Chinese companies distress prediction: an application of DEA

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Abstract:

Early warning of financial distress is essential to control corporate credit risk. Failure to do so will result in losses to investors and even bring a crisis to economy. Traditional distress prediction models employ financial ratios and market prices to predict distress prior to its happening. This research will investigate the predictive accuracy of corporate performance measures along with standard financial ratios. Data Envelopment Analysis (DEA) is used to generate corporate performance measures. The assumption of Variable Return to Scale (VRS) is proposed and three variables, technical efficiencies, scale efficiencies and returns to scale (decreasing, increasing and constant) obtained by DEA are introduced into Logistic Regression. The results show that the predictive power is improved by this corporate performance information. Furthermore, the DEA model is compared with other classical models, Altman's Z-score and Merton's model. The data of this research cover more than 2,000 Chinese listed companies over 13 years (1998~2010). The industries Real Estate is the one with most distressed cases so it is selected for modelling. The results show that not only technical efficiency but also scale efficiency is significant in prediction and the level of returns to scale help predict future business distress.

Keywords:

1. Introduction

Credit risk, along with market risk and operational risk are the three major components of financial risk that a bank faces (refer to BASEL II). The recent financial crisis recalls the importance of credit risk to the development of all economies in the world. Once a corporate failure happens, it will bring huge losses to managers, investors and shareholders, and even cause a series of consequences to the whole society. Therefore, giving an early warning of financial failures is rather important to prevent the happening of potential losses and so to avoid any further serious outcomes. Credit scoring models are such tools to generate early signals of corporate bankruptcy and they have received academic attentions since over 60 years ago and now they are well developed and employed at many places.

There are various credit models which have been used in this field. For example, there are traditional statistical methods Altman’s (1968) Multiple Discriminant Analysis (MDA), Ohlson’s (1980) Logistic Regression (LR), and nonparametric statistical models, K-Nearest Neighbour (Henley and Hand 1997), Classification Trees (Davis et al. 1992). There is also Merton-typed structure model (1974). In recent years, along with the rapid development of computing techniques, some intelligent models like Neural Networks (NN) (Desai et al. 1996), Support Vector Machine (SVM) (Gestel et al. 2003) and Generic Algorithm (GA), and Genetic Programming (GP) (Ong et al. 2005). More recently, because of the dynamic feature and incorporation of time varying covariates, survival models are preferred in the latest research (Shumway 2001). But one limitation in survival models is that it has higher requirements on the data for analysis and usually it is hard to get full data to cover all life cycles of individuals.

In all credit risk prediction models, variable selection is always a fundamental issue in the modelling because it has significant impact on the prediction accuracy of models. Financial ratios which are the quotient of two items in financial statements are the most popular ones tried in the past. It is believed that a company’s financial statement appropriately report its characteristics, information and financial conditions. Beaver (1966) was the first one who introduced financial ratios into bankruptcy prediction. Following him, Altman (1968) and Ohlson (1980) in their classic models all use financial ratios and achieved great success. Even until now, financial ratios are still the key source where we can distinguish the good and bad one from. However the sensitivity of ratios selection is still a problem attaching to them. Later on, Merton (1974) digs information from the market prices and its volatility (option or share prices) by option pricing models and the distance to default is given by his model which is intuitive to tell how far away to default or how health a company is. Corporate governance measures are another group of information which can help prediction in analysis and they can roughly be classified into four kinds of measures: board composition, ownership structure, management compensation and director’s characteristics. Some paper by Campbell et al. (2008), Ashbaugh-Skaife et al (2006), and Lee and Yeh (2004) has tried corporate governance measures and found they are helpful in prediction. Since the emphasis on macroeconomic factors by BASEL II, macroeconomic variables receive more attention which can be found in research paper Duffie et al.(2007), Carling et al. (2007) and Bonfim (2009). This is evidence that the macroeconomic conditions change the survival risk for corporations. From the literature reviewed, it can be found that financial ratios are still dominating the variable selection, however it is widely recognized that a main cause of financial failure is its poor management (Gestel et al., 2006). And the management performance can be measured by its efficiency which is the output over input according to the normal definition.

The fact is to calculate the efficiency of a corporation is not easy given a single company's information. In Operational Research, the efficiency can be optimised by the ratio of weighted output over weighted input in Data Envelopment Analysis (DEA) and DEA is the tool to compute relative efficiencies compared to the best practice in the sample. This tool makes it possible to use efficiencies in credit risk modelling and this paper is going to employ four results in DEA: technical efficiency, pure technical efficiency, scale efficiency and level of return to scale under the assumption of Variable Return to Scale (VRS).

The following contents are organized in order as this: in Section 2, a comprehensive literature review in the application of DEA in credit prediction models are discussed; in Section 3, the method Data Envelopment Analysis is introduced there; in Section 4, the data in practice in this research is described and statistical description is given; Section 5 is the model results and following them, it is a short conclusion.

2. Literature review

As improving productivity is naturally preferred in any organization, the measurement of efficiency becomes a key issue in it. However performance is a general concept that cannot be numerically measured easily. Farrell (1957) was the first people who successfully constructed an index of efficiency by a group of weighted inputs over outputs. He tried an empirical experiment on four inputs and one output. Twenty years later, building on Farrell's work, Charnes et al. (1978) extended the relative efficiency theory to multi-input and multi-output production units, which is a more realistic and powerful methodology named Data Envelopment Analysis (DEA). The idea of it is to find out the ones yielding best practice within a set of comparable Decision Making Units (DMUs). And they can form an efficient frontier then relative efficiencies of all other DMUs can be measured by the distance to the efficient frontier. Based on the assumptions of constant returns to scale (CRS) and non-negative variables, they create CCR (Charnes, Cooper and Rhodes) model in the original paper. Banker et al. (1984) then followed the earlier work of Charnes et al. (1978), formulated a BCC model by dealing with variable returns to scale (VRS). They use an additional constraint to control the convexity of the efficient frontier. It is an effective way to model variable returns to scale problem.

