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Decision Support

Financial ratios and corporate governance indicators in bankruptcy prediction: A comprehensive study

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ABSTRACT

Effective bankruptcy prediction is critical for financial institutions to make appropriate lending decisions. In general, the input variables (or features), such as financial ratios, and prediction techniques, such as statistical and machine learning techniques, are the two most important factors affecting the prediction performance. While many related works have proposed novel prediction techniques, very few have analyzed the discriminatory power of the features related to bankruptcy prediction. In the literature, in addition to financial ratios (FRs), corporate governance indicators (CGIs) have been found to be another important type of input variable. However, the prediction performance obtained by combining CGIs and FRs has not been fully examined. Only some selected CGIs and FRs have been used in related studies and the chosen features may differ from study to study. Therefore, the aim of this paper is to assess the prediction performance obtained by combining seven different categories of FRs and five different categories of CGIs. The experimental results, based on a real-world dataset from Taiwan, show that the FR categories of solvency and profitability and the CGI categories of board structure and ownership structure are the most important features in bankruptcy prediction. Specifically, the best prediction model performance is obtained with a combination in terms of prediction accuracy, Type I/II errors, ROC curve, and misclassification cost. However, these findings may not be applicable in some markets where the definition of distressed companies is unclear and the characteristics of corporate governance indicators are not obvious, such as in the Chinese market.

1. Introduction

Bankruptcy or business failure can have a negative impact both on the enterprise itself and the global economy. Business practitioners, investors, governments, and academic researchers have long studied ways to identify the potential risk of business failure in order to reduce the economic loss caused by bankruptcy (Balleisen, 2001; Zywicki, 2008).

In short, bankruptcy prediction is a very important task for many related financial institutions. In general, the aim is to predict the likelihood that a firm may go bankrupt. Financial institutions are in need of effective prediction models in order to make appropriate lending decisions.

In the literature, many techniques have been employed to develop bankruptcy prediction models, including statistical and machine learning techniques (Balcaen & Ooghe, 2006; Kumar & Ravi, 2007; Lin, Hu, & Tsai, 2012; Verikas, Kalsyte, Bacauskiene, & Gelzinis, 2010) with machine learning techniques shown to outperform statistical techniques.

Although many studies have aimed at proposing novel machine learning techniques which will enhance the models' prediction performances, there have been very few which have focused on the effect of the input variables (or features) on prediction performance. In general, financial ratios (FRs), recognized as one of the most important factors affecting bankruptcy prediction, are used to develop prediction models (Altman, 1968; Beaver, 1966; Ohlson, 1980). FRs can be classified into seven categories: solvency, profitability, cash flow ratios, capital structure ratios, turnover ratios, growth, and others.

On the other hand, though, several recent studies have found that corporate governance indicators (CGIs) also play a key role in predicting bankruptcy (Bredart, 2014; Chen, 2014; Lee & Yeh, 2004; Lin, Liang, & Chu, 2010; Wu, 2007). Generally, CGIs can be classified into five categories: board structure (Collier & Esteban, 1999; Liang, Xu, & Jiraporn, 2013; Yeh & Woidtke, 2005),

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ownership structure (Berkman, Cole, & Fu, 2009; Cheung, Chung, Tan, & Wang, 2013; Jian & Wong, 2010; La Porta, Lopez-de-Silanes, & Shleifer, 1999), cash flow rights (Claessens, Djankov, & Xu, 2000; La Porta et al., 1999), key person retained (Albring, Robinson, & Robinson, 2014; Dan, 2010), and others. However, only some of the CGIs have been considered in these works to prove that model performance improvement can be obtained with them.

To fill this gap, the aim of this current work is to fully examine the discriminatory power of CGIs combined with FRs for bankruptcy prediction. Specifically, the model performances obtained using different categories of CGIs combined with FRs are assessed to see whether combining CGIs with FRs can enhance the model performance. In addition, since the combined features contain very high dimensionality, feature selection (Guyon & Elisseeff, 2003) is also performed over the combined features for dimensionality reduction. Consequently, this study allows us to identify the best combination of FRs and CGIs for bankruptcy prediction and assists the relevant financial institutions to make better lending decisions. Moreover, the optimal performance of the prediction model developed based on the identified features can be used as the baseline prediction model for future studies.

The rest of this paper is organized as follows. Section 2 overviews literature related to CGIs. Sections 3 and 4 present the research methodology and experimental results respectively. Finally, in Section 5 some conclusions are offered.

2. Literature review

2.1. Corporate governance indicators

The general definition of corporate governance includes the mechanisms, processes and relations by which corporations are controlled and directed (Shailer, 2004). An integrated set of internal and external control mechanisms will allow shareholders to exercise appropriate oversight of a company to maximize firm value and ensure that it generates a return on their holdings (Chen, 2014).

Many corporate governance indicators (CGIs) have been identified in the literature which have been used for solving bankruptcy or financial crisis problems. These can be broadly classified into five categories including board structure, ownership structure, cash flow rights, key person retained, and others (cf. Appendix). However, not all the CGIs used for predicting bankruptcy in related works are the same. In other words, different categories of CGIs have been considered in different studies. For instance, Lee and Yeh (2004) used 6 FRs belonging to the solvency, profitability, and others categories and 10 CGIs in the board structure and ownership categories. They found that model performance could be enhanced by using a combination of CGIs and FRs by using logistic regression.

2.2. Related works using financial ratios and corporate governance indicators

In Wu (2007), factor analysis was used to select 6 FRs out of the 13 suggested by Altman (1968) and Ohlson (1980). These FRs belonged to the solvency, profitability, and turnover categories, while 10 CGIs were chosen from the ownership and board structure categories.

Lin et al. (2010) used an exhaustive search method to select 4 and 6 FRs and CGIs out of 23 and 42, respectively. They showed that with the chosen CGIs, the prediction model (based on the support vector machine) provided higher prediction accuracy. In particular, the chosen FRs belonged to the solvency and turnover categories, and the chosen CGIs were in the board structure, ownership, and cash flow rights categories.

There have been several studies that have used CGIs alone without considering FRs for financial crisis analysis. In Chen (2014), 23 CGIs were chosen, belonging to 5 categories, and Bredart (2014) chose 4 CGIs in the board structure category. Principal component analysis was used in the former study while logistic regression was used as the analysis method in the latter.

In summary, although related studies have shown that combining FRs and CGIs can make the prediction model perform better than using FRs alone, not all studies used the same set of CGIs for the analysis. This means that not all five categories of CGIs have completely been considered in literature. Consequently, this raises the question: Will a prediction model developed based on all related FRs and CGIs perform better than a model based on FRs alone? More specifically, we assume that some combination of specific categories of FRs and CGIs would be more representative (i.e. have more discriminatory power) that would allow the prediction model to provide higher prediction accuracy, which can better distinguish between bankrupt and non-bankrupt cases over a given set of testing cases.

