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Predicting restaurant financial distress using decision tree and AdaBoosted decision tree models

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ABSTRACT

The restaurant industry has been facing tough challenges because of the recent economic turmoil. Although different industries face different levels of competition and therefore the likelihood of financial distress can differ for firms in different industries, scant attention has been paid to predicting restaurant financial distress. The primary objective of this paper is to examine the key financial distress factors for publicly traded U.S. restaurants for the period from 1988 to 2010 using decision trees (DT) and AdaBoosted decision trees. The AdaBoosted DT model for the entire dataset revealed that financially distressed restaurants relied more heavily on debt; and showed lower rates of increase of assets, lower net profit margins, and lower current ratios than non-distressed restaurants. A larger proportion of debt in the capital structure ruined restaurants' financial structure and the inability to pay their drastically increased debt exposed restaurants to financial distress. Additionally, a lack of capital efficiency increased the possibility of financial distress. We recommend the use of the AdaBoosted DT model as an early warning system for restaurant distress prediction because the AdaBoosted DT model demonstrated the best prediction performance with the smallest error in overall and type I error rates. The results of two subset models for full-service and limited-service restaurants indicated that the segments had slightly different financial risk factors.

1. Introduction

The restaurant industry has been facing tough challenges because of recent economic turmoil. Indicative of the economic downturn is the fact that the number of restaurants operating in the U.S. has declined for the first time in a decade (Anonymous, 2010) as 5202 restaurants closed their doors forever, leaving 579,416 restaurants operating across the country. Furthermore, several high-profile U.S. restaurant chains including Fuddruckers, Charlie Brown's Steak House, and Uno Chicago Pizza filed for bankruptcy in 2010 (Beahm, 2011). With the number of financially distressed restaurants increasing, it is important to identify which restaurants are most exposed to the risks of financial distress, because recognizing a potentially financially distressed business and identifying its problems provide the best chance for managers to take necessary corrective actions to turn the firm around (Moncarz and Kron, 1993). We defined financial distress as a situation in which a firm cannot fulfill its financial obligations to its creditors, suppliers, and/or vendors. Financial distress conditions, therefore, are of great interests to financial managers, credit and financial analysts, individual investors, and financial and operational researchers. Hence, there is an urgent need to develop efficient tools to assess the financial distress risk in the restaurant business. The motivation for this study was to develop an efficient and accurate restaurant financial distress prediction model.

Even though different industries face different levels of competition and the likelihood of financial distress can differ for firms in different industries, scant attention has been paid to restaurant financial distress prediction with the exception of Gu (2002), Jang et al. (2010), Kim and Gu (2006), Lipovatz et al. (2000), Parsa et al. (2005), Upneja and Dalbor (1999), and Youn and Gu (2010). Most previous studies have focused on the prediction of bankruptcy rather than financial distress. However, whereas some prior studies defined a financial distress condition to be synonymous with business failure or bankruptcy (Altman, 1968; Altman et al., 1977; Ball and Foster, 1982; Moses and Liao, 1995), others have suggested that a financial distress situation was heterogeneous with bankruptcy, with diverse characteristics that evoked various information signals (Gilbert et al., 1990; He et al., 2010; Laitinen, 2005; Lau, 1987; Pastena and Ruland, 1990; Ward and Foster, 1997). Furthermore, as Gilbert et al. (1990) suggested, not all firms experiencing financial distress will ultimately file bankruptcy; thus, the factors that contribute to a financial distress condition are not necessarily the same as those that motivate the filing for bankruptcy.

Connelly et al. (2010), Gudmundsson (2002), Hoi (2007), Hou and Chuang (2007), Keasey and Watson (1987, 1988) and Wu (2004) provided in-depth information that encouraged investors to examine their investment risks, creditors to assess the creditworthiness of the

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firms, and managers to asses and manage the financial turnaround of distressed companies. This raised the interests of researchers, causing them to question whether further informative data other than pure financial ratios will provide better information for efficiently and accurately predicting financial distress.

Multivariate Discriminant Analysis (MDA) and logit analyses have traditionally been popular tools for financial distress prediction (Dimitras et al., 1996). However, these methods suffer from the obvious disadvantages associated with parametric and distribution-dependent approaches (Dragos et al., 2008; Grice and Dugan, 2001; Lenox, 1999; Peat, 2008; Zmijewski, 1984). Drawbacks to MDA are the assumptions of normally distributed independent variables and equal variance–covariance matrices across distressed and non-distressed firms (Balcaen and Ooghe, 2006), whereas the shortcomings of logit analysis are the assumptions of the variation homogeneity of data (Lee et al., 2006) and the sensitivity to multicollinearity (Doumpos and Zopounidis, 1999).

Among the top 10 algorithms in data mining, C4.5 DT, support vector machine (SVM), k nearest neighbors (kNN), and naïve Bayes are commonly used techniques for classification mining (Wu et al., 2008). Specially, the non-parametric prediction method known as decision tree (DT) or recursive partitioning has been used in an attempt to bypass the above mentioned assumptions in MDA and logit (Frydman et al., 1985; Marais et al., 1984). In addition to the previous DT studies (e.g., Jeng et al., 1997; Lee et al., 1996; Olmeda and Fernandez, 1997; Tam and Kiang, 1992), more recent studies used DT in financial distress prediction (Bastos, 2008; Gepp et al., 2010; Huarng et al., 2005; Joos et al., 1998; Koh, 2004; Li et al., 2010; Lin and McClean, 2001; Quinlan, 1996; Shirata, 1998).

