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STEP TOWARDS A GENERAL BANKRUPTCY PREDICTION MODEL FOR LISTED NON-FINANCIAL FIRMS: THE USE OF ACCOUNTING, MARKET, AND MACROECONOMIC VARIABLES

Abstract: The purpose of this research is to move a step forward toward developing a bankruptcy model that provides globally relevant predictors for firms listed on stock exchanges across different economies. This study has developed a general bankruptcy model including accounting, market and macroeconomic variables that are universal and consistent for non-financial firms across the globe. Data for the study was obtained from higher-income upper middle income and lower-middle-income (a total of 18) countries for the period 2001–2017. In the first stage, the predictor variables that affect firms' bankruptcy are identified. In the second stage, the effect of predictors on the dependent variable is estimated at a time one year (*t*-1) and two years (*t*-2) prior to bankruptcy. In this step, logistic regression is used to check the impact of accounting, market and macroeconomic variables on corporate bankruptcy. The study identified that accounting variables: liquidity ratio, profitability ratio, asset turnover ratio and financial leverage ratio are consistent across all the models. In addition, market variables: change in stock return, past excess return and market to book value impact the bankruptcy of firms. The study also found that macroeconomic variables including change in Gross domestic product, change in retail price index, change in real effective exchange rate, change in real interest rate and change in stock market capitalization are significant predictors of bankruptcy. Countrywide bankruptcy prediction models are plentiful and have been used widely in different countries. This study provides predictors of bankruptcy that are consistent during different times period and across different countries.

Keywords: corporate bankruptcy, financial distress, non-financial firms, global, logit regression

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INTRODUCTION

Bankruptcy is a critical financial event that not only signals the failure of a firm to meet its financial obligations but also carries wide-ranging implications for stakeholders and the broader economy (Tokarski, 2018). For firms, bankruptcy often results in severe reputational damage, loss of investor confidence, disruption of operations, layoffs, and eventual liquidation or restructuring. On a macroeconomic scale, a surge in corporate bankruptcies can undermine financial stability, reduce capital market efficiency, and hamper economic growth, especially during periods of financial distress. These challenges highlight the urgent need for early detection mechanisms and robust prediction models that can identify financial vulnerability well in advance. This study aims to contribute to this need by developing a comprehensive bankruptcy prediction model, which integrates accounting, market, and macroeconomic variables to enhance predictive accuracy across different economic settings.

In the past fifteen years, the world has experienced several waves of financial turmoil which have resulted in economic contraction, business decline and financial distress. Due to these conditions, the number of corporate bankruptcies reported in this period has soared significantly. The US is the country ranked first in terms of the number of bankruptcies reported in this period. The UK is the second, and Taiwan is the third country ranked for reported corporate bankruptcies. The world experienced a financial crisis in 2008 that resulted in a significant increase in the number of bankruptcies around the world (Alaminos et al., 2016). According to the Global Bankruptcy report 2016, the United States has reported 24457 companies that undergo bankruptcy. In the same quarter, the number of bankruptcies reported in Hong Kong are 6460 firms. In Italy, 3640 firms go bankrupt during the first quarter and the number increased to 3800 during the second quarter. During 2016, the number of bankrupt firms in the UK increased from 3617 companies in the second quarter to 3633 firms in quarter three. During the same year in Taiwan, the bankrupt firms count increased from 1981 in October to 2132 firms in November (Global Bankruptcy Report, 2016).

After experiencing the recent financial crisis and rising corporate bankruptcies, researchers emphasized that there is a need to study this phenomenon and predict business failures not only at the country level but also at the global level (Alaminos et al., 2016). There is a need to identify the characteristics which commonly affect companies and lead to bankruptcies (Tinoco and Wilson, 2013). Nevertheless, researches that focus on the global prediction of firm bankruptcies are very limited (Chen, 2008; Pindado et al., 2008; Zhou, 2013).

It is of first-order importance for individual investors and institutions that the market participants are capable of assessing the likelihood of firm bankruptcy. Along with Altman (1968) model for US, and Altman et al. (1979) model for Brazil, several other researchers (Ohlson, 1980; Shumway, 2001; Chava and Jarrow, 2004) have worked extensively to develop models for capital markets in U.S. Aliakbari (2009: 23), Charalambakis et al. (2009), Neophytou et al. (2001) models along with several others are also in place for firms in UK. Kirkham (2012) has worked on bankruptcy prediction for telecommunication firms in Australia. Kitowski et al. (2022) studied the bankruptcy prediction in Poland. Liu and Wang (2016) and Wang and Campbell (2010) have worked on failure prediction for publicly listed firms in China. Altman (1968) score, accounting-based, bankruptcy prediction model using discriminant analysis and Shumway, market-based model, using hazard function for bankruptcy prediction are among the most used models. However, the efficiency and predictive accuracy of these models and all the various models designed for a specific country is not consistent when tested in other countries. Maffett et al. (2012) documented significant variations across countries in bankruptcy prediction using market and accounting information-based models. Charalambakis and Garrett (2015) also pointed out the heterogeneity in the accuracy of bankruptcy prediction models across different countries. While testing for the efficiency of different models in different countries Charalambakis and Garrett (2015) documented that a hazard model performs well in the UK while the same model is outperformed by the Z-score model in India. Results suggested that the bankruptcy model developed in the US based on accounting and market measures performs well for firms in the developed economy (the UK in this case). However, the same model cannot be successfully applied to an emerging country (India in this case). Laitinen and Suvas (2013) studied the predictability of different bankruptcy prediction models across European countries and identified the differences in the form and strength of prediction models across different European countries.

The emergence of globalization phenomenon has experienced an increase in complexity of international relationships across the business world (Dopfer, 2005: 78). Business is operating not only in the one country but have expanded globally. Several businesses are operating in more than one country and the differences in terms of location or factors relevant to a particular country have reduced. Arestis and Basu (2004) and Toporowski (2010) emphasized that the process of globalization has caused the homogenization of methods of finance and the financial behavior of business. Henceforth, there is a dire need to develop a bankruptcy model, which accurately predict the phenomenon not only for a given country but in different parts of the world (Korol, 2013). Despite the need for such a rigorous model, researchers have centered on developing and predicting bankruptcy for businesses in a single country/sector (Odom and Sharda, 1990; Laitinen and Laitinen, 2000; Tinoco and Wilson, 2013; Cultrera and Brédart, 2016) or comparing results of various models in the same country, without understanding the need for a general model with consistent predictive accuracy (Korol, 2013).