In the 1990s, data envelopment analysis was introduced in credit risk evaluation as in Troutt et al. (1996). He provides an idea of how to apply DEA in credit application system. The efficient frontier in

DEA could be used to develop an acceptance boundary and any case lies on or above the efficient frontier can be accepted in the DEA sense. Then Simak (1999) in his thesis compared the average DEA efficiency between bankrupt and non-bankrupt firms. Generally, the average efficiency in bankrupt group is less than that in non-bankrupt group and there is a trend that when approaching the time of bankruptcy, the efficiency is getting smaller. His pioneering work is of great meaning but the application is very limited, it requires further analysis of relative efficiencies. Recently, Premachandra et al. (2009) use the additive DEA model to compare with Logistic Regression. Their conclusion is that under sampling conditions, the DEA is superior because LR is unable to obtain a good estimated equation. But in within-sample evaluations, LR appears to be superior to DEA.

It is widely recognized that a main cause of financial failure is poor management. And the efficiency of a corporation is quite informative for its operation and financial health. So many researchers have done experiments to incorporate efficiency as a predictor in other models. Xu and Wang (2009) put the efficiency obtained through DEA in SVMs, LR and MDA. Yeh et al. (2010) also use the efficiency score in DEA in the integrated Rough Set Theory (RST) with SVM. Their results validate their hypothesis that efficiency as a predictor will to some degree increase the prediction power. However, they both utilize the relative efficiency directly in other algorithms. It is acceptable when making in-sample prediction but if they want to predict the failure probability of a case out of the sample, there may be some troubles that any new case entering the DEA will affect the overall programming, optimal weights may change and efficient frontier may move. Therefore DEA model should be run again. If the sample size is large enough, as long as the new observation falls in the productivity probability set, its relative efficiency still can be measured by fixed efficient frontier. The situation is not true at most time because normally we cannot get a large sample in a single industrial sector.

To make DEA’s efficiency transferrable and easy to be calculated, Emel et al. (2003) proposed a credit scoring system which consists of seven steps. In its last but most important step, they don’t use relative efficiencies in univariate comparison or in other models as a potential predictor, but instead, they go to validate the inputs and outputs variables by a regression or discriminant model or judgmental analyses. As it is known that DEA does not provide statistic test for input and output variables, the significance level of them are unsure when using DEA. Now a statistical validation step makes up this limitation. Min and Lee (2008) developed the approach of Emel et al. (2003). Similarly, they fitted the DEA scores by over 1000 cases in the sample and found that the DEA score can indeed be linearly approximated by DA with five financial ratios which are ensured by statistical tests. It can be used to give credit score of applicants without recalculate the DEA programming. At last, according the Good/Bad distribution, the DEA score could be adjusted to cope with the real situation by the relevant cut-off point.

Unlike many applications of DEA measuring relative efficiency to the best practice, Paradi et al. (2004) introduced a reverse concept: the worst practice DEA. Where normal DEA selects potentially distressed firms by measuring how inefficient they are being good, worst practice DEA picks out distressed firms based on how efficient they are at being bad. This requires indicators of poor performance on the output side and result in placing the distressed firms on the 'efficient' frontier. This approach ideally suit credit risk evaluation problem where it is the worst performing firms needed to be clearly identified. The same idea can be found in the paper of Premachandra et al. (2009).

To solve the two group classification (Good/Bad) problem, Chang and Kuo (2008) propose a novel model based on DEA. Their idea is that if observations belong to the same group, they should be in the same production possibility set (PPS) and dominated by the same 'efficient' DMUs on the frontier. The 'efficient' DMUs can be identified by DEA and a pair of nonlinear discriminant frontiers can be formulated. So unlike most existing discriminant approaches with a single classification line, DEA generates two discriminant frontiers for Good and Bad groups which can deliver better classification accuracy.

DEA, when being applied in credit risk evaluation, has several advantages. Firstly, it gives a single measure of performance, which can take into account all dimensions of corporate activity, by simultaneously handling multiple inputs and outputs in different units of measurement without making judgements on their relative importance (Paradi et al. 2004). Second, it does not require an a priori specification of a functional form for the input and output's relationship (Paradi et al. 2001). Besides them, DEA has additional features of non-parametric, distribution-free, no assumption on covariance (Premachandra et al., 2009), which are all superior to statistical DA methods. Even though, DEA still has some inherent disadvantages. The model results are potentially sensitive to the selection of inputs and outputs. The number of efficient firms on the frontier tends to increase with the number of inputs and output variables. When there is no relationship between explanatory factors (within inputs and/or within outputs), DEA views each company as unique and fully efficient and efficient scores are very close to 1, which results in a loss of discriminatory power of the method. There are some other issues regarding variable selection, negative values and time shift models when applying DEA and possibly causing some troubles. They will be discussed in the next section.