Furthermore, feature selection is performed to filter out some unrepresentative features (i.e. variables) from the combined FRs and CGIs, such as in Wu (2007) and Lin et al. (2010). However, using different methods mean that different sets of features will be selected, so they only used one specific feature selection method for limited FRs and CGIs. Therefore, here, in order to find the best combination of different categories of FRs and CGIs, different feature selection methods will be used in the comparison (cf. Section 3.2).

3. Research methodology

3.1. The data source

In this study, data were collected from the Taiwan Economic Journal[1] for the years 1999–2009. Company bankruptcy was defined based on the business regulations of the Taiwan Stock Exchange.[2] In addition, there were two criteria used in collecting the data samples. First, the sample companies had to have at least three years of complete public information before the occurrence of the financial crisis. Second, there should be a sufficient number of comparable companies of similar size in the same industry for comparison of the bankrupt and non-bankrupt cases. The resultant sample includes companies from the manufacturing industry composed of industrial and electronics companies (346 companies), the service industry composed of shipping, tourism, and retail companies (39 companies), and others (93 companies), but not financial companies.

It should be noted that if there is a significant difference between the number of bankrupt and non-bankrupt cases, this results in a class imbalance problem, which is likely to lead to a degradation in the final prediction performance. Therefore, we use the method of stratified sampling (Altman, 1968) to collect the same number of bankrupt and non-bankrupt cases. Consequently, the collected dataset is composed of 239 bankrupt and 239 non-bankrupt cases, with each company (i.e. case) represented by 95 FRs and 95 CGIs as the input variables (cf. Appendix). Moreover, each of the variables is normalized into the range from 0 to 1 by

$$\forall x \in F, \ \text{normalize}(x) = \frac{x - \min(F)}{\max(F) - \min(F)}, \tag{1}$$

[1] http://www.tej.com.tw/twsite/.

[2] http://twse-regulation.twse.com.tw/ENG/EN/law/DOC01.aspx?FLCODE=FL007304&FLNO=49++++.

Table 1
The parameters used for the feature selection methods.

Methods	Parameters
GA	- Objective function (fitness function): average accuracy - Selection: roulette wheel selection - Crossover method: uniform crossover - Generations: 20 - Population size: 60 - Crossover rate: 0.7 - Mutation rate: 0.01 - Elite chromosome: 2
REF	The smallest ranking criterion: 100
SDA	- SLENTRY: 0.05 - SLSTAY: 0.1
t-test	The feature is selected if its p-value is smaller than 0.05.

where F is a set of one specific feature (i.e. variable), x is the feature value, and max(F) and min(F) are the maximum and minimum values of the specific feature set, respectively.

To avoid variability of the samples, which may affect the model performance and minimize any bias effect, the 10-fold cross validation method (Kohavi, 1995) is used to divide the dataset into 10 distinct training and testing subsets with which to train and test the prediction model. The final prediction performance is based on the average of the 10 testing results over the 10 testing subsets individually.

3.2. Feature selection

The aim of feature selection or dimensionality reduction is to reduce irrelevant or redundant features by selecting more representative features having more discriminatory power over a given dataset (Dash & Liu, 1997; Guyon & Elisseeff, 2003). According to Lin et al. (2012), although there are many methods for feature selection, most related works only apply one specific method. Five well-known feature selection methods are compared in this study in order to identify the best one for bankruptcy prediction.

In particular, three filter and two wrapper based methods are considered, specifically, the filter based methods of stepwise discriminant analysis (SDA) (Fisher, 1936), stepwise logistic regression (SLR) (Fisher & Yates, 1963), and *t*-testing (Zimmerman, 1997)[3] and the wrapper based methods of the genetic algorithm (GA) (Holland, 1975) and recursive feature elimination (RFE) (Guyon, Weston, Barnhill, & Vapnik, 2002). Table 1 lists the parameters used in these methods. Note that SLR does not require any parameters to perform feature selection.

3.3. Prediction models

Similar to feature selection, there are many common and well-known techniques which can be employed to develop prediction models. In this work, five related techniques are compared, namely support vector machines (SVM), *k*-nearest neighbor (KNN), naïve Bayes (NB) classifier, classification and regression tree (CART), and multilayer perceptron (MLP) methods. These are not only the most widely used techniques for bankruptcy prediction (Lin et al., 2012), but also the top 5 supervised machine learning techniques used in data mining (Wu et al., 2008).

Table 2 lists related parameters for the techniques used to develop the prediction models.

[3] The SAS software was used to perform filter based feature selection methods.

Table 2
The parameters used in the five techniques.

Techniques	Parameters
SVM	Kernel: linear
KNN	$K = 7$
CART	Tree pruning: cross-validation
MLP	- No. of hidden layers: 1 - No. of hidden layer nodes: 64 - Learning epochs: 50
NB	Kernel: kernel density estimate

Table 3
Prediction performance of models A and B.

	A (percent)	B (percent)
Average accuracy	82.05	83.64
Type I error	17.73	12.73
Type II error	18.18	20.00

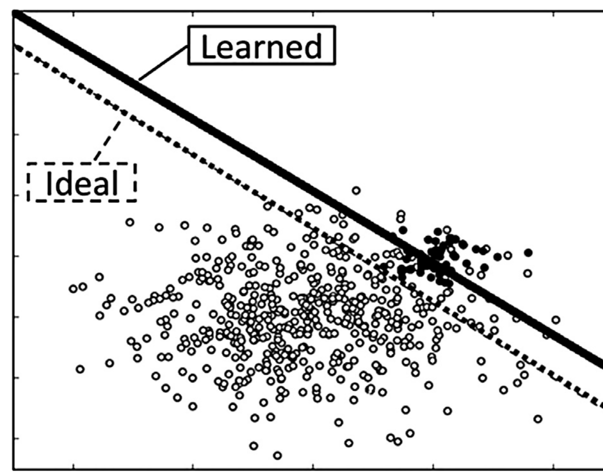


Fig. 1. The decision boundary of a prediction model.

3.4. Evaluation metrics

To examine the prediction performance of the developed models, two evaluation metrics are usually considered, which are the average prediction accuracy and the Type I error. The average prediction accuracy rate is calculated based on how many data samples are correctly classified by the prediction model over a given testing set. The Type I error rate is a measure of the number of data samples where the prediction model incorrectly classifies a bankrupt firm into the non-bankrupt class. The Type I error can sometimes be more critical than the average prediction accuracy since a larger Type I error rate requires financial institutions to expend larger costs.

In addition to these two generally used metrics, we also examine the receiver operating characteristic (ROC) curve (Fawcelt, 2006) of each prediction model. This is a graphical plot used to illustrate the prediction model as its discrimination threshold is varied. In our case, the Types I and II errors of the prediction model are plotted on the x- and y-axis of the ROC curve.

For example, the prediction performance for two prediction models, namely A and B, over a given testing set, is summarized in Table 3. Generally speaking, model B performs better than model A as evidenced by the higher accuracy rate and lower Type I error rate.