The current research fills the literature gap in several ways. Firstly, it is a step forward towards the development of a general bankruptcy framework, which is consistent across countries, provides a set of consistent predictors. Secondly, the researcher has used data for firms from high income, upper middle income and lower middle-income countries to develop a general model. Using Logit model, the study also tests the consistency of predictor variables of the bankruptcy framework in different time frames.

The structure of the paper is as follows. In section 2, we discuss the corporate bankruptcy and different theories for model. In section 3, we have discussed the predictor variables, data sample, model and research method. Section 4 and 5 provides the analysis and conclusion of the study.

LITERATURE REVIEW

Corporate bankruptcy, for both developing and developed countries, is a phenomenon where financial failure causes the firm to cease to its operations. Taffler (1983) considered financial failure as "administration, receivership or creditors voluntary liquidation". Bhunia and Sarkar (2011) and Sormunen and Laitinen (2012) considered that bankruptcy is a failure of corporate where the firm is unable to continue as an ongoing concern. The same view is also supported by Beaver et al. (2012). While Aliakbari (2009) defines bankruptcy as the failure of a firm or business to pay back its outstanding obligation.

Bankruptcy prediction has been studied actively in the fields of accounting and finance since the work of Beaver (1966), Altman (1968), Ohlson (1980) and Zmijewski (1984). Several methods and models are developed, at both macro and micro-level, to keep stakeholders informed about expected bankruptcy (Žiković, 2016). The goal aligned with prediction of bankrupt firms is the timely identification of firms which may cease to fulfill their financial obligations and separating them from those which have the ability to fulfil their obligations. The likelihood of bankruptcy is a binary choice measure where we distinguish failed and non-failed firms. The major purpose of bankruptcy measures is to check the probability of a firm to go bankrupt. As we talk about the probability, it is well received that no such model can perfectly distinguish bad and good firms with 100 percent accuracy. Nevertheless, researchers have made serious efforts to use different methods and develop various measures to enhance the accuracy of such models.

The majority of researchers employed accounting ratios in predicting corporate bankruptcy (Lin et al., 2011; Beaver et al., 2012; Xu et al., 2014). Although the accounting ratio (AR) models were quite successful, studies argue that they lack a definitive theoretical foundation (Aziz and Dar, 2006). Gambling (1985: 420) entertainingly complains that:

> The problem with present-day accounting research is that it so frequently fails to deal with accounting itself. Possibly this is because accounting seems incapable of developing a research tool of its very own. As a result, people borrow from other disciplines and produce work which is often excellent research in mathematical economics, social psychology or whatever, but says nothing to accountants about what they are doing and how it works.

Several researcher considers Altman model as a baseline model and theoretical basis for bankrutpcy prediction. However, Agarwal and Taffler (2007) argued that Z-score models by Altman are only devices for pattern recognition and they are not theories of success or failure. Bankruptcy prediction models indicate the probable existence of problems and help in tracking improvement and retrieval from organizational illness. As it is inappropriate to claim a simple instrument founds a scientific theory, the same is the case with bankruptcy prediction models (a measure of financial risk), to be considered as a theory for corporate failure or bankruptcy. This study takes the help of some related theories such as Grey System Theory and Option Pricing Theory to understand the background and to integrate impact of different predictors. Building on prior literature, this study integrates Grey System Theory (GST) and Option Pricing Theory (OPT) to refine our selection of bankruptcy predictors. GST, which discusses about handling uncertain and incomplete data, help in our inclusion of macroeconomic variables that takes financial distress at a systemic level. OPT explains the role of market-based indicators, such as stock volatility and market capitalization, in assessing a firm's financial health. By aligning these theories with our variable selection, the model enhances its predictive capability beyond traditional accounting-based approaches.

1) Grey systems theory

Grey system theory is a quantifiable method established by Deng (1982). The grey systems help in dealing with partially available informations (Liu et al., 2012) and is applied for modeling, prediction, analysis and decision making in various domains such as finance and economics (Kayacan et al., 2010), energy (Hsu and Chen, 2003), and tourism (Huang and Lee, 2011). Unlike other theories found in interdisciplinary literature, Grey systems theory has managed to retain its place and is recognized by researchers due to its application in real world settings (Delcea and Scarlat, 2009). The theory has overcome the drawbacks found in the use of statistical models and probability theory (Kayacan et al., 2010).

Grey data analysis provides the foundation of many ecnonmic applications and also in applications related to prediction and diagnosis of firm diseases (Lin et al., 2009; Liu et al., 2012). Delcea et al. (2013) and Scarlat and Delcea (2011) have established that the processes taking place in the firm and that of a human body are closely linked. In both the firm and humans, survival is the element of concern when we are dealing with serious disease. It is very easey to explain and understand that when we are referring to some syndromes, we are talking about various symptoms associated with it, which if not treated timely may result in the death of the human, and bankruptcy in case of a firm. Scarlat and Delcea (2011) referred that the accounting ratios are the sympotms that predict bankruptcy. The theories developed, after the researh in this area has began, are manifold and have a same purpose. These theories are focused on finding a way through which occurrence of such event of bankruptcy, in case of a firm, or disease in case of a human, can be highlighted or anticipated (Scarlat and Delcea, 2011).

During the diagnosis stage, when we are trying to predict the firms disease, the main focus should be on the rightly identification of the symptoms and their quantification (Delcea and Scarlat, 2009). In their study, Scarlat et al. (2010) a symptom matrix was constructed by utilizing the model provided by the grey systems theory. They attempted to determine a way where the symptoms that affect the health of a firm/firms are ranked (Scarlat et al., 2010).

Over the last few years, grey system theory was widely used in studies related to prediction and default pobability of firms (Lin et al., 2009; Chuang, 2013). Delcea and Scarlat (2009) used grey system theory to develop a symptom matrix using accounting ratios. The matrix was a combination of grey incidences having a total of nine symptoms and use to determine the intensity of symptoms at various level for all businesses. Cheng et al. (2009) developed a hybrid model for default prediction of firms using historical performance data. In this model, 14 symptoms or financial ratios were used and the model was supported by both rough set and grey system approaches.

