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# Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam

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ABSTRACT

This paper aims to develop a comprehensive model, the first of its kind in Vietnam, for the purpose of predicting financial distress and bankruptcy at Vietnamese listed firms. The period 2003–2016 is used to study the likelihood of financial distress in different scenarios. Various factors are utilized, including (1) accounting factors in the emerging market score model; (2) market factors in the distance-to-default model; and (3) macroeconomic indicators. The area under the receiver operating characteristics (AUC) curve is used to compare the usefulness of various models that predict financial distress and bankruptcy. Empirical findings from this study show that accounting and market factors, together with macroeconomic fundamental factors, both affect financial distress when they are considered in isolation. However, in a comprehensive model, the effects from accounting factors appear to be more significant than those from market-based factors. The default prediction model, which includes accounting factors with macroeconomic indicators, appears to perform much better than the model comprising market-based factors with macroeconomic fundamentals.

## 1. Introduction

The liberalization of financial institutions in various regions has stimulated competition, which has also had an immeasurable effect in individual countries. The global financial crisis (GFC) in 2008 exposed many countries to economic risk. Vietnam is no exception. Countries around the world experienced various macroeconomic problems, including a sharp spike in unemployment because of the free fall in economic growth/output. In particular, credit risk substantially increased, leading to the bankruptcy of many businesses. According to the General Statistic Office of Vietnam (GSO), new firms established in 2015 numbered 92,264, but over 14,480 firms stopped doing business. Also in 2015, a record of 8,510 firms went bankrupt. 12,478 firms went bankrupt in 2016, an increase of 31.8 percent compared to the previous year.

Accounting- and market-based models are standard approaches for measuring credit risk at listed firms. In this regard, both accounting-based models (e.g., the Altman Z-score and emerging market score models) and market-based models (e.g., the Merton models) are employed to estimate the probability of default at listed firms in a country.

This study departs from the current practice by developing a new model that considers the three pillars of credit risk: (1) factors derived from market-based models; (2) factors derived from accounting-based models; and (3) selected macroeconomic factors, based on strong theoretical grounds. This approach is used to obtain comprehensive evidence regarding financial distress and bankruptcy at

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listed firms in Vietnam. Our detailed literature review indicates that this study is the first of its kind on Vietnam and probably one of the first on the Asian region.

## 2. Literature review

A corporate bankruptcy takes place in four stages. Stage 1 is the incubation of the firm's financial situation. In Stage 2, the management becomes aware of the firm's financial distress, generally called financial embarrassment. Stage 3 is financial insolvency, in which the firm does not have enough funds to meet its financial obligations. Finally, in Stage 4, insolvency is confirmed. The firm's bankruptcy is made official by a court determination, as its assets must be sold to pay creditors (Poston et al., 1994). Financial distress is, therefore, different from bankruptcy; it occurs when the firm may not be able to meet its financial obligations because of a decrease in the firm's business operations, illiquid assets and high fixed costs. By contrast, bankruptcy is a final state in which firms stop doing business because of that financial distress. In some cases, financial distress can be detected before the company falls into insolvency. Therefore, financial distress does not always progress to bankruptcy.

Numerous studies have been conducted to predict corporate financial distress early. The first accounting-ratio-based model was developed by Beaver (1966). His study used a dichotomous classification test to determine financial ratios that could predict bankruptcy. In particular, the best discriminant components in the study include the ratio of working capital to debt, which was able to predict bankruptcy a year before it happened with an estimated 90 percent accuracy, and the ratio of net income to total assets, which did so correctly with 88 percent accuracy.

A multivariate statistical model that was able to distinguish failed firms from non-failed firms was developed by Altman (1968). It examined 22 financial ratios, divided into five categories: profitability, activity, liquidity, solvency and leverage. A multivariate discriminant analysis (MDA) was conducted on these five categories of ratios. Altman et al. (1977) explored a new financial distress model (ZETA) focusing on specific sectors. Altman (2000) improved his models from 1968 and 1977 with the introduction of the Z-score model, which includes four financial ratios. The final version of the Z-score model was the emerging market score (EMS) model, which includes typical characteristics of emerging markets and seems appropriate for estimating the default probability in developing countries and ranking firms with a specific score. Altman (2005) used the EMS model to study Mexican firms before the 1994 crisis.

The major causes of insolvency are a decline in asset value, a reduction in liquidity, and a decrease in the ability to raise capital. Business default has three components: (1) the value of assets, (2) the asset value of uncertain risks, and (3) financial leverage. The options-based approach has been widely adopted in the commercial world. Black and Scholes (1973) and Merton (1974) discussed the call-option theory, which is a fundamental theory behind the market-based approach. Their contingent claims approach has been widely used in predicting corporate default.