However, to create the ROC curve for a prediction model, we need to adjust its penalty threshold, which makes the model produce different accuracy and Type I/II errors. Fig. 1 shows the

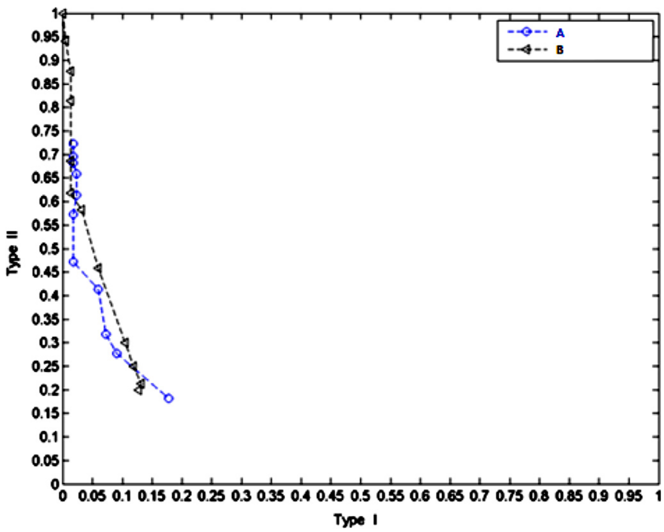


Fig. 2. ROC curves for models A and B.

data sample and the decision boundary of a model with a fixed penalty where the black and white points represent cases of bankruptcy and non-bankruptcy, respectively. Based on the fixed penalty, the decision boundary of the model needs to 'sacrifice' several bankrupt cases (i.e. increasing the Type I error) to obtain the highest average accuracy.

Suppose that the cost of misclassification is higher for bankruptcy cases than for non-bankruptcy cases. Increasing the penalty moves the decision boundary toward the 'ideal' line. In this case, the model is able to detect all of the bankruptcy cases, but at the 'sacrifice' of a number of non-bankrupt cases (i.e. increasing the Type II error). Using different penalty threshold values to create the ROC curve of a prediction model allows us to examine the differences between the Type I and Type II errors.

Fig. 2 shows the ROC curves of models A and B. In comparison to the results shown in Table 3, model A performs better than model B, as can be seen in the ROC curves. This is because the area under the curve (AUC)[4] is smaller for model A than for model B.

However, it may be the case that two or more models' ROC curves are very close to each other which would make it very hard to determine the best model. To overcome this limitation, we introduce a misclassification cost and cost ratios. Specifically, the misclassification cost aims to measure to what extent people can tolerate the misclassification result. For some, the cost of misclassifying a bankrupt company into the non-bankrupt class would be the same as the cost of misclassifying a non-bankrupt company into the bankrupt class. However, for others, the cost of misclassifying a bankrupt company would be much higher than the cost of misclassifying two or more non-bankrupt companies.

The misclassification costs for the different models are calculated based on

$$\begin{aligned}&(\text{Type I error no. bankrupt cases cost ratio})\\&\quad+(\text{Type II error no. non}-\text{bankrupt cases}).\end{aligned}\tag{2}$$

In order to further compare different models' performances, different penalty thresholds and cost ratios are examined as shown in Table 4.

[4] AUC represents the probability that a model will rank a randomly chosen positive instance higher than a randomly chosen negative one (assuming that 'positive' ranks higher than 'negative').

Table 4
Different penalty thresholds and cost ratios.

Evaluation parameters	Values
Penalty thresholds	1, 1.5, 2, 3, 5, 7.5, 10, 15, 20, 25, 30, 40, and 50
Cost ratios	1, 1.5, 2, 3, 5, 7, 10, 15, 20, 25, and 30

4. Experiments

4.1. The preliminary results

4.1.1. The performance of different prediction models using FRs and CGIs

The first experiment is designed to compare the prediction performances of different models based on FRs and CGIs alone. The results are shown in Table 5. As we can see, the prediction models using CGIs alone perform worse than the ones using FRs alone in terms of average accuracy and Type I/II errors. Therefore, the following experiments focus on comparing the prediction models using FRs and the combined FRs and CGIs, respectively.

4.1.2. The performance of different prediction models

Following up on the previous results, the next experiment is designed to compare the five prediction models based on FRs (hereafter FR) and FRs with CGIs (hereafter FC) in order to find the best model for later analysis. Table 6 shows the comparative results. It can be seen that the SVM prediction model performs the best in terms of average accuracy and Type I/II errors no matter what features are used.

The stability of the SVM model is further examined using the three filter based feature selection methods (c.f. Section 3.2) to reduce the dimensions of FR and FC. Tables 7– 9 show the *t*-test, SLR, and SDA results, respectively.

The results are consistent with the ones shown in Table 6, indicating that, regardless of which filter based feature selection method is performed over the FR and FC datasets, the SVM model always performs the best. Therefore, only the SVM model will be used for the later experimental studies.

4.1.3. The performance of SVM using different cost ratios

Table 10 lists the Types I and II errors of SVM obtained using different cost ratios. The results indicate that when the cost ratios are larger than 5, the differences between Types I and II errors are very large, which makes this method not suitable for use with real world problems. Therefore, cost ratios from 1 to 5 are used in the later experiments.

4.1.4. The ROC curves of SVM by FR and FC with and without feature selection

The performance of the SVM based on FR and FC is examined with and without feature selection. Figs. 3 and 4 show the ROC curves obtained with SVM over the FR and FC datasets, respectively. The results show that *t*-test + SVM and SDA + SVM perform the best over the FR and FC datasets, respectively.

Fig. 5 further shows the ROC curves obtained for these two models. As we can see, the curve of SDA + SVM is almost completely beneath the one obtained with *t*-test + SVM. In addition, Table 11 shows the misclassification costs for these two curves. The results demonstrate that when the cost is larger than 1, SDA + SVM (over FC) performs significantly better than *t*-test + SVM (over FR). Note that the level of performance significance is measured by the Wilcoxon test (Demsar, 2006). If the misclassification cost is set to 1, even though there is no significant difference between them, the SDA + SVM performs slightly better than the *t*-test + SVM. In short, this preliminary study demonstrates that combining CGIs with FRs can make the prediction model perform better than using FRs alone.

Table 5
The performance of different prediction models (FRs/CGIs).

	SVM (percent/percent)	KNN (percent/percent)	CART (percent/percent)	MLP (percent/percent)	NB (percent/percent)
Avg. accuracy	79.1/67.9	76.5/60.6	78.4/60.2	76.1/61.4	68.6/58.3
Type I error	20.2/27.7	22.5/30.7	23.3/37	24.1/40	26.4/60.6
Type II error	21.6/36.5	24.5/48.1	19.9/42.5	23.8/37.2	36.5/22.8

Table 6
The performance of different prediction models (FR/FC).

	SVM (percent/percent)	KNN (percent/percent)	CART (percent/percent)	MLP (percent/percent)	NB (percent/percent)
Avg. accuracy	79.1/81.3	76.5/74.5	78.4/78.6	76.1/70.4	68.6/68.7
Type I error	20.2/17.8	22.5/18.5	23.3/22.3	24.1/26.6	26.4/23.1
Type II error	21.6/19.7	24.5/32.5	19.9/20.4	23.8/32.5	36.5/39.6

Table 7
The performance of different prediction models followed by *t*-test·FR and *t*-test·FC.

