Using market variables in financial distress prediction for Vietnamese listed companies

Uso de variables de mercado en la predicción de dificultades financieras para las empresas que cotizan en Vietnam

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ABSTRACT

This paper aims to investigate the classification power of market variables as predictors in the financial distress prediction model for listed companies in a frontier market as Vietnam securities market. Data is collected from 70 financially distressed companies that suffer a loss in 3 consecutive years and 156 non-financially distressed companies in Vietnam from 2010 to 2017. Four different models have been constructed using Logit regression and SVM analysis technique to make a prediction in 1 to 3-year ahead. The analysis results show that combining accounting ratios with market variables such as price volatility and P/E can improve the classification ability of the ex-ante model. In addition, contrary to the results of related previous researches in emerging markets, in this study, Logit models outperform SVM models. Therefore, for future research, models that apply other machine learning classifiers such as Decision Tree (DT) or Neural Network (NN) should be investigated.

Keywords: Financial distress prediction, SVM model, Market variables

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RESUMEN

Este artículo tiene como objetivo investigar el poder de clasificación de las variables del mercado como factores predictivos en el modelo de predicción de dificultades financieras para las empresas que cotizan en bolsa en un mercado fronterizo como el mercado de valores de Vietnam. Los datos se recopilan de 70 compañías con dificultades financieras que sufrieron una pérdida en 3 años consecutivos y 156 empresas sin dificultades financieras en Vietnam desde 2010 a 2017. Se han construido cuatro modelos diferentes utilizando regresión Logit y la técnica de análisis de SVM para hacer una predicción en 1 a 3 años por delante. Los resultados del análisis muestran que la combinación de ratios contables con variables de mercado como la volatilidad de los precios y el P / E puede mejorar la capacidad de clasificación del modelo ex ante. Además, a diferencia de los resultados de investigaciones anteriores relacionadas en mercados emergentes, en este estudio, los modelos Logit superan a los modelos SVM. Por lo tanto, para futuras investigaciones, se deben investigar los modelos que aplican otros clasificadores de aprendizaje automático, como el Árbol de decisiones (DT) o la Red neuronal (NN).

Palabras clave: predicción de dificultades financieras, modelo SVM, variables de mercado.

1. Introduction

Financial distress prediction model is the model to identify the likelihood of being financially distressed of a company. Company's financial distress prediction is a very crucial task for a company's managers and its stakeholders such as creditors, investors and government agencies because of the potential losses brought by this condition. For creditors and investors, financial distress prediction supports them in making investing decisions to manage investment's risks. For the company's managers, prediction of company's financial distress helps them to adjust their management strategies. For government offices, this ex-ante model constructs the early warning scheme to listed companies.

From the pioneering discriminant model proposed by Beaver (1966), the financial distress prediction topic has attracted interests from researchers worldwide. Corporate financial distress is traditionally recognized as bankruptcy (Ohlson, 1980; Altman, 1968; Zhou et al., 2012; Liang et al., 2015; Sánchez et al, 2016; Tinoco, 2018) and recently measured by financially-based definition that separates financial distress recognition with corporate's legal consequences (Pindado et al., 2008; Geng et al., 2014; Koh et al., 2015; Li et al., 217; Santoso and Wibowo, 2018;). Despite numerous studies taken in this area, financial distress prediction is still a challenging topic as there is no answer for an optimal model that exhibits the best level of prediction accuracy in all contexts.

In a financial distress prediction model, the selection of predictors and classifying techniques really matter in producing a high level of accuracy in dividing a company into financially distressed or non-financially distressed group. Reviewing previous studies shows that there is a wide range of predictors from accounting ratios to macroeconomic condition ratios, industry influences ratios as well market variable that can be put in prediction models. The classifying techniques also present their richness and they can be categorized into two groups: modern techniques (Case-Based Reasoning- CBR, Decision Tree-DT, Neutral Networks-NN, Support Vector Machine-SVM) and traditional classifiers (Multiple discriminate analyses – MDA, Logit model).

In spite of the prolificacy of corporate financial distress prediction models worldwide, the construction of failure prediction models for companies listed Vietnam Securities market is limited. As the number financially distressed firms is increasing in Vietnam, an effective financial distress prediction model is expected to support the sustainable development of the securities market as a goal set by the Government in order to upgrade the market into emerging market in the near future.