At last, it is necessary to introduce Sueyoshi's new type of DA model. In four articles (Sueyoshi, 1999; 2001; 2004; 2006) he gradually develops and improves the so called DEA-DA model from DEA addictive model, which can generate an evaluation score for group members. DEA-DA maintains discriminant capabilities while incorporating the non-parametric and distribution-free feature of DEA into its computational structure. It can solve various DA problems using an intensive algorithm on a modern computer. Then by three paper with Goto (Sueyoshi and Goto, 2009a; 2009b; 2009c) he applies his DEA-DA in bankruptcy assessment with a US sample, a machinery and electric equipment industry sample and a construction industry sample. All are proved to be competitive with other DA algorithms. Although DEA-DA does not measure the efficiency as discussed in this paper, it can still be an extended DEA model to be used in credit risk evaluation.

3. Methodology

DEA is a powerful optimizing tool for performance evaluation which measures the relative efficiencies of peer Decision Making Units (DMUs) in multiple input and multiple output settings. In a DEA framework, performance is evaluated with respect to an efficient frontier which is formed by a group of efficient DMUs. In traditional DEA, there are input-oriented and output-oriented models where input-oriented one aims to minimize inputs when satisfying at least the given output levels while output-oriented tries to maximize output when giving a certain level of inputs. There could be no orientation in the model but here input-oriented is used for illustration.

Suppose we have a set of n DMUs, which produce multiple outputs y_j ($j=1,2,...,n$), by utilizing multiple inputs x_j ($j=1,2,...,n$). During a production process, it is expected that minimum inputs be used and maximum output be produced. The Production Possibility Set (PPS) could be one of the following two types:

$$T_C = \left\{ (x,y) \middle| \sum_{j=1}^{n} \lambda_j x_j \le x, \sum_{j=1}^{n} \lambda_j y_j \le y, \lambda_j \ge 0, j=1,2,...,n \right\}$$

$$T_V = \left\{ (x,y) \middle| \sum_{j=1}^{n} \lambda_j x_j \le x, \sum_{j=1}^{n} \lambda_j y_j \le y, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \ge 0, j=1,2,...,n \right\}$$

T_C is under the assumption of Constant Returns to Scale (CRS) while T_V is Variable Returns to Scale (VRS). Simply speaking, Returns to Scale (RTS) is the term to describe what happens as the scale of production increases when all inputs and outputs are variables. When the relative change in output is the same compared to the relative change in input, it is called constant returns to scale (CRS). If the proportional increase in output is larger than the proportional increase of input, it is increasing returns to scale and if the proportional increase in output is smaller than the proportional increase of input, it is decreasing returns to scale. Increasing and decreasing returns to scale both are variable returns to scale (VRS) (Cooper et al. 1999). The CCR model (Charnes et al., 1978) is a typical CRS DEA model, and the BCC model (Banker et al, 1984) is a typical VRS DEA model. When a DMU_0 is evaluated by the CCR model, we have

$$\begin{aligned} &\text{Min} \quad \theta \\ &s.t. \quad \sum_{j=1}^{n} \lambda_j x_j \le \theta x_0 \\ &\qquad \sum_{j=1}^{n} \lambda_j y_j \le y_0 \\ &\qquad \lambda_j \ge 0, j=1,2,...,n \end{aligned}$$

When a DMU_0 is evaluated by the BCC model, we have an extra constraint for λ :

$$
\begin{aligned}
&\text{Min} \quad \theta \\
&s.t. \quad \sum_{j=1}^{n} \lambda_j x_j \le \theta x_0 \\
&\qquad \sum_{j=1}^{n} \lambda_j y_j \le y_0 \\
&\qquad \sum_{j}^{n} \lambda_j = 1 \\
&\qquad \lambda_j \ge 0,\ j = 1, 2, \ldots, n
\end{aligned}
$$

The optimal value θ of above model is the pure technical efficiency of DMU_0, which signifies the extent to which the inputs need to be reduced to bring DMU_0 onto the best practice frontier without worsening outputs under VRS.

Stiglitz (1972) emphasizes that there is association between returns to scale assumptions and the probability of bankruptcy at any given debt-equity ratio. Even it is easy to understand that in reality, the true returns to scale is either increasing or decreasing, it is surprisingly to see most of applications of DEA in corporate failure prediction have an assumption of CRS. So their model to generate relative efficiency is basic CCR model. The examples are Xu and Wang (2009), Yeh et al. (2010). The paper of Psillaki et al. (2010) is one of the few cases which use VRS assumption to evaluate credit risk. They use BCC model with only one output and two inputs.

The points of this research are first, using Variable Return to Scale (VRS) assumption in modelling rather than Constant Return to Scale (CRS) which is not true in reality, and second, under the assumption of VRS, three additional variables would be introduced to prediction models. There are Technical Efficiency Score (CRS efficiency), Pure Technical Efficiency Score (VRS efficiency), Scale Efficiency Score and Return to Scale Estimation. Scale efficiency is the potential productivity gain from achieving optimal size of a firm. Pure Technical Efficiency is the potential productivity which can be achieved by optimization of inputs and outputs, from the technical point of view. Technical Efficiency is simply the product of Pure Technical Efficiency and Scale efficiency in Malmquist model. Based on the definition of Charnes et al. (1978), they have a relationship as:
Scale Efficiency = CRS efficiency / VRS efficiency

Return to Scale Estimation is an indicator to denote on which stage the company is operating, decreasing, increasing or constant, within the same industrial sector (compared with other members).

By these four variables, the DEA models actually provide much more information than the DEA models in the past. Unlike most European companies which have relatively smaller sizes, the Chinese companies give us an example with a lot of large size companies (mainly consist of SOEs) and their largest number of employees excesses 100 thousand and total revenue is over 20 billion GBP.

Therefore, cases with decreasing return to scale are very often and it is expected to have some causality for financial difficulty.