	SVM (percent/percent)	KNN (percent/percent)	CART (percent/percent)	MLP (percent/percent)	NB (percent/percent)
Avg. accuracy	79.8/80.1	77.2/74.4	77.9/78.1	74.2/72.2	75.1/75.1
Type I error	19.5/19.2	21.6/21.6	21.9/22.2	22/24.3	21.3/21.3
Type II error	20.8/20.7	23.9/29.5	22.3/21.6	29.5/31.3	28.5/28.5

Table 8
The performance of different prediction models followed by SLR·FR and SLR·FC.

	SVM (percent/percent)	KNN (percent/percent)	CART (percent/percent)	MLP (percent/percent)	NB (percent/percent)
Avg. accuracy	80.2/81.3	76.6/77.9	77.8/78.2	79.8/80.5	77.9/77.1
Type I error	20.9/16.7	21/20.1	20.8/22.2	21.3/18.8	20/12
Type II error	18.7/20.8	21.8/24.1	23.6/21.4	19.2/20.3	24.2/33.8

Table 9
The performance of different prediction models followed by SDA·FR and SDA·FC.

	SVM (percent/percent)	KNN (percent/percent)	CART (percent/percent)	MLP (percent/percent)	NB (percent/percent)
Avg. accuracy	78/81.5	76.2/74.7	76.5/74.9	77.7/78.1	75/74.8
Type I error	18.1/16.3	20/22.7	22/24.2	22.4/18.7	25.5/21.7
Type II error	25.9/20.8	27.6/28	25/26.1	22.2/25.2	24.5/28.8

Table 10
The Types I and II errors of SVM based on different cost ratios.

	FR		FC	
	Type I error (percent)	Type II error (percent)	Type I error (percent)	Type II error (percent)
1	20	18.1	16	19.3
1.5	12.5	27	10	26.1
2	10.2	30.9	7.1	30.9
3	6.9	38.4	5.4	34.8
5	3.5	50.5	4.8	36.9
7.5	1.9	60.1	4.4	39.4
10	1.3	65.8	4.4	39.4
15	0.9	69.9	4.4	39.4
20	0.9	69.9	4.4	39.4
30	0.9	69.9	4.4	39.4

Table 11
The misclassification costs for *t*-test + SVM and SDA + SVM (***$p < 0.01$; **$p < 0.05$; *$p < 0.1$).

	t-test + SVM (over FR)	SDA + SVM (over FC)
1	**1.01E−01**	**1**
1.5	2.21E−02***	**1**
2	9.30E−04***	**1**
3	9.53E−05***	**1**
5	1.88E−05***	**1**

4.2. Results of SVM using different categories of FRs and CGIs

The remaining experiments are conducted using different categories of financial ratios and corporate governance indicators, respectively. There are seven different categories of FRs and five different categories of CGIs, so that we collect a total of 12 different datasets, each composed of 11 unduplicated categories of FRs and CGIs. In other words, for each dataset, one specific category is removed from the 'complete' dataset, which contains all of the 12 different categories of features. Examination of the model's performance over these 12 different datasets further demonstrates

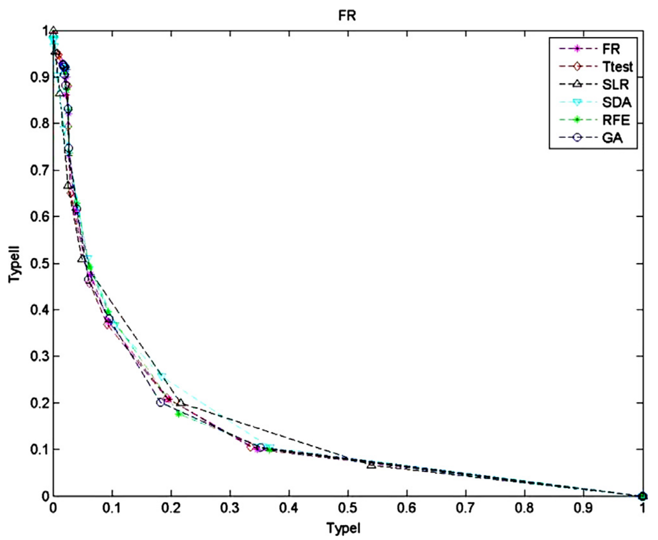


Fig. 3. The ROC curves of SVM over the FR dataset with and without feature selection.

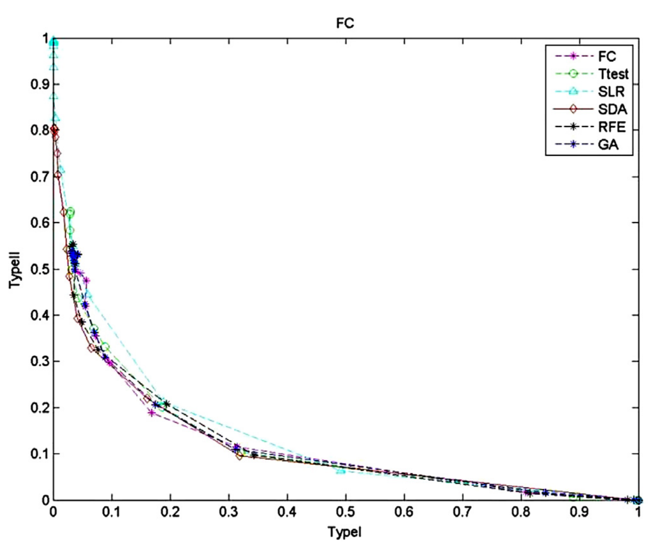


Fig. 4. The ROC curves of SVM over the FC dataset with and without feature selection.

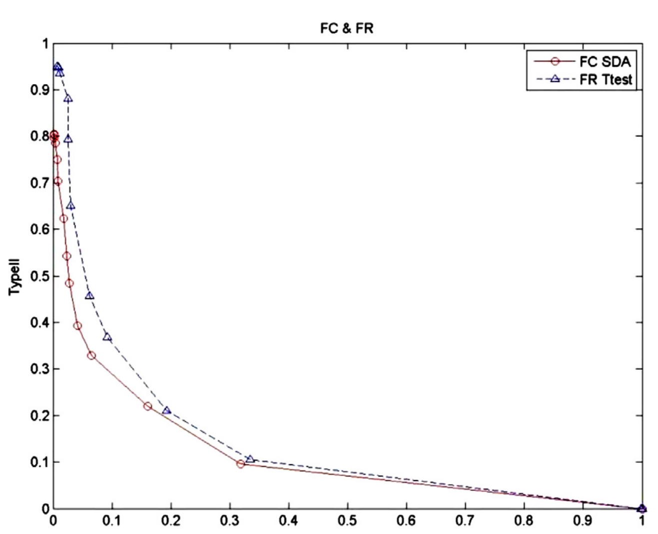


Fig. 5. The ROC curves for FR *t*-test (i.e. test + SVM over FR) and FC SDA (i.e. SDA + SVM over FC).

whether combining FRs with CGIs can improve bankruptcy prediction performance.