In this paper, the authors also aim to investigate whether the market information such as stock price volatility has the ability to predict the failure of a firm in the future. Although the relationship between market information and the firm's financial distress probability has been revealed in previous researches, this research question is still constructed to find out any different outcomes in a frontier securities market like Vietnam securities market. Choosing the condition of being delisted from suffering losses in 3 conservative years as financial distress recognition of a company, the main objectives of this paper are:

(i) discover the power of market variables in predicting the corporate financial distress; (ii) compare the accuracies of models using Logit regression (traditional classifier) analysis and SVM algorithm (modern technique).

Data is collected from Vietnam securities markets from 2010 to 2017 with 70 distressed companies and 156 non-financially distressed companies. There are 4 models constructed in 3 years of prediction with different set of predictors using Logit analysis and SVM classifier. The findings of the paper show that models using Logit analysis create higher level of accuracies than SVM models. In terms of predicting power of independent variables, models that combine accounting ratios and market variables exhibit the best performance.

2. Literature review of financial distress models

2.1. Financial distress recognition

Financial distress was firstly introduced by Beaver (1966) as failure when a company lacks ability to cover the financial obligations such as debts, preferred dividend payments. The financial distress events can be bankruptcy, bond default, overdrawn bank accounts or nonpayment of preferred stock dividend. Chan and Chen (1991) defined financially distressed firms as those that "have lost market value because of poor performance, they are inefficient producers, and they are likely to have high financial leverage and cash flow problems." Short and direct definition of financial distress is stated by Mselmi et al. (2017) and Beaver et al. (2010) as the situation where a firm's cash flows are not enough to meet contractually required payment

Bankruptcy is a traditional measure of the firm's financial distress (Beaver, 1966, Ohlson; 1980 Altman, 1968). Bankruptcy is still a favorite measure as it is widely used in a variety of papers in the field of financial distress prediction taken by Zhou et al. (2012); Liang et al.(2015); Altman et al. (2016); Tinoco et al. (2018).

Literature recently introduces another definition of financial distress which is known as financially-based definition (Pindado et al., 2008). In this measure, the financial distress condition of a company is recognized regardless of its legal consequences. A company is financially distressed when it faces problems in cash flows to support financial obligations or market value fall. A financially distressed company may not go bankruptcy or business discontinuance (Pindado et al., 2008). Financially-based definition of financial distress has shown its popularity in studies of Lin et al. (2011, 2014); Alifiah (2014); Gepp and Kumar (2015); Altman et al. (2016); Sánchez et al.(2016); Liang et al.(2016); Mselmi et al. (2017); Tinoco et al. (2018); Santoso and Wibowo (2018).

2.2. Financial distress predictors

Literature review on financial distress prediction reveals that there is no common agreement about the predictor selection and the level of importance of each predictor in a financial distress prediction model (Balcaen & Ooghe, 2006). Finding the answer for the question about the predictors' classification power has been an interesting and challenging topic for studies on ex-ante models in recent decades. Despite the argument on predictors selection in a model, literature discloses that the predictors can fall into 3 categories of accounting ratios, macroeconomic ratios, and market base variables (Tinoco et al., 2018). As can be seen from studies taken in different contexts, the financial distress prediction models that combine accounting ratios, market based variables and macroeconomic condition variables can obtain quite high level of accuracies (Beaver et al., 2010; Tinoco and Wilson, 2013; Alifiah, 2014; Geng et al., 2014; Lin et al., 2014; Bhattacharjee and Han, 2014; Koh et al., 2015; Gepp and Kumar, 2015; Bagher and Milad, 2016; Tinoco et al., 2018).

In a financial distress prediction model, accounting ratios are the main source of predictors because of their availability and their ability to reflect the firm's financial situation as they are computed from items in company's financial statements such as balance sheet, income statement and cash flow statement which are constructed periodically from accounting framework. Altman (2002) states that accounting ratios measuring a firm's profitability, liquidity, and efficiency exhibit higher classification power in the existing studies. Furthermore, accounting ratios have been demonstrated their classification abilities at 5 years before the financial distress event (Beaver et al., 2005). However, there are a few problems relating to accounting ratios application in an ex-ante model from the fact that accounting ratios reflect the company's information in the past so that the prediction ability for future financial performance can be limited. Moreover, some accounting assumptions such as cost assumption and going concern assumption affect the financial statement's preparation so that the market value may differ from the book value of a firm's assets and liabilities. In addition, the existence of management purposes may manipulate the figures in the statements (Hillegeist et al., 2004)

The idea that the company's probability of failure can be influenced by its business environment leads to the criticism of financial distress prediction model that relies on the accounting ratios only (Schwartz, 1997). Altman (1997) is the pioneer to discover the role of GNP, S&P and monetary supply in financial distress prediction model. Similarly, Cheung and Levy (1987) finds out the positive relation between company's bankruptcy and GNP deflator. There is also an evidence on the connection between the company business's failure likelihood and interest rates as well as inflation (Hill, Perry & Andes, 1996).