The Merton model has become the basis of the distance-to-default (DD) model. In an early work, Vasicek (1984) compared the value of assets with their liability to determine the probability of corporate default. Delianedis and Geske (2003) and Leland (2002) studied whether theoretical probability is a powerful predictor in credit rating and credit transition. Several papers illustrated the usefulness of a structural model as well as the development of an options-based model. Crosbie and Bohn (2003) demonstrated that the probability of bankruptcy is one of the most powerful predictors in managing a credit portfolio. Some recent researchers employed a structural model to measure default risk and examine the correlation between default risk and other variables. As Agrawal et al. (2016); Allen and Powell (2012); Bharath and Shumway (2008); Huang and He (2010); Koutsomanoli-Filippaki and Mamatzakis (2009); Stein (2005), and Vassalou and Xing (2004) discussed, the market-based approach plays a key role in predicting default probability.

The market-based model is appealing on several grounds. First, the timeliness of corporate bankruptcy predictions may be increased exponentially by combining market-based variables. Second, the volatility of market-based variables is calculated directly using a market index to enhance the power of indicators of default risk. The fluctuation plays a key role in default prediction. Third, information from financial and other statements are not part of accounting statements, which generally reflect the market price. Fourth, the market price is likely to be more suitable for default prediction because it reflects forward-looking information or future expectations of cash flow, whereas the accounting-based model reveals only backward-looking or past performance. In addition, Hillegeist et al. (2004) indicated that the stock market contains almost all the information in accounting statements. Byström (2006) explores a simple version of the DD model that employs only three components or observable parameters to estimate default probability, such as the book value of firm liability, market value and the volatility of equity. The way to calculate the modified DD value is likely to be simpler and similar to the original model, but with higher accuracy than the old model as well as greater suitability for an emerging market such as Vietnam.

## 3. Comparing multivariate discriminant analysis and the DD models

Among various models for default prediction, including accounting-based, market-based and even comprehensive models, which is the most appropriate for default prediction? The utility of the three models depends on the pseudo $R^2$ as well as the receiver operating characteristics (ROC) area. In fact, we cannot calculate a single coefficient of determination ($R^2$) in binary logistic regression models, so two methods, including the Cox and Snell $R^2$ and the Nagelkerke $R^2$, are employed to estimate the significance of the model. According to Cox and Snell (1989) as well as Nagelkerke (1991), the Cox and Snell $R^2$ depends on comparing the log likelihood of their model with that of the original model, whereas the Nagelkerke $R^2$ and the modified Cox and Snell $R^2$ test cover the full range from 0 to 1 by adjusting the scale of the statistic. Therefore, these tests have similar notions and are interpreted like the $R^2$ in the linear regression. The ROC score, moreover, is indicated at some length in Chava and Jarrow (2004) and Vassalou and Xing

(2004). In particular, the ROC curve is a popular technique that can be used to rank the usefulness of different models for default prediction. The ROC score is built by changing the threshold probability. For each threshold probability, the ROC curve is defined by the percentage of bankruptcy that the model accurately classifies as bankruptcy on the vertical axis ($y$-axis), whereas the false positive rate or the percentage of bankruptcy that the model wrongly classifies as bankruptcy is on the horizontal axis ($x$-axis). The accurate ratio of the model is defined by the area under the ROC curve (AUC):

$$\textit{Accuracy ratio by ROC curve (AR)} = 2\ x\ (\textit{Area under ROC curve of the model} - 0.5).$$

The perfect model may have an AR of one or an ROC score equal to 1, while the model that has no discriminatory power has an AR of 0 or an ROC equal to 0.5. As a result, the model with the higher AR (accuracy ratio) will outperform on the default prediction.

## 4. Data and definition of variables

This study is conducted on a dataset consisting of 800 listed firms on the Hanoi Stock Exchange (HNX) and the Ho Chi Minh Stock Exchange (HOSE) for the period 2003 to 2016. All data for the 10 different sectors come from Bloomberg. Macroeconomic data come from the World Bank website.