4.2.1. Results for datasets without solvency, profitability, turnover ratios, and capital structure ratios

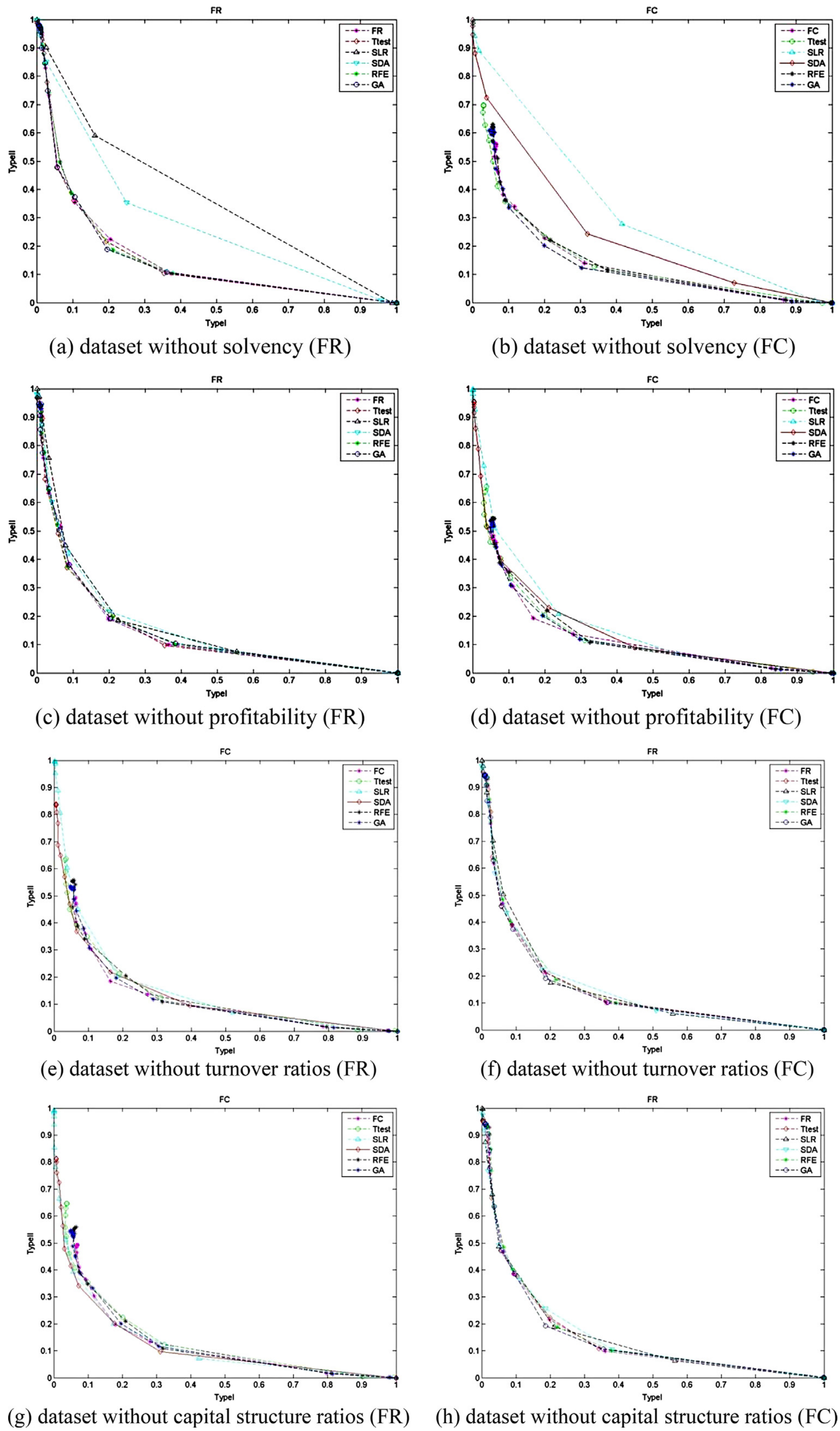
Fig. 6 shows the datasets obtained without using one specific category of FRs in combination with CGIs. The findings are summarized below.

- For the dataset without the solvency category (i.e. Fig. 6(a) and (b)), GA + SVM and *t*-test + SVM perform the best over the FR and FC datasets, respectively, although the ROC curves are very similar. Therefore, we further examine the misclassification costs, as in Section 4.1.4. We find that when the costs are between 1 and 2, GA + SVM (FR) performs better, but when the costs become larger, namely 3–5, *t*-test + SVM (FC) provides better performance. This indicates that no certain performance improvement is obtained when CGIs are combined with FRs without the solvency category.
- For the dataset without the category of profitability (i.e. Fig. 6(c) and (d)), *t*-test + SVM and SDA + SVM perform the best over the FR and FC datasets, respectively. Similar to the previous results, the two ROC curves are close to each other. In addition, when the costs are between 1 and 2, *t*-test + SVM performs better, but SDA + SVM is better when the costs are between 3 and 5. This also indicates that combining CGIs with FRs without the profitability category leads to no obvious improvement in performance.
- For the dataset without the category of turnover ratios (i.e. Fig. 6(e) and (f)), the results, including the best prediction models and their misclassification costs, are the same as for the dataset without the profitability category. It can be seen from this that turnover ratios are an important feature in bankruptcy prediction. The SVM based on the FC dataset without the turnover ratios does not perform significantly better than the one based on the FR dataset.
- The results obtained for the other categories, such as capital structure ratios, cash flow ratios, growth, and so on, are similar. Therefore, we only show the results for the dataset without the category of capital structure ratios (i.e. Fig. 6(g) and (h)) are shown. It is found that *t*-test + SVM and SDA + SVM are the best models over the FR and FC datasets, respectively. Specifically, the ROC curve for SDA + SVM is always beneath the one for *t*-test + SVM. In addition, according to the misclassification cost, SDA + SVM performs significantly better than *t*-test + SVM no matter which cost ratio is used (i.e. from 1 to 5). Therefore, combining CGIs with the FRs without these categories still allows for improvement in model performance.

4.2.2. Results for datasets without board, ownership, and cash flow rights

Fig. 7 shows the datasets without one specific category of CGIs and their combinations with FRs. The findings are summarized below.

- For the dataset without the category of board structure (i.e. Fig. 7(a) and (b)), the best models are *t*-test + SVM and SDA + SVM, over the FR and FC datasets, respectively, although their ROC curves are close to each other. The misclassification costs for these two models show that board structure is important for bankruptcy prediction. It can be seen that the model based on all of the CGIs except for the category of board structure (combined with FRs) does not outperform the one based on FRs alone. In other words, to enhance the model performance, board structure should be considered when combining CGIs and FRs.