For the DEA, informative input and output variables should be selected to enter the model. As Kao and Liu (2004) state, ‘Selecting proper inputs and outputs is probably the most important task in successfully applying DEA to measure the relative efficiency of the DMUs since they deter mine the context for comparison’. But so far, there is no certain rule or the best way to be followed in selecting inputs and outputs. Consequently, different DEA users may select different combinations of inputs and outputs, which is a shortcoming of DEA (Premachandra et al., 2009). First of all, DEA requires a careful identification of inputs and outputs that is meaningful within the framework of the competitive environment of the sample to be compared (Oral and Yolalan, 1990). Usually, DEA provides better contrast with respect to the relative efficiency of the sample units when the number of units selected for comparison is significantly larger than the sum of the number of inputs and outputs considered (Parkan, 1987). This is normally true in recent research. And the number of input variables is chosen to be larger than or equal to the number of output variables (Yeh, 1996).

Generally, the input variables for a corporation are capital, liability, human resources, technology, real property etc. and the output variables are commonly profit and sales. For example, in Psillaki et al. (2010) paper, they used one output (value-added) and two inputs, capital stock and number of full time equivalent employees to generate a firm’s efficiency measure relative to best practice in each industry. It is not clear what value-added is and it is hard to calculate it. The same thing happened in Yeh et al. (2010) paper, they selected R&D expense, R&D designers and the number of patents and trademarks as input variables and the output variable included gross profit and market share.

Rather than physical or monetary items used as the input and output sets, to eliminate scale or size and unit effects in the values, more popularly, financial ratios are used instead. In Min and Lee (2008), three input ratios to be minimized are financial expenses to sales, current liabilities ratio and total borrowings and bond payable to total assets and three output ratios to be maximized are capital adequacy ratio, current ratio and interest coverage ratio. But as the authors stated in their paper, the rule to select final financial ratios entering the DEA is the loan officers and credit department officers’ expert knowledge and ‘the literature survey, and the authors’ best judgement’. It is obviously a little bit subjective because people’s experiences are not always true. Cielen et al. (2004) setup an instruction that financial ratios with a positive correlation are defined as input factors while those with a negative correlation are defined as output factors. Premachandra et al. (2009) proposed another similar but not exact rule for variable selection. It is that the smaller (inferior) values in the financial ratios, which could possibly cause financial distress, are considered to be input variables whereas the larger (superior) values in those ratios, which could cause financial distress, are considered as output variables.

Xu and Wang (2009) did a Chinese case study in their paper. Their variable selection goes back to the original definition of efficiency. They use total assets, total liability and costs of sales as the inputs and output is the income of sales. Considering the structure of my research, since financial ratios are going to be used with other models such as LR and it is better to not employ them again to avoid the homogeneity in variables. Therefore as financial reports are the best data source, some physical quantities such as total assets and number of employees in them will be picked as input as outputs. Based on the general rule, variables are chosen from capital, liability, human resources. They are 'total cost', 'total assets', 'total liabilities', 'share capital', 'number of employees' as 5 inputs, and 'total sales', 'total profit', 'cash accrued' as 3 outputs.

There is a key issue attached to DEA is how to deal with negative values in inputs and outputs. This is inevitable since no matter they are physical data or financial ratios, there are cases of negative values such as in 'profit' or 'grouth'. In the case of dealing with negative values in DEA models, there are three popular methods which are reviewed and referred most in this field. They are RDM (Range directional measure) proposed by Portela et al (2004), MSBM (modified slack-based measure) proposed by Sharp et al (2006), and SORM (semi-oriented radial measure) proposed by Emrouznejad et al (2010). MSBM was extended from RDM. And there's a new method, a variant of radial measure (VRM) introduced by Cheng et al. (2011) in their MaxDEA package.

Units invariant and translation invariant are two key points in dealing with negative values in DEA. Units invariant means that it is independent of the units in which the input and output variables are measured. Translation invariant is that if translating the original input or output data values results in a new model that has the same optimal solution as the old one, which means that the results will not change after a positive scalar is added to any input or output in the additive model.

The key feature of RDM is that it uses the subtraction between the input value of the evaluated DMU and the smallest value of the input as the input direction vector. For RDM, the efficiency measurement process applied is similar to but not exactly the same as that of radial model. Directional distance function model can deal with negative data in itself, and under VRS it is translation invariant. In VRM, the original values are replaced by their absolute values to quantify the proportion of improvements in order to reach the best-practice frontier. The VRM model is units invariant and can deal with every case of negative values presence in the dataset under assessment. In addition, the VRM model preserves the proportionate improvement property of the traditional radial model, and also yields the same results with the traditional model in the cases in which the latter one is applicable.

Radial models mean that it measures the necessary proportional improvements of relevant factors (inputs / outputs) for the evaluated DMU to reach the frontier. And in the Real estate sector, the real output is building and properties which is planned before its production. Therefore the output is fixed while the inputs should be minimised to achieve the optimal efficiency.

From the methodological view of DEA, the model suit our case is radial, inputs-oriented, and VRS. The negative data exists in the outputs, and mixed. VRM is both unit invariant and translation invariant. VRM can handle positive and negative mixed data and generates the same results as conventional radial model. Therefore, the software MaxDEA and its method how to employ negative values are applied in this research.