2) Option-pricing theory

According to the Option-pricing theory (OPT) by Black and Scholes (1973) and Merton (1973) BSM, a market-based measure, reflect all available information about bankruptcy prediction. The OPT model is useful as it provide theoretical support for the determinants of bankruptcy and provide the required framework to extract market prices information that relates to predicting bankruptcy (Hillegeist et al., 2004). The OPT model further explained that the information obtained from Stock market is most relevant in predicting bankruptcy because the information provided is an aggregate of financial statements and other related sources.

Following BSM, the firm's equity can be viewed as a call option on the value of the firm's assets. As assets value fall below the liabilities, the call option cannot be excercised and the firm in distress is turned over to its creditors. Hillegeist et al. (2004) discussed that bankruptcy probabilities are embedded in BSM OPT model. They used standard deviation of equity returns and market value of equity as primary measures to approximate the BSM (Hillegeist et al., 2004).

Market-based models using BSM contingent claims method provides a more appealing alternative and various researchers have used this method in predicting coporate bankruptcies (Agarwal and Taffler, 2008; Bharath and Shumway, 2008; Campbell et al., 2008; Charitou et al., 2013). This methodology has countered several criticisms of financial models as: 1) the BSM model provides the theoretical basis for prdicing bankruptcy, 2) the information which was partially available through the use of accounting ratios is fully reflected in the stock prices and inefficient markets, 3) the accounting policies of the firm cannot influence the market variables, 4) market prices of a firm provides reflection of expected future cashflows, henceforth are better predictors of a firm performance and 5) the output of market based models are not sample or time dependent.

The above insights from OPT by BSM described the payoff from a default-risky bond in terms of the pay-offs on a risk-free bond and a put option on the value of the firm's assets. The borrower holds a put option and its value depends on the maturity period of the bond, the asset volatility value, face value of loan and assets of firm, and the yield on a default-free bond having similar maturity period. The credit spread is estimated by taking a difference between the yield of default-free and risky bonds and is a premium put option whose value increases with volatility of asset and leverage.

The KMV model employed the practical use of Merton model as described in Kealhofer and Bohn (1998) and Fong and Vasicek (1997). KMV Corporation is a firm owned by Moody's and are recognized for credit risk analysis. The KMV model uses an Expected Default Frequency (EDF), which is firm-specific and a function of the capital structure of the firm, the volatility in the returns of assets, and the current asset value. In estimating EDF, the initial step is to determine the volatility of returns on asset and the value of the asset. The estimation of asset value would have been simple if the liabilities of the firm are traded publicly. Since it is not a general practice, the Merton approach is used to estimate the value of liabilities. In the second step, the distance to default is estimated, which is defined as the number of standard deviations between the mean of the probability distribution of the future asset value and the so-called default point, defined as the sum of the short-term debt and half the long-term debt. In the last step, The third and last step, the distance-to-default statistic is related to historical data on default frequencies of firms with different distances-to-default. Thereby, the probability of default for a firm is estimated.

Like the Z-statistic, the EDF statistic depends on firm-, industry- and macroeconomic factors. Thus, the contribution of macroeconomic factors could in principle be analyzed by estimating the contribution of macroeconomic factors to volatility and asset values. Tang and Yan (2010) and Amato and Luisi (2006) investigate the impact of output and inflation on the credit spreads term structure. In the second study, researchers studied how macroceonomic factors contribute to the EDF. The author in their study assumed that macroeconomic indicators are significant contributors and have high bankruptcy prediciton power. Collin-Dufresne et al. (2001) also describe the impact of macroeconomic variables on credit spreads.

Pesaran et al. (2007) link a global macroeconomic model to a credit risk model of the type described. The researchers used oil prices, output, real money balances, inflation, interest rates and equity indices to detail changes in credit risk across businesses. Pesaran et al. (2006) further enhanced the model and considered credit risk diversification. The macroeconomic factors are imprtant and they determine the opportunities for diversification. Morgan (1997) used the described model to develop Credit Metrics model and also intoduced the credit migration approach. The model linked the risk probability of firm default with specific credit rating. Henceforth, KMV model validate the use of macroeconomic indicators in credit risk and default models.

RESEARCH MODEL AND VARIABLES

1) Variables selection

The required framework needs the definition of response variable (bankruptcy in our case) and predictor variables. In line with the previous literature, bankruptcy is not only a certain event but an outcome of a phenomenon. It is a legal procedure where such businesses which fail to comply with their financial obligations are liquidated. Bankruptcy may be declared by insolvent debtor or be announced by the court on the petition of a creditor. Upon court order, business discontinue their operations as a going concern. Firms that undergo merger, acquisition, name change or cease operations due to fraudulent activities are not considered bankrupt in this study. The financial institutions including banks and leasing institutions are also not included.

The predictor for bankruptcy includes firm specific variables or accounting variable, market variables and country specific or macroeconomic variables. The selection of predictor variables is a result of extensive review of existing literature.

Accounting Variables

The accounting variables selected for this study are divided into four groups: liquidity, profitability, asset turnover and financial leverage ratios. Liquidity ratio of a firm is measured by working capital to total assets (WCA) (Altman, 1968; Chava and Jarrow, 2004; Christidis and Gregory, 2010). Working capital estimates a company's efficiency and its short-term financial health. Profitability ratios reflect the outcomes of the operating decisions and the financing policies of a firm (Brigham and Houston, 2012: 364–397). Several studies have found that profitability ratios are one of the significant indicators while predicting corporate bankruptcy (Cheng et al., 2010; Coats and Fant, 1993; Hillegeist et al., 2004). This study used two different proxies for measuring profitability which are: the net profit margin (NPM) and earning retention ratio (ERR). The NPM is used to measure a firm's income out of the total sales, higher value for NPM indicates that firm is efficiently converting its sales into profit. The ERR is a financial measure that consider the percentage of earnings retained by a firm at year end. An increase in value of ERR indicates that firm has retained more of its earnings to grow its business. Asset turnover ratio (ATR) is the ratio of firms sales to total assets and estimates how efficiently firm use its asset to generate sales (Coats and Fant, 1993; Gombola et al., 1987). A higher value of ATR indicates that firm is efficiently doing its operations and are generating higher revenues by efficiently using its assets which is good for the business. Lastly, financial leverage (FLR) determines the debt burden of a business relative to its assets and is estimated using total liabilities to asset ratio. The measure includes all liabilities: long term and short term, and total assets: current and fixed.