»The studies taken previously especially emphasizes the capacity of market variables such as stock price changes and company's capitalization in improving the performance of ex-ante models for listed companies (Campbell et al., 2011; Tinoco, M. H., Wilson, N. (2013); Gepp and Kumar, 2015; Bagher and Milad, 2016; Tinoco et al., 2018). Campbell (2011) advises that market variables have strong power to predict the time of financial distress event of a company compared to accounting ratios. Several studies taken by Beaver (1966); Beaver et al., (2005); Agarwal & Taffler (2007) show that there is negative relationship between market variables and the likelihood of companies' financial distress.

Recent studies taken for listed companies in emerging markets show that there are some principles for choosing the set of predictors in an ex-ante model. Sayari (2016) states that useful variables in a model should be stable over time, vary on the industry characteristics and should be free from redundant information. Alfaro et al. (2008) lists some rules for financial ratios selection based on their popularity in previous studies and the availability of the ratios. Similarly, Ugurlu (2006) conducts factor analysis to select 20 variables from 80 commonly used variables in a study taken in Turkey, Zhou et al. (2012) uses variables that appear more than 3 times in 128 reviewed studies while Lin et al. (2014) combine expert knowledge with wrapper method to choose 20 predictors from 44 variables for model conducted in Taiwan.

2.3. Model's classifiers

The importance role of computer science development on the improvement of a financial distress prediction model cannot be denied. With the application of various classification techniques, a number of financial distress prediction models have been constructed that can reach impressive levels of accuracy. Zhou et al. (2012) summarizes the related empirical researches and divided classification classifiers in these models into 2 groups: traditional classifier and modern classifier.

Beaver (1966), Altman (1968) and Ohlson (1980) are researchers constructing financial distress prediction models with traditional classifiers. Beaver (1966) is the pioneer in presenting univariate model in classifying companies. Altman (1968) introduced Multiple Discriminant Analysis (MDA) model that identifies a function from financial ratios which is known as Z-score model. Until 1980s, the MDA model had been a dominated model in researches on financial distress prediction (Balcaen and Ooghe, 2006). The domination of MDA decreased by the introduction of Logit analysis model by Ohlson (1980) because Logit model avoids the assumptions of normal distribution and equal covariance requirements. The modern classification techniques have been developed with the support of Artificial Intelligence (AI), data mining and machine learning technologies. There is an increase in applying algorithms of Decision Tree – DT, Neural Network – NN or Support Vector Machines – SVM for constructing a financial distress forecast model.

There have been several studies on the performance's comparison between models applying traditional and modern classifier. Ugurlu (2006) finds out that Logit model provide better accuracy level and overall fit than MDA model. The same conclusion is made in the study of Pindado et al. (2008). Wilson and Sharda (1994) in a similar study states that NN outperforms linear model in bankruptcy prediction. Recent studies taken by Lin et al., (2011, 2014), SVM model outperforms not only traditional models but also other data mining models.

3. Research design

3.1. Models' variables

In this paper, a company is considered to be financially distressed when it is required to be delisted by Vietnam Stock Exchanges because of suffering losses in 3 consecutive years. Literature reveals that the larger number of predictors cannot ensure the higher classification accuracy of a prediction model. As stated by Ugurlu (2006), Tinoco and Wilson (2013), Geng et al. (2014), the popular ratios existing in ex-ante models fall into six categories reflecting a company's profitability, solvency, leverage, efficiency, and size. Therefore, in this study, the researches select accounting ratios (from X1 to X7) on profitability, solvency, leverage, efficiency, and size that have demonstrated their prediction power in Logit models taken by Ohlson (1980), Agarwal & Taffler (2007), Tinoco et al. (2013) and Geng et al. (2014). In this study, the variable INONE receiving 1 if a firm suffers loss in the previous year and 0 otherwise is used instead of INTWO which receives 1 if the firm suffers loss in 2 consecutive years and 0 otherwise.