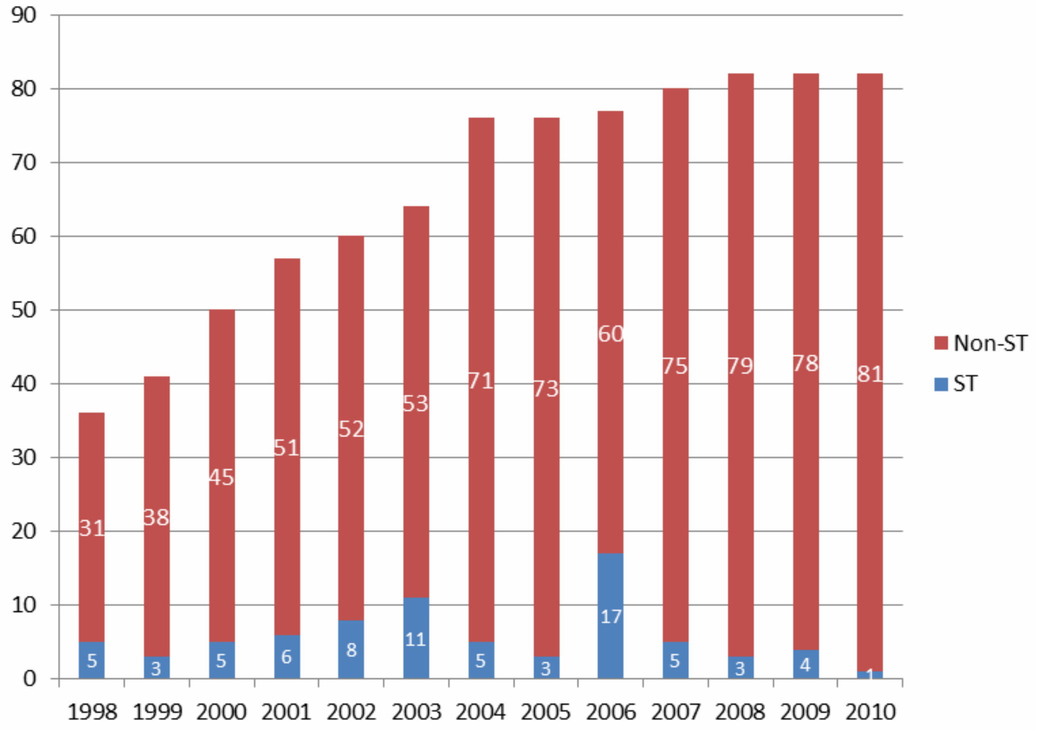
4. Data

The data used in this research is from the Chinese security markets, Shanghai Stock Exchange and Shenzhen Stock exchange. And the database Wind provides all information for those companies listed in both markets and covers the historic records as many as possible.

The original sample of my research contains the annual data of 2014 listed companies in China over 1998 to 2010. Because one of the important input variables in DEA modelling is 'number of employees' and it was until 2001 that the companies started to report this information in their statements, the reports prior to 2001 are excluded in the sample. Additionally, even though there are many reasons that could lead to 'Special Treatment' (an indicator used in this research and defined by the government to give a notice of financial distress), the majority of ST cases are regulated by the rule 'losses in two successive fiscal years'. The ST cases happened in 2010 should depend on year 2008 and 2009 at the latest. Therefore the reports of 2009 and 2010 are also excluded from the sample but the indicator of ST in 2009 and 2010 are remained.

DEA models calculate relative efficiencies within the same sector where ensure the companies in the sample share the same productivity process. So in order to keep as many defaults as possible, the sector Real Estate is the one with the most ST cases. Their number of ST and non-ST companies are displayed in the figure 1.

Figure 1. Number of ST and non-ST companies in Real Estate over 1998~2010



4.1 DEA variables

The inputs and outputs in this research are selected to be ‘total cost’, ‘total assets’, ‘total liabilities’, ‘share capital’, ‘number of employees’ as 5 inputs, and ‘total sales’, ‘total profit’, ‘cash accrued’ as 3 outputs. It is noted that there are some negative values in ‘total cost’, ‘total profit’ and ‘cash flow’. It is reasonable that a firm has negative profit and cash flow but negative ‘cost’ seems unusually. After checking the original copies of reports, there were actually some reasons for them to have their cost to be negative. However, negative physical inputs violate the assumption of DEA. These 9 negative costs are replaced by 0. And for negative outputs, MaxDEA can deal with it. The descriptive statistics are in the table below

Table 1 Descriptive statistics of DEA inputs and outputs

year		totalsales	totalcost	totalprofits	totalassets	totaldebts	sharecapital	cashaccrued	staff
2001	N	130	130	130	130	130	130	130	130
	Mean	5.16E+08	4.89E+08	3.92E+07	1.54E+09	7.92E+08	2.85E+08	4.70E+07	1.15E+03
	Median	3.15E+08	3.02E+08	2.77E+07	1.09E+09	4.99E+08	2.19E+08	4.40E+06	7.29E+02
	Std. Deviation	6.72E+08	6.20E+08	1.23E+08	1.47E+09	9.40E+08	2.27E+08	1.58E+08	1.57E+03
	Minimum	0.00E+00	1.39E+07	-5.38E+08	5.85E+07	6.49E+06	5.35E+07	-3.30E+08	1.50E+01
	Maximum	4.46E+09	4.16E+09	5.02E+08	9.69E+09	7.38E+09	1.87E+09	8.19E+08	1.33E+04
	Kurtosis	13.028	13.205	5.923	9.012	18.980	18.103	6.160	28.093
	Skewness	3.253	3.266	-.479	2.555	3.563	3.257	1.979	4.246
2002	N	132	132	132	132	132	132	132	132
	Mean	5.74E+08	5.50E+08	3.10E+07	1.70E+09	9.25E+08	2.95E+08	3.20E+07	1.15E+03
	Median	3.72E+08	3.50E+08	2.76E+07	1.22E+09	6.32E+08	2.33E+08	6.31E+06	6.31E+02
	Std. Deviation	7.28E+08	6.52E+08	1.53E+08	1.58E+09	1.02E+09	2.34E+08	1.56E+08	1.92E+03
	Minimum	2.55E+06	7.27E+06	-6.90E+08	8.86E+07	7.03E+06	5.35E+07	-6.75E+08	1.00E+01