### 4.1. The dependent variable

Expenditure is the firm's operating revenue. The major cause of firm financial distress and bankruptcy is financial debt. In this regard, many researchers have attempted to estimate the probability of default. They use indicators of business operating efficiency and financial expenses. For instance, financial distress is defined as the difference between earnings before interest, tax, and depreciation (EBITDA) and interest payments. Firms may not generate sufficient revenue to cover their financial obligations, leading to default. Studying public companies in the US, Asquith et al. (1994) added depreciation to earnings because they considered depreciation to be a non-cash expenditure in the accounting cycle. Whitaker (1999) used the difference between the firm's cash flow and current maturities of long-term debt. In Vietnam, when listed firms face a shock or sudden debt repayment, it is not easy for them to mobilize sufficient capital to meet their obligations.

On balance, based on the definition of financial distress, a firm's failure to meet its financial obligations, the probability of default could be predicted by the difference between returns and interest payments. Pindado et al. (2008) and Tinoco and Wilson (2013) use EBITDA as an indicator of financial distress when it is less than interest payments. Therefore, in Vietnam, the probability of firm default is measured by the interest coverage ratio between returns/earnings before interest and taxes (EBIT) and interest payments. If this ratio is lower than one or the EBIT is less than interest payments, the firm falls into the financial distress zone.

### 4.2. Independent variables

#### 4.2.1. Accounting variables

All potential factors have been carefully tested and collected through empirical studies. Four accounting variables—financial liquidity, the productivity of assets, solvency, and the sales-generating ability of assets—are utilized in this study. First, the ratio of working capital to total assets (WC/TA) measures the assets' net financial liquidity. Altman (1968) demonstrated that this is the most valuable of the three ratios showing a firm's liquidity and strongly contributes to distinguishing the default and non-default groups. Second, profitability is estimated by the ratio of retained earnings (RE) to total assets (TA). RE relative to TA is the business's cumulative profitability over its entire lifetime. Firms with a high RE/TA ratio have little financial debt or a low default probability, as Altman (2000) suggests. Third, earnings before interest and taxes over total assets (EBIT/TA) shows the productivity of the company's assets, excluding tax and leverage components or the earning power of assets. This variable is applied efficiently in many previous studies, such as Altman (1968, 2005). Finally, the book value of equity over total liability (BVE/TL) indicates the firm's ability to cover its financial debts with assets. Altman (2005) employed this variable to measure default in emerging markets, and the higher the BVE/TL, the lower the default probability.

#### 4.2.2. Market variables

Similarly, four market variables are employed in this study. First, the market value of equity (*MVE*) is calculated as a multiple of the stock price to the number of outstanding shares, as discussed by Agarwal and Taffler (2008). Second, following Zhang et al. (2009), higher equity volatility ($\sigma_E$) leading to greater volatility of the asset is used. Third, leverage is computed as total debt over the total market value of equity and total debt, as shown by Byström (2006). Fourth, the price indicates the market base, which is calculated as the price on the last trading day of the calendar year. Rees (1995) revealed that the level of the stock price can indicate the liquidation of that firm, the cash flow, and investor expectations of future earnings. It also expresses the financial statement and macroeconomic information in Beaver et al. (2005).

#### 4.2.3. Macroeconomic variables

The effect of the macroeconomic environment on the default model is significant in two major respects. Our research examines the interest rate of short-term Treasury bills in one year (*SHTBRDEF*). Tinoco and Wilson (2013) show that when the Treasury bill has a higher value, leading interest rates to climb sharply, the bankruptcy rate will rise. Another variable is inflation. High inflation indicates that the economy will become unstable in a weak macroeconomic environment and is positively related to the probability of financial distress at firms. Furthermore, Mare (2012) demonstrates that inflation is positively related to the probability of financial distress in the banking sector.

In summary, in this study, a combination of accounting-based, market-based and macroeconomic variables that affect financial distress is used to cover various aspects of default risk. Thus, we construct a comprehensive model as follows:

$$Y = \beta_1 \frac{WC}{TA} + \beta_2 \frac{RE}{TA} + \beta_3 \frac{EBIT}{TA} + \beta_4 \frac{BVE}{TL} + \beta_5 ln(MVE) + \beta_6 lnLEVERAGE + \beta_7 \sigma_E + \beta_8 PRICE + \beta_9\, Treasury\ bill + \beta_{10} Inflation + \varepsilon \tag{1}$$

where:

| | |
|---|---|
| $Y$ (*Classify*) | : The binary of the non-default (Y = 0) and default (Y = 1) |
| $\frac{WC}{TA}$ | : Ratio of working capital to total assets |
| $\frac{RE}{TA}$ | : Ratio of retained earnings to total assets |
| $\frac{EBIT}{TA}$ | : Ratio of earnings before interest and taxes (operating profit) to total assets |
| $\frac{BVE}{TL}$ | : Ratio of book value of equity to total liabilities |
| *MVE* | Market value of equity |
| *LEVERAGE* | Leverage ratio |
| $\sigma_E$: | Volatility of equity |
| *PRICE* | . Price |
| *Treasury bill* | A one-year Treasury bill |
| *Inflation* | Inflation |
| ε | Error term |

