are unaffected by the filing and yet experience significant increases of 27.380% on day F0. Furthermore, a significant price rebound is observed for the period surrounding the final resolution for our entire sample. This may be due to the resolution of substantial uncertainty and/or the fact that the investor optimistically expects to make a gain at the time of plan confirmation. Another notable observation is that we find significant insider sales (buy) prior to a decrease (increase) in the mean of stock returns around day F-5 (day R-3), that is to say that insiders seem to exploit private information about the firm for their own personal gains.

We have realized that every winning system will have losses and that these losses have to be avoided or minimized as much as possible. Very simply, one must see the market as either confirming a trade or moving against it. In this study, we focus on finding an improved method for creating lucrative investment opportunities. Furthermore, in our study as much attention is allocated to the selections of key variables and model evaluation method as is allocated to the selection of the modeling method. ROC curves allow the summary and comparison between different modeling performances. In addition, the curve provides information that will enable the researcher and practitioner to optimise the use of a method through targeted selection of cut-off values for particular grouping strategies. However, the selection of which method to use is contingent upon the information available regarding misclassification costs. If no information is available, the ROC curve and the θ measurement are the most appropriate evaluation method. As the ROC curve integrates all possible iterations of misclassification error severities, many irrelevant ranges will be incorporated in the computation.

We have shown the superiority and effectiveness of the neuro-fuzzy system for both training and predictive performance. Specifically, our study suggests that distressed stocks with a 36.92% (50.77%) probability of being a winner generate $CAR_{\mathrm{F0\ to\ F+30}}$ ($CAR_{\mathrm{R0\ to\ R+30}}$) of +23.230% (+27.956%).

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