	Maximum	4.57E+09	4.06E+09	6.03E+08	8.42E+09	6.67E+09	1.87E+09	5.77E+08	1.81E+04
	Kurtosis	11.660	11.336	7.965	5.691	10.470	15.169	5.057	46.784
	Skewness	3.068	3.029	-.746	2.144	2.766	3.021	-.058	5.809
2003	N	132	132	132	132	132	132	132	132
	Mean	6.43E+08	6.17E+08	3.05E+07	1.91E+09	1.10E+09	3.11E+08	-6.95E+06	1.07E+03
	Median	4.23E+08	4.27E+08	2.08E+07	1.38E+09	7.39E+08	2.39E+08	-1.88E+06	5.60E+02
	Std. Deviation	8.49E+08	7.59E+08	1.75E+08	1.80E+09	1.14E+09	2.58E+08	2.03E+08	1.90E+03
	Minimum	2.82E+06	0.00E+00	-6.42E+08	1.26E+08	6.24E+06	5.35E+07	-5.06E+08	2.40E+01
	Maximum	6.38E+09	5.56E+09	8.30E+08	1.06E+10	6.70E+09	1.87E+09	1.38E+09	1.64E+04
	Kurtosis	19.442	17.415	7.850	6.139	7.701	12.191	17.230	35.689
	Skewness	3.749	3.558	.457	2.179	2.402	2.914	2.451	5.200
2004	N	134	134	134	134	134	134	134	134
	Mean	7.32E+08	7.03E+08	2.68E+07	2.02E+09	1.20E+09	3.28E+08	2.71E+07	9.45E+02
	Median	4.38E+08	4.66E+08	2.66E+07	1.36E+09	7.89E+08	2.50E+08	-1.93E+06	4.79E+02
	Std. Deviation	9.39E+08	8.21E+08	2.29E+08	2.10E+09	1.28E+09	2.98E+08	3.04E+08	1.63E+03
	Minimum	0.00E+00	0.00E+00	-9.54E+08	1.20E+08	4.52E+06	5.35E+07	-6.00E+08	2.40E+01
	Maximum	7.67E+09	6.42E+09	1.26E+09	1.55E+10	9.23E+09	2.27E+09	2.16E+09	1.36E+04
	Kurtosis	22.438	17.881	9.682	13.345	11.856	18.044	22.745	31.744
	Skewness	3.791	3.370	.328	2.917	2.727	3.566	3.742	4.919
2005	N	134	134	134	134	134	134	134	134
	Mean	7.21E+08	6.81E+08	3.10E+07	2.16E+09	1.32E+09	3.50E+08	-1.81E+07	8.96E+02
	Median	4.06E+08	4.14E+08	1.59E+07	1.33E+09	8.15E+08	2.54E+08	-8.84E+06	4.32E+02
	Std. Deviation	1.10E+09	9.19E+08	2.73E+08	2.62E+09	1.59E+09	3.87E+08	2.01E+08	1.65E+03
	Minimum	0.00E+00	0.00E+00	-1.14E+09	2.73E+07	7.04E+06	5.35E+07	-1.10E+09	1.70E+01
	Maximum	1.06E+10	8.53E+09	1.98E+09	2.20E+10	1.34E+10	3.72E+09	5.98E+08	1.26E+04
	Kurtosis	48.620	39.561	21.441	24.913	25.396	44.775	9.707	28.590
	Skewness	5.794	5.106	2.400	4.028	4.028	5.690	-1.712	4.827
2006	N	136	136	136	136	136	136	136	136
	Mean	1.00E+09	9.13E+08	1.14E+08	3.15E+09	2.03E+09	4.25E+08	1.26E+08	9.90E+02
	Median	5.01E+08	4.49E+08	3.71E+07	1.59E+09	1.08E+09	2.84E+08	7.08E+06	3.57E+02
	Std. Deviation	1.77E+09	1.49E+09	3.78E+08	5.35E+09	3.64E+09	5.21E+08	7.66E+08	2.02E+03
	Minimum	1.30E+06	0.00E+00	-8.66E+08	2.23E+05	3.77E+07	5.35E+07	-5.11E+08	1.70E+01
	Maximum	1.79E+10	1.47E+10	3.43E+09	4.99E+10	3.25E+10	4.37E+09	7.49E+09	1.52E+04
	Kurtosis	61.656	54.210	44.909	43.953	39.056	30.997	70.956	28.401
	Skewness	6.804	6.281	5.388	5.665	5.473	4.908	8.020	4.875
2007	N	137	137	137	137	137	137	137	137
	Mean	1.41E+09	1.21E+09	2.62E+08	4.50E+09	2.83E+09	5.02E+08	2.32E+08	1.02E+03
	Median	7.44E+08	6.14E+08	1.06E+08	1.92E+09	1.13E+09	3.30E+08	2.05E+07	3.01E+02
	Std. Deviation	3.30E+09	2.67E+09	7.31E+08	9.99E+09	6.66E+09	6.87E+08	7.77E+08	2.20E+03
	Minimum	0.00E+00	0.00E+00	-9.33E+08	1.94E+06	4.43E+07	5.35E+07	-2.67E+09	6.00E+00
	Maximum	3.55E+10	2.81E+10	7.64E+09	1.00E+11	6.62E+10	6.87E+09	6.30E+09	1.65E+04
	Kurtosis	85.361	77.037	77.439	63.265	62.084	56.169	31.180	29.539
	Skewness	8.476	7.975	7.946	7.119	7.084	6.590	4.207	4.975
2008	N	139	139	139	139	139	139	139	139
	Mean	1.50E+09	1.28E+09	2.71E+08	5.63E+09	3.53E+09	6.78E+08	4.94E+07	1.03E+03