## 5. Empirical results and analysis

In this study, the interest coverage ratio is employed to distinguish failed from non-failed firms. If their EBIT is lower than interest, firms may fall into financial distress. We use data from 800 firms listed on the Vietnamese stock market for the period 2003 to 2016, for a total of 6736 observations. Table 1 shows the panel data divided into two groups using this ratio, with 5161 observations of non-financial distress (accounting for 76 percent of the total number of observations) and 1575 observations of financial distress.

As presented in Table 2, this study uses the following independent variables: *WCTA* (working capital over total assets), *RETA* (retained earnings over total assets), *EBITTA* (earnings before interest and taxes [operating profit] to total assets), *BVETA* (book value of equity to total liabilities), *MVE* (market value of equity), *PRICE* (stock price), *VOL_MVE* (volatility of market value of equity), *LEVERAGE* (leverage ratio), *INFLATION* (inflation) and *SHTBRDEF* (short-term Treasury bill in one year).

Table 3 presents a correlation matrix of all independent variables. These variables are generally independent, except for a strong correlation between inflation and *SHTBRDEF*, with a coefficient of 0.86.

In this study, the emerging market scoring (EMS) model for rating emerging market credit in Altman (2005) is used to estimate default probability. Among the factors that account for this choice is that the EMS model depends on a basic financial review taken from a qualitative risk model, that the EMS model is a final modified rating of the assessment of specific credit risks, and that the modified EMS model, with the specific characteristics of the emerging market, is well designed for developing countries such as Vietnam. Moreover, the EMS model is generated by capturing the advantages as well as improving on the disadvantages of previous models, including Z, Z' and Z''-score models. The coefficients for the four variables, from X1 to X4, are similar to those in the Z''-score model, and the EMS scores are added to the constant term +3.25.

**Table 1**
Description statistics of the dependent variable.

| Classify | Freq. | Percent | Cum. |
|---|---|---|---|
| 0 | 5,161 | 76.62 | 76.62 |
| 1 | 1,575 | 23.38 | 100 |
| Total | 6,736 | 100 | |

**Table 2**
Summary of statistics for independent variables.

| Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| *Working capital/Total assets* | 0.211 | 0.242 | −1.362 | 0.99 |
| *Retained earnings/Assets* | 0.039 | 0.134 | −2.76 | 0.529 |
| *EBIT/Total assets* | 0.033 | 0.108 | −2.291 | 0.98 |
| *Book value of equity/Total liabilities* | 0.665 | 0.307 | −0.568 | 1.00 |
| *Price* | 20853 | 24776 | 317 | 350000 |
| *Ln (Market value of equity)* | 12.163 | 1.914 | 6.947 | 22.284 |
| *Volatility of equity* | 1701 | 53500 | 18.3 | 336000 |
| *Leverage* | 1.026 | 1.132 | 0.003 | 13.455 |
| *Inflation* | 8.36 | 5.71 | 0.9 | 23.1 |
| *Treasury bill* | 7.1 | 2.9 | 4 | 12.4 |

**Table 3**
Correlation matrix and multicollinearity diagnostic statistics.

| Variable | WCTA | RETA | EBITTA | BVETL | PRICE | MVE | VOL_MVE | LEVERAGE | INFLATION | SHTBRDEF |
|---|---|---|---|---|---|---|---|---|---|---|
| *WCTA* | 1 | | | | | | | | | |
| *RETA* | 0.3961*** | 1 | | | | | | | | |
| *EBITTA* | 0.1643*** | 0.2768*** | 1 | | | | | | | |
| *BVETL* | 0.5038*** | 0.3743*** | 0.1886*** | 1 | | | | | | |
| *PRICE* | 0.1402*** | 0.2834*** | 0.1381*** | 0.127*** | 1 | | | | | |
| *MVE* | 0.0362*** | 0.2942*** | 0.0686*** | 0.0781*** | 0.4484*** | 1 | | | | |
| *VOL_MVE* | −0.0127 | 0.0121 | 0.0347* | 0.0215* | 0.0184 | 0.1068*** | 1 | | | |
| *LEVERAGE* | 0.2721*** | 0.2831*** | 0.2154*** | 0.5403*** | 0.4327*** | 0.3928*** | 0.1257*** | 1 | | |
| *INFLATION* | 0.0597*** | 0.0929*** | 0.1132*** | 0.0494*** | 0.0496*** | 0.0812*** | 0.0213* | 0.0224* | 1 | |
| *SHTBRDEF* | 0.0355*** | 0.1048*** | 0.0736*** | 0.0332*** | 0.1225*** | 0.0801*** | 0.0142 | -0.0303** | 0.8598*** | 1 |