Past research has justified the search for the new financial distress prediction approaches of DT models and Adaptive boosted (AdaBoosted) DT models in the context of the restaurant industry. The main objective of this paper is to examine the key financial distress factors of publicly traded U.S. restaurants for the period from 1988 to 2010. This study provides several unique opportunities. First, we extended the boundary of study from bankruptcy prediction to financial distress prediction to overcome the limited database of bankrupt restaurant. Second, we included additional information to explore underlying factors that jeopardize the endurance of the restaurant. Finally, we attempted to improve the efficiency of the prediction model by using user-friendly DT and AdaBoosted DT methods.

2. Literature review

2.1. Definition of financial distress

The most common way to measure a firm's financial risk is through accounting methods. These approaches vary from simple univariate analysis to more complex distress classification models such as Altman's Z-score (Altman, 1968), Ohlson's O-score (Ohlson, 1980), or the Zmijewski score (Zmijewski, 1984). Many current studies confirmed that the latter scores could be used as proxies for financial distress (Altman et al., 2010; Grice, 2000; He et al., 2005). Acharya et al. (2007) found that a modified Altman's Z-score and the Zmijewski score were significant as determinants of recoveries for defaulted firms. Saunders and Steffen (2011) used the Zmijewski score, Altman's Z-score, modified Altman's Z-score, and Ohlson's O-score as default predictors to determine a significant loan cost disadvantage in privately held firms. Grice and Dugan (2001, 2003) found that because the Zmijewski and Ohlson models were not sensitive to various distress situations, they were better suited for predicting financial distress than for predicting bankruptcy. The authors further noted that the Zmijewski model was not sensitive to industry classifications whereas the Ohlson model was.

Similar to Acharya et al. (2007), Haskins and Williams (1990), Meyer et al. (2007), and Munsif et al. (2011), we used the Zmijewski (1984) score as an indicator of financial distress conditions for U.S. restaurants. The Zmijewski score described the financial distress probability as a results of probit equation in which a restaurant is observed under financial distress when B^* exceeds zero.

$$P(B=1)=\mathrm{P}(B^*>0); B^*=a_0+a_1ROA+a_2FINL+a_3LIQ+u$$

where P = probability; B = 1 if financial distress, 0 otherwise; ROA = net income/total assets; $FINL$ = total debts/total assets; LIQ = current assets/current liabilities; and u = a normally distributed error term. The higher the Zmijewski score, the greater the financial distress. We used the Zmijewski score as a dependent variable. If the Zmijewski score for a specific restaurant exceeds zero, the restaurant will be classified as being in financial distress. The advantage of using the Zmijewski-score to define a financial distress condition is that it is not limited by industry sensitivity.

2.2. Financial ratios and further independent variables in financial distress prediction models

Independent variables used in the model are financial ratios and further predictive variables. The use of financial ratios for corporate failure prediction has been well established since the study by Beaver (1966). Based on previous studies, we considered the financial ratios of profitability, solvency, liquidity, activity, and growth to develop a restaurant financial distress prediction model.

Profitability ratios are assumed to reflect a firm's longevity (Altman, 1968; Altman et al., 1977; Chen and Shimerda, 1981; Fama and French, 2004; Flagg et al., 1991; He et al., 2010; Kim, 2011; Laitinen, 1991). Many firms face financial distress when they have negative earnings (Fama and French, 2004). The predominant performance indicators are return on sales and measures of asset profitability. We included net profit margin, operating income margin, return on common equity, return on equity, and operating income to shareholders' equity ratio in profitability ratios because the solvency of the firm affects its endurance (Altman and Lavallee, 1981; Chan and Chen, 1991; Flagg et al., 1991; Hambrick and D'Aveni, 1988; Platt and Platt, 1990; Sharma and Mahajan, 1980). Chancharat et al. (2007) revealed that financial leverage increases the probability of becoming financially distressed. The solvency was measured by the debt-to-equity ratio, the fixed assets to long-term capital ratio, and the operating cash flow to total debt ratio. A lower level of liquidity has a positive relationship with financial failure (Kim, 2011; Laitinen, 2005). Current ratio, quick ratio, account receivable turnover, and the operating cash flow to current liability ratio were used to measure the liquidity of restaurants. The activity ratios that measure the efficiency of a firm's asset utilization are another critical dimension affecting firms' financial distress (Deakin, 1972; Lau, 1987; Moses and Liao, 1995; Platt and Platt, 1990). We measured the activity of the firms based on total asset turnover, inventory turnover in days, and fixed asset turnover. Altman (1968), Argenti (1976), Laitinen (2005), Kim (2011), and Lincoln (1984) further specified the importance of growth ratios for financial distress prediction. Accordingly, we used growth in revenue, growth in assets, growth in operating income, and growth in owners' equity for this purpose.

Current studies increased the accuracy of financial distress prediction by adding further independent variables to the traditional financial ratios. Wu (2004), for example, used non-financial information of the board holding ratio, changes in external auditor, and stock price trend to predict the characteristics of failed firms. The results showed that the prediction model with non-financial information provided better prediction accuracy than models without the non-financial information. Board holding ratio and stock price trend were statistically significant at 1% and 5%, respectively. Hou and Chuang (2007) added a corporate governance variable to construct a financial distress prediction model for Taiwanese business and revealed that companies with higher pledge ratio of directors more easily entered financial distress situations. Connelly et al. (2010) explained how firm ownership influenced firm-