Three variables from X8 to X10 are put to measure the prediction power of market information in a financial distress prediction model. While MCTD and PV are used in previous studies (Tinoco et al., 2013), P/E is added to the models in this paper because this ratio attracts interest from the investors of listed companies. The accounting ratios and market variables are described below:

1. NITA: Net income on total assets, measuring the profitability of the firm. This ratio is expected to have negative coefficient in the model.

2. WCTA: Working capital divided by total assets. It is expected to have negative coefficient in the model.

3. NOCREDINT: No Credit Interval. This variable measures the time of financing a firm's expenses.

4. TLTA: Total Liabilities to Total Assets. This variable is used in models is expected to be negative related to financial distress likelihood.

5. TFOTL: Total Funds from Operations to Total Liabilities. This ratio is expected to be negatively related to financial distress likelihood.

6. SIZE: measures the logarithm of firm's total assets.

7. INONE: receive 1 if the firm suffered loss in previous year and 0 otherwise.

8. MCTD: Market Capitalization to Total Debt

9. PV: Price volatility, measures the standard deviation of firm's stock price over the year.

10. P/E: Price-to-Earnings ratio. This ratio demonstrates the relationship between corporates stock price and its earnings.

3.2. Sample size description

As recommended by Beaver (1966), the sample size should include the companies that have been successfully escape from the business failure that may lead to financial distress condition. For example, if a company suffers loss this year, but it makes profit next year, this company is considered to be successful in avoiding financial distress. Therefore, the sample size should consist 3 types of companies: financially distressed companies who are required to be delisted because of losses in 3 consecutive years (group 1), non-financially distressed companies who suffer 1 negative income in the previous years but having positive income in the current year (group 2), and non-financial distress companies with positive net income in all 3 consecutive years (group 3).

There are 78 companies are required to be delisted in the study period because of suffering loss in 3 consecutive years from 2010 to 2017. Therefore, the researchers decide to chose 78 delisted companies for group 1; 78 companies for group 2 and another 78 companies for group 3. However, because of data insufficiency, only data from 70 delisted companies could be collected. The sample size finally decreases from 234 companies to 226 including 70 delisted companies in group 1; 78 companies in group 2; and 78 companies in group 3. In other words, the sample consists of 70 financially distressed companies and 156 non-financially distressed companies in 7 years from 2010 to 2017. Data are collected in 3 years prior the financial distress event thus, the firm-year sample size is 678 companies. For example, if a company is required to be delisted in 2017, the data will be collected in 3 years from 2014 to 2016.

3.3. Data analysis procedure

In order to discover the prediction ability of market information, in this paper, 4 models are established with different sets of independent variables and classifiers of traditional and modern classifiers. Using Logit analysis as a traditional classifier, model 1.1 consists of accounting ratios from X1 to X7 while model 2.1 adds market variables (from X8 to X10) model 1.1. Model 1.2 and 2.2 apply SVM as a modern technique for classification using the same set of predictors as ones in model 1.1 and 2.1.

In Logit model, binary logistic regression is designed to estimate the probability of "financial distress" of a company from the set of predictors as discussed. The binary dependent variable is measured by two values: 1 or " financially distressed" and 0 for non-financially distressed. The probability of being non-financially distressed is P(Y=0) and the probability of being financially distressed P(Y=1) are computed as below. Before conducting the analysis, data are separated randomly into 2 sets for training and predicting.

$$P(Y = 1) = \frac{e^{-(\propto + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}{1 + e^{-(\propto + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}} \quad (1)$$

SVM is a machine learning algorithm which is applied commonly in classification. SVM tries to identify a hyperplane that segregate two classes (financially distressed and non-financially distressed companies). Exactly, SVM solves the problem of finding optimization of hyperplane, with maximal margin to separate two groups of companies.

$$\min \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \quad (2)$$

$$\textit{subject to } y_i(w^T \emptyset(x_i) + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0$$

The optimized hyperplane is identified by constructing a function called kernel from the training data using C as the penalty parameter of error term. There are four type of kernel functions in SVM: linear function, polynomial, radial basis function (RBF), and sigmoid function. For simplicity, this study construct RBF which is for SVM. The choice of C and really maters in order to get high level of prediction accuracy. As recommended, the selection of is performed by grid search to identify the best pair When the best pair of two parameters is revealed, data are trained again to obtain better classifier. Before conducting the classification techniques, the data are separated into 2 sets for training and predicting.

4. Results and discussions

4.1. Descriptive analysis and Multicollinearity detecting

Before presenting the discussion of model's accuracies in forecasting the financial distress of companies listed in Vietnam Stock exchanges, the statistical description with mean and standard deviation of 10 variables relating to accounting ratios and market variables is shown in table 1.