*Notes:* Variable definitions: *WCTA* – working capital over total assets, *RETA* – retained earnings over total assets, *EBITTA* – earnings before interest and taxes [operating profit] to total assets, *BVETA* – book value of equity to total liabilities, *MVE* – market value of equity, *PRICE* – stock price, *VOL_MVE* – volatility of the market value of equity, *LEVERAGE* – leverage ratio, *INFLATION* – inflation, and *SHTBRDEF* – short-term Treasury bill in one year.

The EMS model is presented as follows:

$$EMS - Score = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 + 3.25 \tag{2}$$

where:

| | |
|---|---|
| $X_1$ | Ratio of working capital to total assets (WC/TA) |
| $X_2$ | Ratio of retained earnings to total assets (RE/TA) |
| $X_3$ | Ratio of earnings before interest and taxes (operating profit) to total assets (EBIT/TA) |
| $X_4$ | Ratio of book value of equity to total liabilities (BVE/TL) |

The EMS score standard for the probability of insolvency:

- EMS − Score > 5.85:Safe zone, in which firms have healthy finances or no risk of bankruptcy.
- 4.15 ≤ EMS − Score ≤ 5.85: Grey zone, warning zone. Financial exposure is low, or the potential for bankruptcy exists.
- EMS − Score < 4.15:Bankruptcy zone, danger zone. The default probability is high.

Unlike the accounting-based approach or the EMS model, the DD model uses the market value of equity and trading prices to measure financial distress. In particular, the Kealhofer, McQuown and Vasicek (KMV)-Merton model was explored in 1974 by Merton (1974), based on the option theory of Black and Scholes (1973). However, the original model's assumption of constant debt does not have empirical support, so the DD model was adjusted to overcome this disadvantage and focus more on default, such as including the firm leverage ratio as well as equity volatility in this research. In particular, the modified version of the DD model, advocating a constant leverage ratio, is likely more realistic and dynamic than the traditional Merton model. Consequently, the new DD model can estimate the default probability for many kinds of firms. In particular, the modified version can effectively measure financial distress in emerging markets or volatile markets, such as Vietnam (Byström, 2006).

Byström (2006) explores the simple version of the DD model, which has only three components or observable parameters to estimate default probability, such as the book value of firm liability, market value and the volatility of equity. The simplification depends on three assumptions. First, in reality, the drift term ($(\mu - 0.5\sigma_v^2)T$) is revealed to be relatively small, and it seems to be difficult to measure the drift rate of stocks and other assets. Thus, we assume that the drift term is small or zero. Second, in the extreme case, the market value of assets (V) is close to the book value of liabilities; the highlighted asset volatility is relatively high

**Table 4**
The relationship between the default probability and EMS, DD.

| Variable | Coeff. | Std. Err. | z | P > z | 95% Conf. Interval | |
|---|---|---|---|---|---|---|
| *EMS* | −0.0407 | 0.0082 | −4.97 | 0.000 | −0.0568 | −0.0247 |
| *Distance to default* | −16.2379 | 7.8814 | −2.06 | 0.039 | −31.685 | −0.7907 |
| *_cons* | −1.434 | 0.0997 | −14.38 | 0.000 | −1.6295 | −1.2385 |

and $N(d_1)$ is significantly different from 1. Therefore, $N(d_1)$ is supposed to be 1. Third, the book value of liabilities must be paid back or is not calculated by market value. Therefore, the book value of debt is used for the accounting leverage ratio.

Based on the Merton model, the modified DD model is rewritten as follows:

$$DD_{AdjustedMerton} = \frac{\ln\left(\frac{1}{L}\right)}{\sigma_E(1-L)} = \frac{Ln\,(L)}{(L-1)}\frac{1}{\sigma_E} \tag{3}$$

where:

The leverage ratio (L) is calculated by the market value of equity (E) and the book value of debt (F) and $L = \frac{F}{(E+F)}$

$\sigma_E$: The volatility of the firm's equity

We find a close relationship between DD and the probability of default or expected default frequency (EDF). The cumulative normal distribution is used to measure EDF from the DD value. Then, this result is mapped to the S&P rating, as seen in Table 5.