Market variables

The market variables used in this study are obtained from Altman and Shumway's model. These variables include market-book value of equity (MTV), past excess return (PER), and change in firm stock return (CSR). The MTV is calculated by the ratio of market value of equity to book value of total equity (Tinoco and Wilson, 2013). Past excess return is measured as the return of the firm in year t-1 minus the value-weighted stock market index return in year t-1 (Shumway, 2001). The annual return of each company is estimated by adding monthly returns. Change in firm stock return is a representation of idiosyncratic standard deviation of each firm's stock returns. It is defined as the standard deviation of the residual of a regression using each stock's monthly return in year t-1 on the value-weighted stock exchange index return for the same year (Shumway, 2001).

Macroeconomic Variable

In this study we have used macroeconomic variables to develop a framework for bankruptcy. These variables include gross domestic product (GDP), retail price index (RPI), real effective exchange rate (REER), real interest rate (RIR) and market capitalization of stock exchange. GDP estimate the monetary value of a country's goods and services produced in a specific time period.

GDP can be calculated on either monthly, quarterly or annual basis. The data for annual GDP was obtained and the study uses annual *change in GDP* for bankruptcy prediction. The retail price index estimates the goods and services consumed by the households in a country for a specific time period (Tinoco and Wilson, 2013). Data for RPI is obtained on annual basis and annual change in RPI is measured to test for the model. The REER is the weighted average inflation adjusted value of currency relative to an index of major currencies. The index value is obtained by estimating the weighted average of relative trade balance of currency against each indexed currency (Sharabany, 2004). The annual change in REER is calculated to be used in this model. According to Fisher equation, RIR is calculated by taking the difference of inflation rate and nominal interest rate (Hudson, 1986). This study considers the change in real interest rate on annual basis. *Change in market capitalization of stock exchange* is calculated by taking the market capitalization of all companies in the stock market and adding them together to arrive at the capitalization for the market as a whole (Levine and Zervos, 1998). The measure is used to see the increase or decrease in the size of the market on yearly basis. Change in market capitalization is measured by taking the difference between market capitalization of year t and year t-1, where t represents the value for current year.

2) The Data

Data for the current study is obtained from DataStream. The raw data for the variables was collected for all the firms in the study period, which spans from the period 2001 to 2017 for 18 countries, covering both economic expansion and downturn phases, which helps mitigate the short-term impact of business cycles on predictor variables. In addition, the incorporation of macroeconomic variables such as (such as GDP growth, inflation, and interest rates) covers the impact of broad economic fluctuations. However, the model may still be sensitive to some local or sectoral shocks that further researchers. The countries are selected using income classification by World Bank. Based on income level, the economies are categorized into 4 different levels: high income, upper middle income, lower middle income, and low income. Among each economy, the countries are selected having similar income level. While selecting countries it was considered that the data is easily accessible and available on DataStream, and the selected countries also represent the specific income groups. The current study does not include the countries from low-income economies, as they do not tend to report the data on regular basis for the study time period. The classification of economies and countries by World Bank based on the income level used in this study are given in Table 1. The selection of countries based on income level was made to ensure the balanced representation of diverse economic environments in the analysis and to check if the predictors remain consistent across different economic conditions.

Table 1: Data sample of non-financial firms

High Income		**Upper-Middle Income**		**Lower-Middle Income**	
Country	**No. of firms**	**Country**	**No. of firms**	**Country**	**No. of firms**
Singapore	297	Malaysia	964	Pakistan	498
Germany	749	Thailand	388	South Africa	852
Japan	2340	Brazil	510	Indonesia	460
Poland	148	Mexico	318	Philippines	273
Israel	565	Turkey	233	Sri Lanka	225
Total	4099	**Total**	2413	**Total**	2308

Source: DataStream (author consolidation).

The sample includes all non-financial firms which are registered on their stock exchanges. The sample further excluded all those firms whose life on stock exhange was less than 24 months, to make sure that post-listing business information is obtained (Agarwal and Taffler, 2008). This constitutes a total of 4099 firms from high income countries, 2413 firms from upped middle income countries and 2308 form the lower middel income countries. Data from the period 2001–2017 was collected for all these firms.

3) The Model

In this study, the probability of bankruptcy is estimated by analyzing the values of explanatory variables. This can be done by considering a simple linear equation.

$$Y = a + a_1X_1 + a_2X_2 + a_3X_3 + a_4X_4 + a_5X_5 \dots\dots + a_iX_i + u_i \quad (1)$$

where:

Y is dependent variable,
a_i is unknown constant,
X_i is independent variable,
u_i is random error term.

For the above function, there are two requirements: (1) as Xi, the value of predictor changes, the estimated probability values always lies in the 0–1 interval, and (2) there is a nonlinear relationship between Xi and Pi (Aldrich and Nelson, 1984: 11–12)

The logit model satisfies these requirements. Therefore, we consider logit model in this study due to its comparative mathematical simplicity (Gujarati, 2012: 154). According to Gujarati (2012: 155–156), It is reasonable to assume that: Yi = 1 (if a firm is bankrupt), and Yi = 0 (if a firm is non-bankrupt). The logit model can best be understood by using the equation followed by Gujarati;

$$L_i = \ln\left[\frac{P_i}{1-P_i}\right] = Y_i = aX_i + u_i \qquad (2)$$

where:

L_i is the logit function,

P_i is the probability of bankruptcy (i.e. Y_i = 1),

aX_i is the linear function of the independent variables.

In order to better understand the Logit model, see Gujarati (2012: 185). The characteristics of logit model are best explained by Shumway (2001). Shumway (2001) study employed Logit model on a sample of 300 bankrupt firms for the period of 1962–1992. Following Shumway, other studies have used multiple-period logit regression for predicting corporate bankruptcy. For instance, Nam et al. (2008) developed a duration-dependent hazard model and included macroeconomic variable as a baseline hazard.