Table 1: Statistic analysis and multicollinearity testing

	Mean	Std. Deviation	Tolerance	VIF
NITA	-0.01	0.13	0.72	1.39
WCTA	0.11	0.29	0.68	1.47
NOCREDINT	-403.72	12,013.52	0.98	1.02
TLTA	0.53	0.28	0.54	1.87
TFOTL	0.14	1.23	0.80	1.26
SIZE	8.55	0.68	0.84	1.20
INONE	0.35	0.48	0.68	1.47
MCTD	2.76	9.44	0.45	2.22
PV	-0.02	0.36	0.94	1.06
P/E	38.90	366.52	0.55	1.83

In a regression model, Multicollinearity should be detected to avoid the instability problem of the coefficients estimation. Multicollinearity exists when there is dependency among two or more predictors in a model (Tinoco et al., 2013). Multicollinearity problem can be detected by identifying Variance Inflation Factor (VIF). VIF is better to be around 1 to avoid the variables' collinearity. In this paper, variable with VIF over than 2 should be removed.

4.2. Comparison of models' performance

Logit models use the same set of variables as SVM models but apply Binary Logit analysis as classifier. The models' overall fit can be identified by Omnibus Tests, Hosmer and Lemeshow Test and other identifiers as -2 Log likelihood, Cox & Snell R square and Nagelkerke R square. A better model fit is recognized when the chi-square test for the Hosmer and Lemeshow is insignificant, smaller -2 Log Likehood, higher values for Nagelkerke and Cox & Snell R square. As presented in table 2, all two models demonstrate their overall fit and model 2.1 with a combination of 9 predictors has better overall fit as it obtains higher Cox & Snell R square and Nagelkerke R square and smaller -2 Log likelihood.

Table 2: Overall fit test of Logit models

Model	**t**	**Omnibus Tests**		**-2 Log likelihood**	**Cox & Snell R Square**	**Nagelkerke R Square**	**Hosmer and Lemeshow Test**	
		Chi-square	*Sig.*				*Chi-square*	*Sig.*
Model 1.1	*t-1*	-0.01	0.13	0.72	1.39	-0.01	0.13	0.72
	t-2	0.11	0.29	0.68	1.47	0.11	0.29	0.68
	t-3	-403.72	12,013.52	0.98	1.02	-403.72	12,013.52	0.98

Model 2.1	*t-1*	0.53	0.28	0.54	1.87	0.53	0.28	0.54
	t-2	0.14	1.23	0.80	1.26	0.14	1.23	0.80
	t-3	8.55	0.68	0.84	1.20	8.55	0.68	0.84

For SVM models, there is no requirement of normality assumption for data as in linear regression models. However, in order to construct an optimized hyperplane for firm classification, the best pair of C and for classification should be made. Table 3 presents the best pairs for model 1.2 to model 2.2 corresponding with different time of prediction.

Table 3: Parameters for optimization hyperplane

Model	**t**	**C**		**rate**
Model 1.2	*t-1*	128	0.0	85.8%
	t-2	8.0	8.0	84.1%
	t-3	1.3	0.0	84.1%
Model 2.2	*t-1*	32.0	0.1	88.5%
	t-2	0.5	0.5	85.8%
	t-3	2,048	0.5	86.7%

Table 4 makes the comparison of classification power of 2 models using Logit analysis (model 1.1 to 2.1) and other 2 models applying SVM (model 1.2 to 2.2). The comparison is taken in two aspects: the prediction accuracies and the models' errors. Type I error is detected as a financially distressed firm is forecasted to be non-financially distressed while Type II error is revealed as a non-financially distressed firm is classified as financially distressed. Type I error should be received more notice as its larger potential losses to users of the models.

As can be seen in table 4, regards to the time of prediction, as expected, the models built in 1 year prior to corporate's failure obtain highest level of accuracies. In terms of predictors' choice, models with full variables that combines accounting ratios and market variables have the higher power of prediction (model 2.1 and 2.2) compared to other models with predictors of accounting ratios only. In terms of classifying technique, models using logistic regression outperform SVM analysis.