In terms of the KMV EDF value, S&P rating categories classify firms into twenty-two levels, from 0 percent rated AAA to 20 percent rated D.

Because of bivariate analysis, these categories are divided into three EDF categories: (0.00, 0.52] is the safe zone, with no probability of financial distress, (0.52, 6.94] is the grey zone, with a low rate of financial distress, and (6.94, 20.00] is the distress zone, with a high rate of financial distress, as suggested by Lopez (2004). Therefore, the way to calculate the modified DD value is likely to be simpler and similar to the original model, but with an accuracy rate that is higher than in the old model as well as being more suitable for an emerging market such as Vietnam.

It is generally accepted that EMS and DD are two key proxies for firm bankruptcy. Table 4 shows that EMS is negatively significant at 1 percent, while DD is significant at the 5 percent level. This result also indicates that the larger EMS and DD are, the lower is the probability of default.

Table 6 reports the credit ratings of EMS models by Standard & Poor's in 2003–2016: 81.2 percent of firms are in the safe and grey zones, whereas only 18.8 percent are in the distress zone. Moreover, the Z-score model has a result similar to the EMS model in Table 7, where 80 percent of the companies are financially healthy. Consequently, most Vietnamese firms have good and stable economic operations.

Table 8 is a DD discrimination table that distinguishes between healthy and financially distressed firms, applying the mapping of S &P credit rating to KMV EDF values. A firm is classified as non-bankrupt if its EDF is lower than 0.52% and as bankrupt if its EDF is

**Table 5**
Mapping of S&P rating.
*Source:* EDF calibrations from Lopez (2004).

| | S&P Rating | EDF value (%) |
|---|---|---|
| Safe zone | AAA | (0.00, 0.02] |
| | AA+ | (0.02, 0.03] |
| | AA | (0.03, 0.04] |
| | AA- | (0.04, 0.05] |
| | A+ | (0.05, 0.07] |
| | A | (0.07, 0.09] |
| | A- | (0.09, 0.14] |
| | BBB+ | (0.14, 0.21] |
| | BBB | (0.21, 0.31] |
| | BBB- | (0.31, 0.52] |
| Grey zone | BB+ | (0.52, 0.86] |
| | BB | (0.86, 1.43] |
| | BB | (1.43, 2.03] |
| | B+ | (2.03, 2.88] |
| | B | (2.88, 4.09] |
| | B- | (4.09, 6.94] |
| Distress zone | CCC+ | (6.94, 11.78] |
| | CCC | (11.78, 14.00] |
| | CCC- | (14.00, 16.70] |
| | CC | (16.70, 17.00] |
| | C | (17.00, 18.25] |
| | D | (18.25, 20.00] |

**Table 6**
EMS model.

| Rating | EMS value | Percentage |
|---|---|---|
| Safe zone | 3,669 | 54.5 |
| Grey zone | 1,801 | 26.7 |
| Distress zone | 1,266 | 18.8 |
| | 6,736 | 100 |

**Table 7**
Z-score model.

| Rating | Z-score value | Percentage |
|---|---|---|
| Safe zone | 3,669 | 54.5 |
| Grey zone | 1,538 | 22.8 |
| Distress zone | 1,529 | 22.7 |
| | 6,736 | 100 |

**Table 8**
Distance to default (DD) model.

| Rating | DD value | Percentage |
|---|---|---|
| Safe zone | 3,131 | 46.8 |
| Grey zone | 377 | 5.6 |
| Distress zone | 3,190 | 47.6 |
| | 6,702 | 100 |

higher than 6.94%. We conclude that this method is fairly accurate with respect to the DD model. Surprisingly, the safe and grey zones are considerably smaller than in the EMS case with only about 50 percent, that is, the distress zone of the DD model is twice that of the EMS model. This means that half of the Vietnamese firms fall into financial distress, and the result, which differs from that of the accounting- and market-based approach, can easily be interpreted with the accuracy of financial data. In reality, Vietnamese companies usually distort their financial statements to put up a good face before their investors and the State Securities Commission of Vietnam, a governmental agency charged with the mission of organizing and regulating the operations in the field of securities and the securities market. Listing on the stock market may help firms raise capital from their financial investors. The market-based approach can be observed directly in the stock market and may eliminate the adjustment of financial data as well as reflect firms' financial status more honestly. Therefore, the good face of Vietnamese firms only measures their book value.