4) Research Method

The current study tested the significance of the accounting variables including liquidity ratio, profitability ratio, asset turnover ratio, and financial leverage ratio. The significant variables after testing were used in this model to develop a general bankruptcy prediction model. Moreover, the market variables of the market to book value of equity, past excess return, and change in firm's stock returns were used in the current model. Based on different economic environments, significant macroeconomic variables were identified from a change in GDP, change in RPI, change in real effective exchange rate, change in real interest rate, and change in market capitalization of the stock exchange.

The study used the following model.

$$Y = a + bX_1 + cX_2 + dX_3 + eX_4 + fX_5 + gX_6 + hX_7 + iX_8 + jX_9 + kX_{10} + lX_{11} + mX_{12} + nX_{13} \quad (3)$$

where:

$Y = \log[\frac{P}{1-P}]$

P = the probability of bankruptcy measured as 0 or 1 (0 for non-bankrupt firm and 1 for bankrupt firm);

X_1 = WCTA – Working capital / Total assets;

X_2 = NPM – Operating income / Total revenue;

X_3 = NPM – Operating income / Total sales;

X_4 = ERR – (Net income – dividends distributed) / net income;

X_5 = ATR – Sales / Total assets;

X_6 = FLR – Total liabilities / Total assets;

X_7 = MTV – Market value equity / Book value of equity;

X_8 = PER – Past excess return as the return of the firm in year t-1 minus the value-weighted stock market index return in year t-1;

X_9 = CSR – Idiosyncratic standard deviation of each firm's stock returns;

X_{10} = CGDP – Annual change in GDP;

X_{11} = CRPI – Annual change in RPI;

X_{12} = CREER – Annual change in real effective exchange rate;

X_{13} = CRI – Annual change in real interest rate;

X_{14} = CMC – Annual change in market capitalization of stock exchange.

In order to assess the predictive power of the proposed model at different time horizons prior to bankruptcy, we run separate logistic regression models for different times. Therefore, "t-1" refers to the one-year period before the bankruptcy event, while "t-2" refers to the two-year period before bankruptcy. These temporal designations allow us to test the model's effectiveness in identifying distress signals at different times before a firm fails. By analyzing both t-1 and t-2 models, we aim to assess whether the predictive strength of accounting, market, and macroeconomic variables changes as the bankruptcy event approaches.

ANALYSIS OF FINDINGS AND RESULTS

Table 2 presents the result for the multicollinearity in the model. According to (Gujarati, 2012), the association between the predictor and response variable may represent the best outcome when the variables are not highly correlated. The correlations and VIF column in the table indicates that the predictors are not highly correlated. The VIF values presented in the last column are within the described range as mentioned by (Gujarati, 2002: 362–363). According to Gujarati, VIF value below 10 is acceptable and model may be used for regression. VIF score for the study variables is highest at 7.97 and lowest as 1.001 for the CMC and FLR, respectively. This indicates that all the variables have a score of VIF lower than the threshold level of 10 and there is no problem for the high level of interdependence.

The correlation among the predictor variables including accounting, market and macroeconomic also show the values reported against each variable are within the acceptable range. The correlation among the market variables CSR and PER is 0.754, and macroeconomic variables CRI and CGDP is 0.665 and CMC and CREER are 0.811. Although the values show a high correlation between the reported variable, but the values are still below the threshold value of 0.9 mentioned by (Gujarati, 2012: 291).

1) Descriptive Statistics

This section helps reader to have an in-depth view of the trends in data. Table 3 provide descriptive statistics of accounting, marketing and macroeconomic variables. Panel A provides the entire data set and the mean values for change in GDP is 6.10 with a maximum value of 12.41. Despite the economic pressure and recession period, the economies under the study period are expanding and some are experiencing a high growth rate. The price index – CPI, a measure of inflation having a mean value of 5.49 and a maximum value of 22.5 – indicates the economies are under pressure due to increase in prices. The data further reports a negative value for CPI and a standard deviation of 3.40. Changes in the REER can affect the competitiveness of a country's exports and imports and can, therefore, impact the financial health of companies operating in various industries. The mean value for CREER is 83.35 and a standard deviation of 35.76 shows that the different economies have reportedly high variance in the given data. The variable CRI also have a high standard deviation of 16.34 but it is less than the value reported for CREER. CRI has a reported mean value of 3.53 and a maximum value of 48.34 shows a large variation in the interest rates.

Table 2: Correlation Matrix

IV	WCTA	NPM	ERR	ATR	FLR	MTV	PER	CSR	CGDP	CRPI	CREER	CRI	CMC	VIF
WCTA	1.000													1.048
NPM	0.208***	1.000												1.048
	(0.00)													
ERR	0.002	0.001	1.000											1.001
	(0.853)	(0.899)												
ATR	-0.029***	0.028***	0.011	1.000										1.032
	(0.000)	(0.001)	(0.183)											
FLR	0.003	0.000	-0.008	0.008	1.000									1.001
	(0.701)	(0.976)	(0.359)	(0.340)										
MTV	0.003	-0.020***	-0.001	0.015	-0.014	1.000								1.002
	(0.709)	(0.014)	(0.861)	(0.072)	(0.086)									
PER	0.002	0.003	-0.002	0.065***	0.012	-0.001	1.000							2.404
	(0.851)	(0.742)	(0.777)	(0.000)	(0.153)	(0.902)								
CSR	-0.011	-0.008	0.002	0.025***	0.002	0.012	0.754***	1.000						2.403
	(0.163)	(0.324)	(0.799)	(0.003)	(0.783)	(0.128)	(0.000)							
CGDP	-0.020**	0.003	-0.003	0.062***	-0.013	-0.015	0.034***	0.009	1.000					2.401
	(0.013)	(0.729)	(0.714)	(0.000)	(0.117)	(0.071)	(0.000)	(0.271)						
CRPI	-0.005	0.007	-0.005	0.094***	-0.012	-0.008	-0.013	0.036***	0.113***	1.000				1.076
	(0.559)	(0.420)	(0.521)	(0.000)	(0.148)	(0.314)	(0.115)	(0.000)	(0.000)					
CREER	0.000	-0.006	0.010	-0.071***	0.007	-0.004	0.009	-0.023***	0.132***	-0.071***	1.000			6.129
	(0.979)	(0.479)	(0.215)	(0.000)	(0.398)	(0.658)	(0.256)	(0.006)	(0.000)	(0.000)				
CRI	-0.025***	-0.006	-0.022***	0.026***	-0.009	-0.007	-0.023***	0.045***	0.665***	0.197***	-0.072***	1.000		2.587
	(0.003)	(0.449)	(0.008)	(0.002)	(0.284)	(0.424)	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)			
CMC	-0.015	-0.013	0.006	-0.062***	-0.003	0.003	0.016	0.018***	0.520***	-0.026***	0.811***	0.370***	1.000	7.977
	(0.067)	(0.100)	(0.442)	(0.000)	(0.729)	(0.748)	(0.057)	(0.026)	(0.000)	(0.001)	(0.000)	(0.000)		