Table 4: Performance's comparison between models

		Percentage Correct (%)	**Type I error (%)**	**Type II error (%)**
Logit model				
Model 1.1	*t-1*	86.7	31.4	5.1
	t-2	82.3	34.3	10.3
	t-3	68.1	62.9	17.9
Model 2.1	*t-1*	92.0	11.4	6.4
	t-2	88.5	17.1	9.0
	t-3	72.6	34.3	24.4
SVM model				

Model 1.2	t-1	76.1	9.0	51.4
	t-2	69.9	68.6	15.4
	t-3	68.1	45.7	25.6
Model 2.2	t-1	81.4	42.9	7.7
	t-2	72.6	62.9	11.5
	t-3	71.7	62.9	12.8

4.3. The independent variables' prediction power

The assessment of variables' power in predicting financial distress for firms listed in Vietnam stock exchanges is taken by looking at their coefficients and their significance in model 2.1 which is the best model in this paper. WCTA (Working Capital/Total Assets), that measures the firm's liquidity obtains the strongest classification power in all models built in 3 years of prediction. NOCREDINT (No Credit Interval) is another liquidity measure that exhibits significant predicting power. The two-market variable: PV (Price Volatility) and P/E (Price Earnings Ratio) also demonstrate their ability in financial distress classification. The INONE variable exhibits different sign of coefficient in 3 prediction points of time when the beta's sign is negative in 1 year ahead model and beta are positive in 2 and 3 -year ahead models. Furthermore, the beta coefficients are significantly small in 2 and 3 year-ahead models of prediction. Similarly, SIZE variable's coefficient in 1 year-ahead model is positive while it is negative in 2 and 3 year–ahead prediction models.

Table 5: Variables in the Equation

	t-1			**t-2**			**t-3**		
	B	*Wald*	*Sig.*	*B*	*Wald*	*Sig.*	*B*	*Wald*	*Sig.*
NITA	-4.490	6.490	0.011	-13.231	9.639	0.002	-37.378	11.785	0.001
WCTA	-23.722	5.640	0.018	-24.221	4.592	0.032	-159.737	8.588	0.003
NOCREDINT	-3.636	4.980	0.026	-2.982	15.396	0.000	4.523	13.000	0.000
TLTA	-0.003	12.000	0.001	-0.003	4.321	0.038	-0.010	4.601	0.032
TFOTL	-0.647	7.970	0.005	-3.444	12.628	0.000	-4.420	12.547	0.000
SIZE	1.448	3.990	0.046	-0.122	13.174	0.000	-0.723	13.000	0.000
INONE	-0.096	4.630	0.031	0.000	13.327	0.000	0.001	13.000	0.000
PV	5.008	6.030	0.014	-00148	13.000	0.000	-0.065	12.000	0.001
P/E	1.544	6.390	0.011	0.960	6.490	0.011	1.808	12.000	0.001
Constant	37.909	0.000	0.994	35.468	0.000	0.994	179.403	0,005	0.942

Table 5 also shows that for 1-year prediction, companies with high level of debt, small working capital and small fund on total liabilities and bigger size are more likely to be financially distressed. However, for 2-year ahead prediction, companies with bigger size and highly volatile in stock price are less likely to be financially distressed. In all three times of prediction, companies with higher P/E are more likely to be in financial distress condition. In terms of profitability, there is no evidence that a company with a loss in 1 year ahead is more likely to be financially distressed in the following year.

5. Conclusion

This paper constructs financial distress prediction models using several sets of predictors and different classifiers of Logit analysis and SVM algorithm. The separation of prediction models is to investigate the classification power of accounting ratios market base variables. The analysis results reveal that models built in 1 year prior to the announcement of delisted requirement by Vietnam Stock exchanges to the companies that suffer 3 conservative years of losses produces the highest level of classification. In order to detect the role of market variables, these variables are combined with accounting ratios as independent variables in the model.

The models that add market variables as predictors can exhibit better performance than the models without those variables. In other words, market variables can improve the classification power of a prediction model. Moreover, the outperformance of Logit model that combining accounting ratios and market variables can bring the highest prediction accuracy of 92% for 1-year prediction, over 88% for 2-year prediction and over 72% for 3-year prediction.

This paper contributes to the existing literature by adding P/E ratio as the market variable in the prediction model. The analysis results show that companies with high P/E are likely to be in financial distress prediction. Companies with high price volatility are likely to be financial distress in 1-year ahead prediction but less likely to be in this condition in 2-year ahead and 3-year ahead prediction. The other finding of the paper is the emphasis on the outperformance of traditional model over the modern model (SVM) as Logit models produces better results. However, because of the existence of evidence about the outperformance of data mining algorithm in related studies, for future researches, the other algorithm such as NN or DT should be investigated.

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