Table 9 presents the results of a logistic regression of financial distress. Various models have been used to consider the separate effects from accounting factors, market-based factors and macroeconomic factors on financial distress and bankruptcy at Vietnam's listed firms. In addition, because of the correlations between inflation and short-term Treasury bills, various models are run concurrently to overcome the correlation among the variables. The following models are considered.

- Model 1, which includes all the independent accounting variables;
- Model 2, which includes all market variables;
- Model 3, which includes all accounting variables *plus* the inflation variable;
- Model 4, which includes all accounting variables *plus* the short-term Treasury bill in one year;
- Model 5, which includes the market variables *plus* the inflation variable;
- Model 6, which includes the market variables *plus* the short-term Treasury bill in one year;
- Model 7, which includes the accounting and market variables *plus* the inflation variable;
- Model 8, which includes the accounting and market variables plus the short-term Treasury bill in one year.

All the accounting variables in model 1 are statistically significant at 1–10%. This suggests that the accounting model is a powerful predictor of default probability. Model 2 uses four market variables. Only three market variables are significant at 1%: *PRICE, MVE* and *LEVERAGE*. In models 3 and 4, both inflation and Treasury bills are significant at 1%. The result of two macroeconomic indicators is consistent with the previous expectation, and models 5 and 6 have an outcome similar to that in previous models.

In the logistic regression, the magnitude of the marginal effect in Vietnam from 2003 to 2016 is presented in Table 10. The largest impact on financial distress comes from *EBITTA*, while the smallest impact is from *Vol_MVE*.

Table 11 summarizes the performance of the eight models in this study. All the models are statistically significant. Therefore, they are all useful for measuring financial distress at listed firms in Vietnam. The AUC is used directly to estimate the predictive accuracy of the models. Although the model with no discriminatory power will have an AR of 0 or an ROC of 0.5, the best model in terms of its

**Table 9**
Financial distress at Vietnam's listed firms: Various models.

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
|---|---|---|---|---|---|---|---|---|
| *WCTA* | −0.542 | | −0.550 | −0.533 | | | −0.554 | −0.540 |
| | (1.92)* | | (1.93)* | (1.87)* | | | (1.93)* | (1.88)* |
| *RETA* | −2.960 | | −3.458 | −3.461 | | | −3.133 | −3.136 |
| | (4.85)*** | | (5.30)*** | (5.32)*** | | | (4.73)*** | (4.74)*** |
| *EBITTA* | −151.538 | | −156.358 | −155.116 | | | −156.366 | −155.450 |
| | (26.14)*** | | (26.01)*** | (26.03)*** | | | (25.79)*** | (25.79)*** |
| *BVETL* | −0.461 | | −0.489 | −0.484 | | | −0.765 | −0.767 |
| | (2.08)** | | (2.18)** | (2.16)** | | | (2.90)*** | (2.91)*** |
| *PRICE* | | −0.000 | | | −0.000 | −0.000 | −0.000 | −0.000 |
| | | (7.94)*** | | | (7.89)*** | (8.04)*** | (0.76) | (0.43) |
| *MVE* | | −0.124 | | | −0.149 | −0.136 | −0.073 | −0.084 |
| | | (3.48)*** | | | (4.08)*** | (3.77)*** | (1.75)* | (2.03)** |
| *VOL_MVE* | | 0.000 | | | −0.000 | −0.000 | 0.000 | 0.000 |
| | | (0.18) | | | (0.13) | (0.14) | (0.14) | (0.24) |
| *LEVERAGE* | | −0.190 | | | −0.173 | −0.182 | 0.164 | 0.167 |
| | | (3.22)*** | | | (2.91)*** | (3.08)*** | (1.95)* | (1.99)** |
| *INFLATION* | | | 0.051 | | −0.027 | | 0.049 | |
| | | | (6.69)*** | | (4.70)*** | | (6.41)*** | |
| *SHTBRDEF* | | | | 0.090 | | −0.046 | | 0.087 |
| | | | | (5.93)*** | | (4.07)*** | | (5.67)*** |
| *_cons* | 0.835 | 0.394 | 0.496 | 0.222 | 0.889 | 0.873 | 1.457 | 1.313 |
| | (5.65)*** | (0.97) | (3.15)*** | 1.23 | (2.11)** | (2.06)** | (2.77)*** | (2.44)** |
| *lnsig2u_cons* | 0.367 | 0.940 | 0.403 | 0.384 | 0.950 | 0.946 | 0.446 | 0.438 |
| | (2.41)** | (9.64)*** | (2.64)*** | (2.50)** | (9.71)*** | (9.69)*** | (2.92)*** | (2.85)*** |
| *N* | 6736 | 6736 | 6736 | 6736 | 6736 | 6736 | 6736 | 6736 |

*Notes*: Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. See variable definitions in notes to Table 3.