Source: own calculations; **** P<0.01, ** P<0.05, * P<0.1, Note: BP Bankruptcy* (*Where 0 indicates non-bankrupt and 1 indicates bankruptcy time*), *LR liquidity ratio, NPM net profit margin, ERR earning retention ratio, ATR asset turnover ratio, FLR financial leverage ratio, MTBV market to book value, PER past excess return, CSR change in stock return, CGDP log change in GDP, CPI change in retail price index, CREER change in real effective exchange rate, CRI change in real interest rate, CMC change in market capitalization of stock exchange*

Table 3: Summary Statistics for Accounting, Marketing Variables and Macroeconomic Variables

	WCTA	NPM	ERR	ATR	FLR	MTV	PER	CSR	CGDP	CRPI	CREER	CRI	CMC
Panel A: entire data set													
Mean	-.43	-.732	.645	.813	.50	2.53	0.00	.129	6.10	5.49	83.35	12.98	9.81
Std. Dev.	17.77	23.10	3.90	.713	.28	36.79	0.00	.16	5.42	3.70	35.76	16.34	3.55
Min	-8.98	-2.53	-205.9	-3.22	0	-304.2	-7.646	-1.00	-3.02	-2.29	-.03	-10.24	-3.13
Max	1.2	5.99	112.21	8.96	1	2761.0	0.00	6.20	12.41	22.56	152.4	48.34	12.18
Panel B: Non-Bankrupt firms													
Mean	-.254	-.66	.625	.80	.50	2.53	-.05	.126	5.49	5.57	82.40	12.32	9.57
Std. Dev.	15.21	24.40	4.17	.67	.28	39.26	.5	.09	5.32	3.87	37.61	16.24	3.70
Min	-1.98	-2534	-205.9	-.02	0	-304.2	-4.803	0	-3.02	-2.29	-.03	-10.24	-3.13
Max	1.2	272.9	112.21	8.96	1	2761.0	4.672	1.37	12.41	22.56	152.44	48.34	12.18
Panel C: Bankrupt firms													
Mean	-1.62	-1.20	.78	.88	.50	2.48	0.00	.15	10.15	5.01	89.66	17.42	11.41
Std. Dev.	29.64	11.13	.71	.90	.29	10.04	0.00	.37	4.22	2.17	18.11	16.30	1.66
Min	-9.66	-3.44	-6.59	-3.22	0	-21.29	-7.646	-1.00	1.39	-.87	4.53	-6.77	1.37
Max	.96	3.9	8.11	7.14	1	115.9	0.00	6.20	12.41	20.28	152.4	48.34	12.18

Note: BP Bankruptcy (Where 0 indicates non-bankrupt and 1 indicates bankruptcy time), LR liquidity ratio, NPM net profit margin, ERR earning retention ratio, ATR asset turnover ratio, FLR financial leverage ratio, MTBV market to book value, PER past excess return, CSR change in stock return, CGDP log change in GDP, CPI change in retail price index, CREER change in real effective exchange rate, CRI change in real interest rate, CMC change in market capitalization of stock exchange

2) Logistic Regression

The results for the bankruptcy model are presented in Table 4. As mentioned earlier, the likelihood of bankruptcy is a binary measure, and the response variable is provided a value of 0 for non-bankrupt firms and 1 as the firm goes bankrupt. In the current study, four models are developed to estimate the likelihood of bankruptcy using the accounting, market and macroeconomic variables. Model 0 presents the base model and is developed by identifying the variables from the review of literature and providing a general bankruptcy model.

Model 1 reports the findings for the 'Accounting only' model and includes the accounting ratios: working capital to total asset (WCTA), net profit margin ratio (NPM), earnings retention ratio (ERR), asset turnover ratio (ATR), and financial leverage ratio (FLR). Model 2 represents the 'Accounting plus marketing indicators' and include the indicators market to book value of equity (MTV), past excess return (PER) and change in firm stock return (CSR). Model 3 adds five macroeconomic variables: change in gross domestic product (CGDP) measured by determining the annual change from the previous year and transformed by taking the natural logarithm; the change in retail price index (CRPI) annually, the change in real effective exchange rate (CREER) on yearly basis; the yearly change in real interest rate (CRI); the annual change in market capitalization of stock exchange (CMC), in logarithmic form in model 2.

The model 1, 2 and 3 in Table 4 shows the estimation results in the period t-1 and t-2. The period t-1 in the estimated model determine the likelihood of bankruptcy 1 year prior to the actual event and t-2 is 2 year prior to the bankruptcy event. This helps to identify the best predictors that separate non-bankrupt and bankrupt firms and test the predictive power for each model. Thus model 1, at t-1 present the results for the effect of accounting variables on bankruptcy one year prior to the event, t-2 present the results for 2 years prior to the event. In model 2 the marketing variables in addition to the accounting variables are tested at these time periods. The model 3 provides the estimation outputs at t-1 and t-2 for the model which includes marketing and accounting variable in addition to the macroeconomic variables.