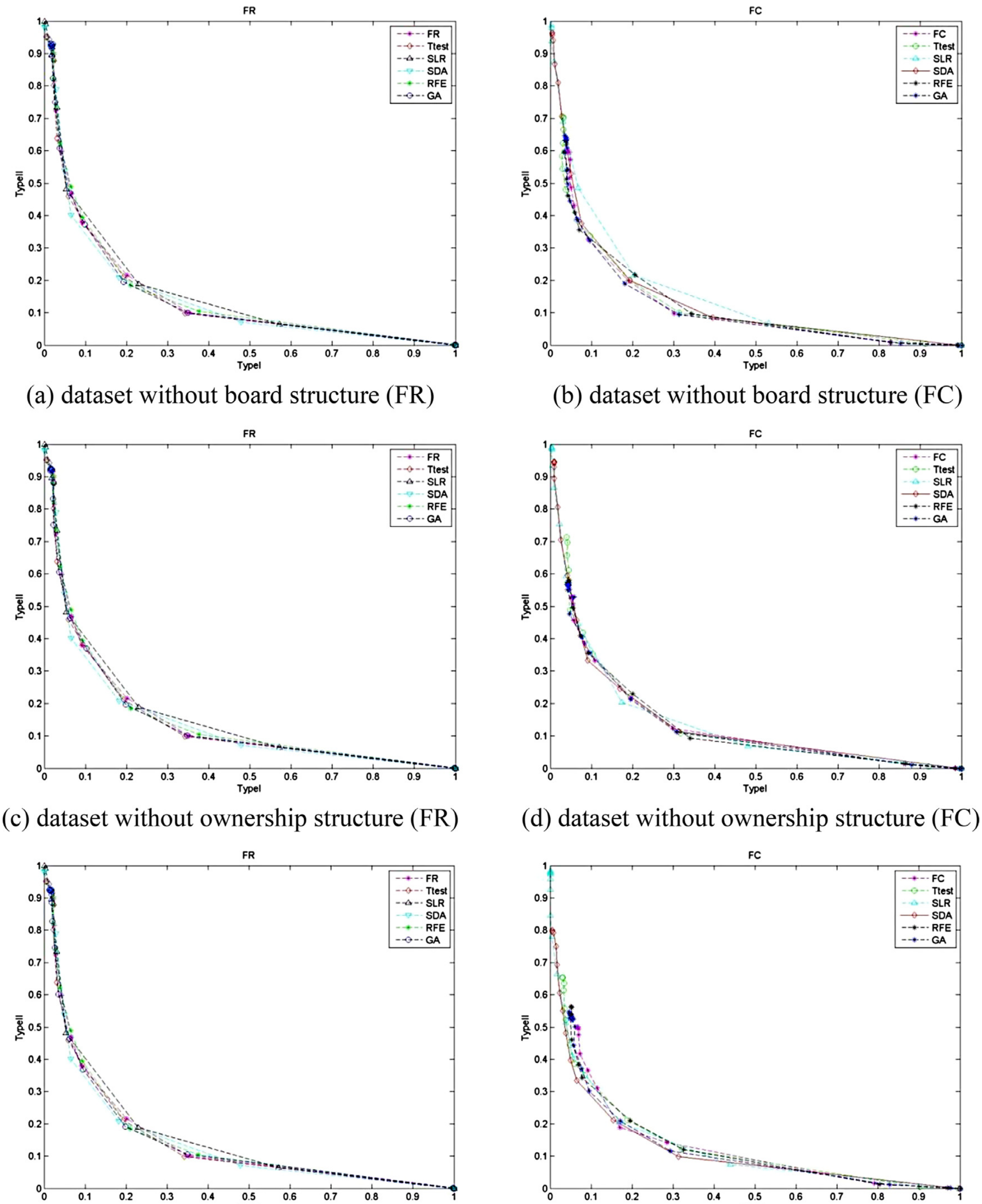
(a) dataset without solvency (FR) (b) dataset without solvency (FC)

(c) dataset without profitability (FR) (d) dataset without profitability (FC)

(e) dataset without turnover ratios (FR) (f) dataset without turnover ratios (FC)

(g) dataset without capital structure ratios (FR) (h) dataset without capital structure ratios (FC)

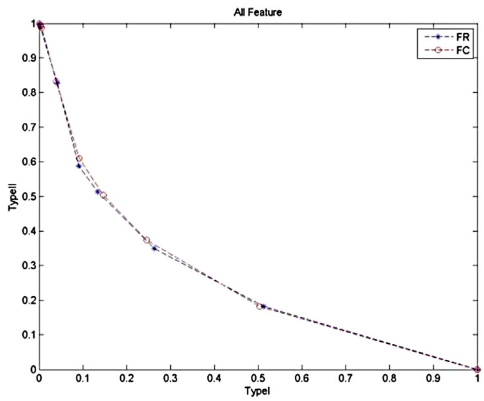
Fig. 6. ROC curves of SVM over the datasets without one specific category of FR.



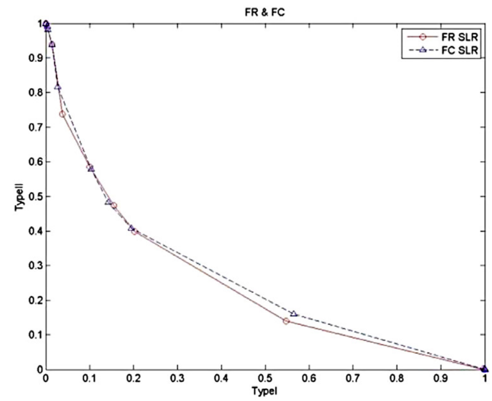
(a) dataset without board structure (FR)
(b) dataset without board structure (FC)
(c) dataset without ownership structure (FR)
(d) dataset without ownership structure (FC)
(e) dataset without cash flow rights (FR)
(f) dataset without cash flow rights (FC)

Fig. 7. ROC curves of SVM over the datasets without one specific category of CGIs.

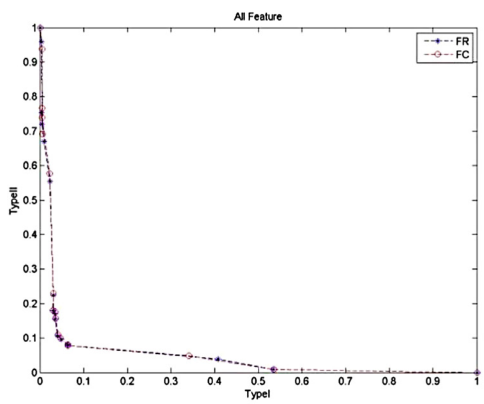
- For the dataset without the category of ownership structures (i.e. Fig. 7(c) and (d)), the best models are found to be the same as in the previous result. Similarly, their ROC curves are very close to each other and the results obtained using different misclassification costs show that ownership structure is also important in CGIs when combined with FRs. Thus, the model based on FC without the category of ownership structures does not perform significantly better than the one based on FR.
- The results are similar for other categories of CGIs, such as key person retained, cash flow rights, and others. Therefore, for brevity, we only provide the results for the dataset without the category of cash flow rights (i.e. Fig. 7(e) and (f)). We can see that the best models are *t*-test + SVM and SDA + SVM over the FR and FC datasets, respectively. In addition, the ROC curve for SDA + SVM is always underneath the one for *t*-test + SVM. Furthermore, the different misclassification cost results show that SDA + SVM significantly outperforms *t*-test + SVM. This means that when CGIs are combined with FRs, the model still provides better performance without considering these features than the model based on FRs alone.