**Table 10**
Marginal effect.

| Variable | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
|---|---|---|---|---|---|---|---|---|
| *WCTA* | −0.005314 | | −0.004902 | −0.004821 | | | −0.00495 | −0.004887 |
| *RETA* | −0.029006 | | −0.030806 | −0.031299 | | | −0.027982 | −0.028382 |
| *EBITTA* | −1.485108 | | −1.393015 | −1.402757 | | | −1.396423 | −1.406831 |
| *BVETL* | 0.004519 | | −0.004354 | −0.004374 | | | −0.006832 | −0.006938 |
| *PRICE* | | −0.000003 | | | −0.000003 | −0.000003 | 0.000,000 | 0.000,000 |
| *MVE* | | −0.014512 | | | −0.017227 | −0.015781 | −0.000651 | −0.000762 |
| *VOL_MVE* | | −0.000000 | | | −0.000000 | −0.000000 | 0.000,000 | 0.000,000 |
| *LEVERAGE* | | −0.022235 | | | −0.020083 | −0.021230 | 0.001464 | 0.001513 |
| *INFLATION* | | | 0.000454 | | −0.003111 | | 0.000441 | |
| *SHTBRDEF* | | | | 0.00081 | | −0.005385 | | 0.000787 |

*Note*: See variable definitions in notes to Table 3.

**Table 11**
A measurement of model performance.

| Measure | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
|---|---|---|---|---|---|---|---|---|
| *ROC* | 0.9337 | 0.6878 | 0.9354 | 0.9352 | 0.6849 | 0.6848 | 0.9341 | 0.9336 |
| *-2 likelihood* $R^2$ | 3983 | 6891 | 3941 | 3947 | 6869 | 6875 | 3939 | 3946 |
| *Prob > LR* | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Cox and Snell $R^2$ | 0.391 | 0.063 | 0.395 | 0.394 | 0.066 | 0.065 | 0.395 | 0.395 |
| Nagelkerke $R^2$ | 0.59 | 0.094 | 0.596 | 0.595 | 0.099 | 0.098 | 0.596 | 0.595 |

usefulness for measuring financial distress has an ROC of 1. While the other models are generally good, models 2, 5 and 6, including market variables, indicate the low prediction ability of market variables on default probability. Moreover, the Nagelkerke $R^2$ and the Cox and Snell $R^2$ have results similar to those of an ROC curve. Two tests indicate that model 3 is the best model, with a Cox and Snell $R^2$ of 0.395 and a Nagelkerke $R^2$ of 0.596. The model with accounting and macroeconomic factors is a good fit. All the evidence is also similar to that obtained from the marginal effect analysis, in that when market variables are added to the model, the magnitude of impact factors on default decreases.

## 6. Conclusions

This paper examines various models for default prediction using a sample of 800 Vietnamese firms over the period 2003–2016, with a total of 6736 observations. Logistic regression is adopted in a comprehensive model including the following key aspects of firm financial distress: accounting factors, market factors and two macroeconomic indicators. Furthermore, the AUC is used to compare various models for default prediction. The intention of this study is to develop a comprehensive model, which is the first of its kind for Vietnam, including various factors derived from accounting-based models, market-based models and macroeconomic factors to consider their effect on the likelihood of financial distress at Vietnamese firms.

The empirical findings from this study show that accounting, market and macroeconomic variables affect the likelihood of financial distress at Vietnamese firms during the period researched. In particular, four accounting proxies derived from the EMS model indicate a negative relationship with the probability of default. These findings mean that the higher financial liquidity, productivity of assets, solvency and profitability are, the lower the likelihood of financial distress is at Vietnamese firms. When market-based variables are considered, a negative relationship between the MVE and the likelihood of financial distress is observed. This finding confirms that large firms have a low probability of default and that the leverage ratio has a positive relationship with firms' financial distress. Inflation and the interest rate for short-term Treasury bills have a positive relation to financial distress.

On balance, proxies from the accounting-based model, the market-based model and typical macroeconomic factors all affect financial distress at Vietnamese listed firms during the period researched when they are considered in isolation. However, in a comprehensive model, the effect appears to be stronger from accounting factors than from market factors. Our findings confirm that the model for default prediction that includes accounting and macroeconomic factors is better than the model with market factors and macroeconomic fundamentals.

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