The second column in Table 4 presents the Model 0 which present the logit regression result of all the predictor variables and bankruptcy. The variables obtained from the literature including accounting ratios, market ratios and macroeconomic variables presented in Model 0 which affect bankruptcy are statistically significant at 5-1%. Some of these variables have a high coefficient value which indicates they are efficient predictor of bankruptcy. The accounting ratios include WCTA, NPM, ERR, ATR and FLR. The negative coefficient signs of the WCTA, which represents a firm's ability to smoothly operate and manage their working capital, suggests that higher the WCTA the higher its performance and the probability of bankruptcy is lower. Bellovary et al. (2007) found that a lower WCTA ratio was associated with an increased risk of bankruptcy for US firms. The study also found that a higher level of profitability and a lower level of debt could help mitigate the negative effect of a low WCTA on the risk of bankruptcy.

Altman (1968) found that companies with low net profit margins were more likely to experience bankruptcy. The study used a statistical model known as the Z-score to predict bankruptcy risk and found that low net profit margins were a significant predictor of bankruptcy. Similarly, Jones and Hensher (2004) analyzed the financial statements of Australian companies and found that companies with lower net profit margins have a higher chance to experience financial distress and bankruptcy. The coefficient estimates for the remaining accounting variables ATR, ERR and FLR displays a positive sign and is statistically significant. This suggests that all the accounting variables selected in the study have the tendency to affect the bankruptcy likelihood of a firm. The NPM coefficient estimate retains the highest absolute value among the accounting ratios, followed by FLR, ERR, WCTA and ATR.

The marketing ratios in model 0 include three variables: MTV, PER and CSR. The coefficient estimates of market to book value, which indicates the investor confidence in future of a business and market perception of company value and future prospect, is significant with a value of 0.98. PER are the returns earned by a company over and above the returns that would be expected based on its risk level. The hypothesis is that firms with a history of strong past excess returns are more likely to experience bankruptcy due to overconfidence and excessive risk-taking. PER has a significant coefficient with positive sign but the value of the coefficient is very small. This indicates that PER has a little effect on bankruptcy of a firm. Another market variable obtained from the literature, CSR, is used in the model. The coefficient of CSR has a value which is higher than PER but is less than MTV and is also statistically significant.

The model also includes the macroeconomic variables. The variables CGDP and CMC were transformed by using the natural logarithm. The coefficient of CGDP and CMC have a positive value of 0.17 and 0.32 and are statistically significant. The sign of the variable CRPI is negative with a coefficient value of 0.10, which indicates that increase in inflation in the country increase the chances of bankruptcy. CPI can affect the purchasing power of consumers, which can impact the demand for goods and services and the financial health of companies operating in various industries which increase the chances of bankruptcy. The coefficient of the other two macroeconomic variables CREER, which measures a country's currency value relative to a weighted average of other currencies, adjusted for inflation and can affect the competitiveness of a country's exports and imports, and CRI which determines the borrowing cost of a firm, also show a negative sign and are statistically significant. This indicates that CREER and CRI are the predictors of the bankruptcy.

Model 1 in Table 4 display the logistic regression results of accounting only indicators on the dependent variable. All of the variables in the model are statistically significant in t-1, with a slight change in significance level, which indicates that all of the accounting ratios used in the study are efficient predictors of bankruptcy. The ERR is now statistically significant at 1 percent and LR at 5 percent, both were significant at 10 percent in the previous model. The results in t-2 or two year prior to bankruptcy of the model 1 shows that all the regressors have retain their statistical significance except FLR, which is now statistically insignificant. It is also evident that the variables WCTA and NPM are still having a negative effect and all the remaining variables including ERR, ATR and FLR have a positive effect. The coefficient value of variables in both t-1 and t-2 is highest for ATR, followed by FLR, ERR, NPM and WCTA which indicates that the coefficient estimates of all the accounting variables are stable over the time.

In Model 2, market ratios of past MTV, PER and CSR are included along with accounting ratios to test for bankruptcy in t-1 and t-2. All the three-market variable have a coefficient estimates which are statistically significant at 10-1% in t-1 and t-2 except for MTV which is statistically insignificant at t-2. The coefficient sign for PER is positive in t-1 and t-2, for CSR is positive in t-1 but negative in t-2, for MTV is negative in t-1. Furthermore, all the accounting ratios previously used in Model 1 have retain their statistical significance except FLR which is insignificant at both t-1 and t-2. A similar result for this accounting variable is reported in Model 1 where it was insignificant at t-2. Apart from this all the other accounting variables have stable coefficients and are statistically significant. The magnitude of market variables is higher than accounting variables and PER has the highest impact.

Table 4: Logit Regression of bankruptcy prediction indicator on predictor variables

Variables	Model 0	Model 1		Model 2		Model 3	
		t-1	t-2	t-1	t-2	t-1	t-2
LR	-0.12*** (0.00)	-0.01** (0.01)	-0.02** (0.01)	-0.01** (0.02)	-0.02** (0.01)	-0.001** (0.02)	-0.01** (0.04)
NPM	-0.32*** (0.00)	-0.03*** (0.007)	-0.02*** (0.003)	-0.05** (0.01)	-0.03*** (.006)	-0.03** (0.01)	-0.03** (0.01)
ERR	0.160*** (0.00)	0.15* (0.06)	0.13* (0.07)	0.10* (0.05)	0.15* (0.06)	0.09* (0.07)	0.23* (0.05)
ATR	0.109*** (0.009)	0.24*** (0.00)	0.26*** (0.009)	0.22*** (0.01)	0.21*** (0.002)	0.29*** (0.005)	0.22*** (0.006)
FLR	0.19** (0.01)	0.21** (0.02)	0.23 (0.20)	0.16 (0.48)	0.19 (0.30)	0.146* (0.05)	0.10 (0.59)
MTV	0.98*** (0.00)			-0.001* (0.07)	0.20 (0.97)	-0.002* (0.07)	-0.001 (0.89)
PER	0.00*** (0.00)			0.62*** (0.00)	0.08* (0.09)	0.021*** (0.00)	0.21*** (0.00)
CSR	0.955*** (0.002)			0.54** (0.04)	-0.59** (0.03)	2.24*** (0.003)	-0.12* (0.08)
LOGCGDP	0.171*** (0.00)					0.14*** (0.00)	0.15*** (0.00)

Table 4 (cont.)