	Median	7.20E+08	6.29E+08	1.17E+08	2.43E+09	1.43E+09	3.90E+08	-1.20E+07	3.20E+02
	Std. Deviation	3.84E+09	3.22E+09	6.93E+08	1.22E+10	8.22E+09	1.05E+09	7.39E+08	2.11E+03
	Minimum	0.00E+00	0.00E+00	-4.32E+08	1.34E+06	1.63E+07	5.35E+07	-1.76E+09	6.00E+00
	Maximum	4.10E+10	3.49E+10	6.32E+09	1.19E+11	8.04E+10	1.10E+10	5.02E+09	1.65E+04
	Kurtosis	83.526	87.587	47.601	55.644	57.839	67.974	21.221	26.530
	Skewness	8.471	8.687	6.161	6.642	6.830	7.255	3.862	4.661
Total	N	1074	1074	1074	1074	1074	1074	1074	1074
	Mean	8.94E+08	8.10E+08	1.02E+08	2.85E+09	1.73E+09	3.99E+08	6.18E+07	1.03E+03
	Median	4.48E+08	4.27E+08	3.70E+07	1.43E+09	8.04E+08	2.67E+08	9.10E+05	4.63E+02
	Std. Deviation	2.06E+09	1.72E+09	4.26E+08	6.31E+09	4.21E+09	5.50E+08	5.04E+08	1.89E+03
	Minimum	0.00E+00	0.00E+00	-1.14E+09	2.23E+05	4.52E+06	5.35E+07	-2.67E+09	6.00E+00
	Maximum	4.10E+10	3.49E+10	7.64E+09	1.19E+11	8.04E+10	1.10E+10	7.49E+09	1.81E+04
	Kurtosis	213.170	208.910	143.673	168.731	174.038	151.487	87.311	32.294
	Skewness	12.599	12.296	9.707	11.049	11.303	9.723	7.458	5.009

4.2 Financial ratios

The financial ratios collected from the database contain 8 groups of measures. There are 15 ratios in ‘indicator per share’, 20 ratios in ‘profitability’, 5 in ‘profit composition’, 9 in ‘capital composition’, 16 in ‘liquidity’, 8 in ‘operation capacity’, 4 in ‘cash flow’, 12 in ‘growth rates’. Those with too many missing values are deleted. And those are highly correlated are also excluded. The final numbers of ratios selected are listed in the table.

Groups(7)	Ratios (52)
Indicator per share(11)	EPS at report date total share
	book value per share(BPS)
	net cash flow from operating per share
	gross revenue per share
	operating revenue per share
	surplus capital per share
	surplus reserve per share
	undistributed profits per share
	retained earnings per share
	net cash flow per share(CFPS)
	EBIT per share(EBITPS)
Profitability(15)	return of equity(ROE)
	return of assets using EBIT(ROA)
	return of assets(ROA)
	return of invested capital(ROIC)
	net profit to sales ratio
	gross margin to sales ratio
	COGS to sales ratio
	total expenses to sales ratio
	Net Profit / Total Revenue

	operating profit / total revenue
	EBIT / Total Revenue
	total cost and expenses / total revenue
	operating expenses / total revenue
	administrative expenses / total revenue
	financial expenses / total revenue
Capital composition(8)	assets to liability ratio
	equity multiplier
	current assets / total assets
	non-current assets / total assets
	tangible assets / total assets
	net assets attributable to equity / invested capital
	Interest bearing liabilities / invested capital
	current liabilities / total liabilities
Liquidity(11)	current ratio
	quick ratio
	cash ratio
	liability to equity ratio
	total equity attributable to equity / total liabilities
	total equity attributable to equity / Interest bearing liabilities
	tangible assets / total liabilities
	tangible assets / Interest bearing liabilities
	EBITDA / total liabilities
	net cash flow from operating / total liabilities
	net cash flow from operating / current liabilities
Operation capacity(3)	inventory turnover
	current assets turnover
	Total Assets Turnover
Cash flow(2)	cash proceeds from goods sold and service / operating revenue
	net cash flow from operating / operating revenue
Growth rates(2)	growth rate relative to last year end-total assets
	growth rate relative to last year end-net assets attributable to equity

5. Results

From Fig.1 it can be noticed that the year 2003 and 2006 have 11 and 17 financial distressed companies, which could be good examples for modelling. Large number of default is always preferred in credit risk modelling. When running Logistic Regression, lag 1 and lag 2 years are applied so the independent variables are year 2001 and 2003 for the STs in 2003, and year 2004 and 2005 for the STs in 2006. The results of them are given in here.

5.1 DEA

MaxDEA is the software to run the DEA model. It generates four results for further analysis. RTScode is the indicator to denote the level of return to scale and it is coded by -1 if it is decreasing return to scale, +1 if increasing and 0 if it is constant. The descriptive statistics for them are in Table 2.