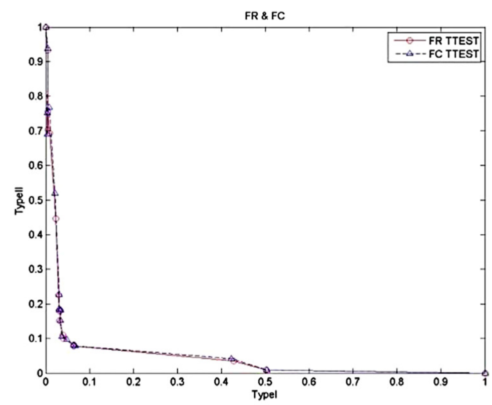
(a) the case one dataset (without feature selection)



(b) the case one dataset (with feature selection by SLR)



(c) the case two dataset (without feature selection)



(b) the case two dataset (with feature selection by t-test)

Fig. 8. ROC curves of FR and FC.

4.3. Further validation

In order to further validate whether the combination of FRs and CGIs is effective in other markets, related case companies from the Chinese market are selected. Since there is no standard definition of distressed companies for this market, we choose a sample composed of special treatment (ST) companies. The special treatment designation is the first step to delisting a stock in the Chinese stock exchange. In other words, ST companies face the risk of being delisted if they do not resolve the conditions leading to the designation. We choose two scenarios, which are to predict the occurrence of ST before one year (case one) and in the first year (case two).

The resulting cases one and two datasets are composed of 287 distressed and 287 non-distressed companies and 348 distressed and 348 non-distressed companies, respectively. In addition, each data sample contains 45 financial ratios and 77 corporate governance indicators. Similar to previous studies, different feature selection methods are used individually to perform the feature selection task to filter out unrepresentative features of FRs and CGIs.

Fig. 8 shows the prediction performance when using financial ratios alone (i.e. FR) and the combination of FRs and CGIs (i.e. FC) with and without feature selection over the two datasets. These results show no significant differences in performance between using FR and FC. In other words, combining CGIs with FRs does not necessarily improve the prediction model's performance for the China market. In other words, CGIs are not the critical factors that affect the prediction of distressed companies. However, combining FRs with CGIs does not have a negative impact on the prediction performance. Please refer to Section 4.4 for a discussion of the results over the Taiwan and China markets.

4.4. Discussion

The preliminary results obtained using the Taiwan market data show better prediction results for those models using CGIs and FRs than the model using FRs alone. The improvement in performance is significant when the misclassification cost is larger than 1. This demonstrates the effectiveness of combining CGIs with FRs for bankruptcy prediction.

Furthermore, we found that the solvency and profitability categories are the critical features of FRs. This is because the SVM model based on the FC datasets that does not have these critical features does not always significantly outperform the SVM model based on FRs.

On the other hand, for CGIs, the categories of board structure and ownership structure play an important role in predicting bankruptcy. That is, there is not a significant difference in the performance of an SVM based on FC without board structure and ownership structure over that of the SVM based on FC.

Although the performance obtained with a combination of FRs and CGIs is better than using FRs alone in the Taiwan market, the differences between them are not significant in the China market. There are two main reasons for this finding. First, there is no standard definition of distressed companies in China. The special treatment (ST) companies are based on the financial status of company operations, where various financial anomalies can be regarded as financial distress, such as taking a financial loss for two or three consecutive years, fraudulent financial statements, the shareholder equity is negative, etc. However, large experience of all of these financial anomalies is needed to determine which are ST companies but is not needed for them to be treated as distressed companies. Clearly, if the definition of distressed companies is not clear, then it is very difficult to assess the performance of prediction models. Second, CGIs are not as critical as FRs to determine which companies are distressed for most Chinese companies. For example, many companies in China are public- or government-owned enterprises, which differ from privately owned enterprises so that board structure related indicators are not representative for most Chinese companies.

In short, determination of whether CGIs are useful or not for financial crisis prediction should be market dependent. In practice, one should be certain about the definition of distressed companies in the chosen market and their characteristics in relation to CGIs.

5. Conclusion

This study focuses on examining the discriminatory power obtained by combining different categories of financial ratios (FRs) and corporate governance indicators (CGIs) for bankruptcy prediction. In particular, seven and five categories of FRs and CGIs are considered, namely the FRs of solvency, profitability, cash flow ratios, capital structure ratios, turnover ratios, growth, and others and the CGIs of board structure, ownership structure, cash flow rights, retention of key personnel, and others.

To determine the best combination of FRs and CGIs, a real-world Taiwan dataset is used. In addition, five prediction techniques are used to develop the prediction models and five different feature selection methods are employed to reduce the dimensions of the combined FR and CGI features for comparison. The results show that the combination of FRs and CGIs can improve the model's performance when compared with the model based on FRs alone. Specifically, stepwise discriminant analysis (SDA) + support vector machine (SVM) performs the best.

Moreover, the most important features for effective bankruptcy prediction are the FR categories of solvency and profitability and the CGI categories of board structure and ownership structure. Without using these features, the prediction model cannot perform significantly better than the one based on FRs alone.

However, the usefulness of using CGIs is market dependent. That is, further analysis shows that the prediction performance in the China market of the combination of FRs and CGIs is no better than that obtained using FRs alone. There are two factors affecting the prediction result of using CGIs. The first one is the definition of distressed companies, and the second one is the extent to which the CGIs relate to the companies' characteristics in the chosen market.

Appendix

Financial ratios		Corporate governance indicators	
Solvency			
X1	Cost of interest-bearing debt	X96	Number of seats on board
X2	Cash reinvestment ratio	X97	Number of directors
X3	Current ratio	X98	Number of supervisors
X4	Acid test	X99	Seats of ultimate controllers serving as individual directors
X5	Interest expenses/total revenue	X100	Seats of ultimate controllers serving as individual supervisors
X6	Total liability/equity ratio	X101	Seats of directors ultimately controlled through an unlisted company
X7	Liability/total assets	X102	Seats of supervisors ultimately controlled through an unlisted company
X8	Interest-bearing debt/equity	X103	Seats of directors ultimately controlled through a foundation
X9	Contingent liability/equity	X104	Seats of supervisors ultimately controlled through a foundation
X10	Operating income/capital	X105	Seats of directors ultimately controlled through a listed company
X11	Pretax income/capital	X106	Seats of supervisors ultimately controlled through a listed company
X12	Working capital to total assets	X107	Seats of directors served by a company manager or group manager
X13	Quick assets/total assets	X108	Seats of supervisors served by a company manager or group manager
X14	Current assets/total assets	X109	Seats of directors served by outside individuals
X15	Cash/total assets	X110	Seats of supervisors served by outside individuals
X16	Quick assets/current liability	X111	Seats of directors served by an unlisted company not controlled by an ultimate controller
X17	Cash/current liability	X112	Seats of supervisors served by an unlisted company not controlled by an ultimate controller
X18	Current liability to assets	X113	Seats of directors served by a foundation not controlled by an ultimate controller
X19	Operating funds to liability	X114	Seats of supervisors served by a foundation not controlled by an ultimate controller
X20	Inventory/working capital	X115	Seats of directors served by a listed company not controlled by an ultimate controller
X21	Inventory/current liability	X116	Seats of supervisors served by a listed company not controlled by an ultimate controller
X22	Current liabilities/liability	X117	Seats of directors and supervisors served by the largest outside shareholder
X23	Working capital/equity	X118	Seats of directors served by the largest outside shareholder
X24	Current Liabilities/Equity	X119	Seats of supervisors served by the largest outside shareholder
X25	Long-term liability to current assets	X120	Seats of directors and supervisors served by an allied group
X26	Current liability to current assets	X121	Seats of directors served by an allied group
X27	One if total liability exceeds total assets; zero otherwise	X122	Seats of supervisors served by an allied group
X28	Equity to liability	X123	Seats of independent directors and supervisors

(continued on next page)

(*continued*)

Financial ratios		Corporate governance indicators	
Capital structure ratios		X124	Seats of independent directors
X29	Equity/total assets	X125	Seats of independent supervisors
X30	(Long-term liability + equity)/fixed assets	X126	Seats of directors and supervisor foreigner serve
X31	Fixed assets to assets	X127	Seats of directors filled by foreigners
X32	Current liability to liability	X128	Seats of supervisors filled foreigner
X33	Current liability to equity	X129	Seats of directors the ultimate controller control
X34	Equity to long-term liability	X130	Seats of supervisors the ultimate controller control
X35	Liability to equity	X131	X_{149}/X_{103}
X36	Degree of financial leverage	X132	X_{150}/X_{103}
X37	Interest coverage ratio	X133	Seats of directors serving as managers
Others		X134	X_{167}/X_{97}
X38	Operating expenses/net sales	X135	Seats of directors serving as managers
X39	(Research and development expenses)/net sales	X136	X_{169}/X_{98}
X40	Effective tax rate	***Cash flow rights***	
X41	Book value per share (B)	X137	Cash flow rights of ultimate controller, excluding shares owned by a foundation of allied groups
X42	Book value per share (A)	X138	$X_{154}-X_{157}$
X43	Book value per share (C)	X139	X_{157}/X_{154}
X44	Cash flow per share	X140	X_{154}/X_{157}
X45	Sales per share	X141	$X_{151}-X_{157}$
X46	Operating income per share	X142	X_{157}/X_{151}
X47	Sales per employee	X143	X_{151}/X_{157}
X48	Operation income per employee	X144	$X_{151}-X_{154}$
X49	Fixed assets per employee	X145	X_{154}/X_{151}
X50	Total assets to GNP price	X146	X_{151}/X_{154}
Profitability		X147	Amount of investments in other enterprises divided by stockholder's equity
X51	Return on total assets (C)	***Ownership structures***	
X52	Return on total assets (A)	X148	Shareholding ratio of board
X53	Return on total assets (B)	X149	Shareholding ratio of directors
X54	Gross profit/net sales	X150	Shareholding ratio of supervisors
X55	Realized gross profit/net sales	X151	Shareholding ratio of main shareholders
X56	Operating income/net sales	X152	Shareholding ratio of ultimate controller through individual
X57	Pre-tax income/net sales	X153	Shareholding ratio of ultimate controller through unlisted company
X58	Net income/net sales	X154	Shareholding ratio of ultimate controller
X59	Net non-operating income ratio	X155	Shareholding ratio of ultimate controller through a listed company
X60	Net income-exclude disposal gain or loss/net sales	X156	Shareholding ratio of company manager and group manager
X61	EPS-net income	X157	Shareholding ratio of ultimate controller through a juridical person

(*continued*)

(*continued*)

Financial ratios		Corporate governance indicators	
X62	Pretax income per share	X158	Shareholding ratio of ultimate controller through a juridical person serving as director and supervisor
X63	Retained earnings to total assets	X159	$X_{126}-X_{127}$
X64	Total income to total expenses	X160	Shareholding ratio of outside person
X65	Total expenses to assets	X161	Shareholding ratio of outside unlisted company
X66	Net income to total assets	X162	Shareholding ratio of outside foundation
X67	Gross profit to sales	X163	Shareholding ratio of outside listed company
X68	Net income to stockholder's equity	X164	Shareholding belonging to the largest outside group
X69	One if net income is negative for the last two years; zero otherwise	X165	Shareholding ratio of allied group
Turnover ratios		X166	$X_{121}+X_{122}+X_{123}$
X70	(inventory + accounts receivables)/equity	X167	Shareholding ratio controlled by the ultimate controller
X71	Total asset turnover	X168	Shareholding ratio of foreign directors and supervisors
X72	Accounts receivable turnover	X169	$X_{124}+X_{125}$
X73	Days receivable outstanding	X170	Shareholding ratio of alliance juridical person
X74	Inventory turnover	X171	Shareholding ratio of alliance juridical person serving as director or supervisor
X75	Fixed asset turnover	X172	$X_{171}-X_{172}$
X76	Equity turnover	X173	Shareholding ratio of outside juridical person
X77	Current assets to sales	X174	Shareholding ratio of outside juridical person serving as director or supervisor
X78	Quick assets to sales	X175	$X_{174}-X_{175}$
X79	Working capital to sales	***Retention of key personnel***	
X80	Cash to sales	X176	Turnover of spokesman within a month
X81	Cash flow to sales	X177	Turnover of chairman within 3 years
X82	No-credit interval	X178	Turnover of CEO within 3 years
Cash flow ratios		X179	Turnover of CFO within 3 years
X83	Cash flow from operating/current liabilities	X180	Turnover of spokesman within 3 years
X84	Cash flow to total assets	X181	Turnover of internal audit within 3 years
X85	Cash flow to liability	X182	Turnover of chairman within a month
X86	CFO to assets	X183	Turnover of CEO within a month
X87	Cash flow to equity	X184	Turnover of CFO within a month
Growth		X185	Number of times CPA was switched in the last 3 years
X88	Realized gross profit growth rate	X186	Turnover of internal audit within a month
X89	Operating income growth	*Others*	
X90	Net income growth	X187	Controlled seats: seats of directors and supervisors the ultimate controller control
X91	Continuing operating income after tax growth	X188	X_{148}/X_{103}
X92	Net income-excluding disposal gain or loss growth	X189	Number of times financial forecast published in a year

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(*continued*)

Financial ratios		Corporate governance indicators	
X93	Total asset growth	X190	Number of times financial report restated in a year
X94	Total equity growth		
X95	Return on total asset growth		

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