Table 2 Descriptive statistics for DEA results

year		Technical Efficiency Score(CRS)	Pure Technical Efficiency Score(VRS)	Scale Efficiency Score	RTScode
2001	N	127	127	127	127
	Mean	0.781	0.821	0.945	0.441
	Median	0.794	0.839	0.992	1.000
	Std. Deviation	0.199	0.188	0.114	0.709
	Minimum	0.081	0.200	0.405	(1.000)
	Maximum	1.000	1.000	1.000	1.000
	Kurtosis	1.814	1.355	8.987	-.518
	Skewness	-1.205	-1.221	-3.005	-.875
2002	N	128	128	128	128
	Mean	0.769	0.804	0.950	0.008
	Median	0.797	0.837	0.989	0.000
	Std. Deviation	0.215	0.208	0.107	0.837
	Minimum	0.044	0.186	0.126	(1.000)
	Maximum	1.000	1.000	1.000	1.000
	Kurtosis	1.270	.710	30.818	-1.576
	Skewness	-1.220	-1.145	-4.857	-.015
2004	N	130	130	130	130
	Mean	0.772	0.806	0.949	0.285
	Median	0.836	0.880	0.992	0.000
	Std. Deviation	0.234	0.221	0.116	0.760
	Minimum	0.053	0.146	0.194	(1.000)
	Maximum	1.000	1.000	1.000	1.000
	Kurtosis	.776	.686	21.684	-1.082
	Skewness	-1.192	-1.196	-4.322	-.531
2005	N	128	128	128	128
	Mean	0.756	0.805	0.930	0.367
	Median	0.823	0.866	0.991	1.000
	Std. Deviation	0.231	0.212	0.146	0.762
	Minimum	0.059	0.128	0.287	(1.000)
	Maximum	1.000	1.000	1.000	1.000
	Kurtosis	.719	.922	9.053	-.903

	Skewness	-1.141	-1.234	-3.016	-.733

Before entering logistic regression, it is better to look at the mean difference between the ST and non-ST groups.

5.2 Logistic Regression

5.2.1 LR with lag 2

The logistic regression with lag 2 are using variables in 2001 to test the ST in 2003 and variables in 2004 to test the ST in 2006.

Firstly, all 52 ratios are entered LR with Forward conditional stepwise model, the results show 3 ratios are significant.

The next step is

5.2.2

6. Conclusion

The results show the classification accuracy is actually improved by efficiencies from DEA model. And the scale efficiency is sometimes significant to help with the prediction.

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Appendix

A

2001->2003 all ratios no efficiencies, Forward conditional stepwise

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
3	42.800[a]	.223	.501

a. Estimation terminated at iteration number 10 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted		
			ST03		Percentage Correct
			0	1	
Step 3	ST03	0	113	3	97.4
		1	7	4	36.4
	Overall Percentage				92.1

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 3[a]	EPSatreportdatetotalshare	-7.500	1.977	14.388	1	.000	.001
	equitymultiplier	-6.532	2.375	7.564	1	.006	.001
	netassetsattributabletoequity / investedcapital	-.207	.075	7.705	1	.006	.813
	Constant	22.367	8.605	6.757	1	.009	5.173E9

a. Variable(s) entered on step 3: netassetsattributabletoequity / investedcapital.

2001->2003 all ratios with efficiencies, Forward conditional stepwise

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
3	38.459[a]	.249	.559

a. Estimation terminated at iteration number 9 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted		
			ST03		Percentage Correct
			0	1	
Step 3	ST03	0	114	2	98.3
		1	6	5	45.5
	Overall Percentage				93.7

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 3[a]	totalexpensestosalesratio	-.072	.031	5.220	1	.022	.931
	currentassetsturnover	3.715	1.306	8.094	1	.004	41.072
	PureTechnicalEfficiencyScoreVRS	-33.704	11.225	9.015	1	.003	.000

	Constant	21.543	7.892	7.451	1	.006	2.270E9

a. Variable(s) entered on step 3: currentassetsturnover.

2001->2003 5 significant ratios with efficiencies, all Enter

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	24.148[a]	.329	.739

a. Estimation terminated at iteration number 11 because parameter estimates changed by less than .001.

Classification Table[a]

Observed			Predicted		
			ST03		Percentage Correct
			0	1	
Step 1	ST03	0	115	1	99.1
		1	3	8	72.7
	Overall Percentage				96.9

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	TechnicalEfficiencyScoreCRS	178.103	98.039	3.300	1	.069	2.235E77
	PureTechnicalEfficiencyScoreVRS	-252.570	126.107	4.011	1	.045	.000
	ScaleEfficiencyScore	-147.702	74.025	3.981	1	.046	.000
	RTScode	-1.538	.911	2.847	1	.092	.215
	EPSatreportdatetotalshare	-3.783	2.122	3.177	1	.075	.023
	equitymultiplier	-2.982	1.936	2.372	1	.124	.051

	netassetsattributabletoequity / investedcapital	-.090	.078	1.317	1	.251	.914
	currentassetsturnover	8.716	3.893	5.013	1	.025	6097.523
	totalexpensestosalesratio	-.225	.098	5.291	1	.021	.798
	Constant	209.707	95.247	4.848	1	.028	1.188E91

a. Variable(s) entered on step 1: TechnicalEfficiencyScoreCRS, PureTechnicalEfficiencyScoreVRS, ScaleEfficiencyScore, RTScode, EPSatreportdatetotalshare, equitymultiplier, netassetsattributabletoequity / investedcapital, currentassetsturnover, totalexpensestosalesratio.