CPI	-0.10***					-0.02	0.04
	(0.00)					(0.78)	(0.50)
CREER	-0.02***					-0.06***	-0.03***
	(0.00)					(0.00)	(0.00)
CRI	-0.02***					-0.02**	-0.02**
	(0.00)					(0.04)	(0.01)
LOGCMC	0.32***					0.72***	0.48***
	(0.00)					(0.00)	(0.00)
Constant	-4.37***	-2.15***	-1.14***	-2.09***	-2.04***	-5.45***	-5.71***
	(0.00)	(0.000)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mean dependent var	0.130	0.153	0.112		0.153	0.160	0.15
Pseudo R2	0.150	0.013	0.011	0.018	0.017	0.177	0.187
SD dependent var	0.337	0.360	0.391		0.360	0.367	0.360
Chi-square	1731.87***	29.090***	39.01***	27.541***	37.90***	272.75***	375.47***
	(0.00)	(0.000)	(0.00)	(0.001)	(0.000)	(0.000)	(0.000)

Source: Own calculations.

Model 3 in Table 4 includes regression result of five macroeconomic variables; CGDP, CRPI, CREER, CRI, CMC along with the variables used in model 2. All the market and accounting variables are statistically significant at 10-1% in t-1, In t-2, all the accounting and marketing predictors have significant coefficients except FLR and MTV which are statistically insignificant. Among the five macroeconomic variables, CGDP, CMC and CREER have significant coefficients at 1 percent in both t-1 and t-2. The coefficient for CGDP and CMC are positive whereas CREER has a negative coefficient. CMC has the highest coefficient value in both t-1 and t-2 followed by CGDP and CREER. The coefficient for CRI is negative and statistically significant at 5 percent. Only one variable CRPI shows statistically insignificant coefficients in both t-1 and t-2.

Table 4 also reports the pseudo R^2 to help in comparing the variation across both the models. The values of pseudo R^2 reported for Model 1 displays an expected decrease in value from t-1 to t-2. A similar marginal decline in pseudo R^2 value for Model 2 is observed from t-1 to t-2. When observed for Model 3 in the table, there is a marginal increase in value of pseudo R^2 over the same period. The values shows that the change is marginal, and the important information is that regressors are stable over time. It is to be noted that the measure is only included to make comparison across different time frames and the values need to be used with caution as they do not present the same meaning as they have for ordinary least square regression. The model effectiveness and fitness are therefore further checked using various other model fit measures presented in table 5.

Table 5 contain multiple measures of model performance for all the Model 1, 2 and 3 estimated in different time periods. The log-likelihood of the model, which measures the goodness-of-fit of the model to the data. A higher log-likelihood indicates a better fit. The various R^2 values such as McFadden's R^2 and its adjusted value are all measures of the proportion of variance in the response variable (bankruptcy) that is explained by the model. For logit model, the value of R^2 is within the acceptable range as Asutay and Othman (2020) show that goodness-of-fit value needs to be between 0.20 and 0.40. Generally, a higher value for these measures indicates a better fit.

Table 5 shows the performance of Model 1, Model 2 and Model 3 in the study. The results in panel A shows model performance estimated in t-1. The performance parameters compared for all the models indicate that in Model 3 'Full Model' has a better fit to the data than the 'Intercept Only' model, as it has a higher log-likelihood. The estimated parameter shows that adding market variables to accounting only model yields a higher R^2. The change in McFadden R^2 for Model 3 after adding macroeconomic variables has shown a substantial increase indicating a positive contribution to the model fit and better performance of the bankruptcy model. When compared for McFadden's R^2 and Adj R^2, Model 3 shows a better fit as the values are within the accepted range estimated by Asutay and Othman (2020). The Model 3 also reported a lower AIC and BIC value which indicates that full model is a better fit for the bankruptcy data.

Panel B in Table 5 provide performance estimates for the models assessed in t-2 or two years prior to the bankruptcy. The loglikelihood representing full model has a better fit for the given data as it has higher for the model having all the variables used in the study. The McFadden's R^2 value for Model 1 and Model 2 have relatively small values but as we add the macroeconomic variables to the data, the value increases significantly. This establish that Model 3, which include accounting, market and macroeconomic variables can contribute significantly and substantially to the bankruptcy prediction. This indicates that the bankruptcy model does not necessarily need a large number of regressors to provide better predictions.

Although the Model 3 in t-2 has a marginally less value reported for McFadden's R^2 when compared for the same in t-1, but still, it is within the acceptable range for logistic regression.

In Panel B, AIC value is low and McFadden's R^2 value is high which shows that the model is fit for given data (Tian et al., 2015).

Overall, based on the information in the table, it appears that the 'Full Model' has a better fit to the data and is therefore likely to be more effective in predicting bankruptcy than the 'Intercept Only' model. Additionally, the outcome of Model 1 and Model 2 fitness measure shows that although accounting only and accounting plus market variables have been used by various existing studies to predict bankruptcy, the predictive ability of the model and the regressors is not strong. There is a significant variation in the R^2 values when the macroeconomic variables are included in the model. Although marginal decrease in value is observed from t-1 to t-2, but still the regressors to response variable relation establish that the general bankruptcy model with accounting, market and macroeconomic variable provide better result.

Table 5: Model Performance Measures

	Log-Lik Intercept Only	Log-Lik Full Model	McFadden's R2	McFadden's Adj R2	Maximum Likelihood R2	Cragg & Uhler's R2	McKelvey and Zavoina's R2	Efron's R2	AIC	BIC
Panel A: models' performance in t-1										
Model 1	769.7	-758.9	0.014	0.006	0.012	0.021	0.09	0.014	0.87	-11522.1
Model 2	-769.7	-756	0.018	0.006	0.016	0.027	0.021	0.019	0.87	-11505.6
Model 3	-769.7	-633.3	0.217	0.199	0.144	0.247	0.4	0.149	0.73	-11713.5
Panel B: models' performance in t-2										
Model 1	-1199.8	-1191.7	0.007	0.002	0.006	0.01	0.012	0.006	0.91	-18253.2
Model 2	-1199.8	-1186.9	0.011	0.003	0.01	0.016	0.087	0.012	0.91	-18239.2
Model 3	-1199.8	-996	0.2	0.198	0.144	0.24	0.386	0.146	0.76	-18581.7

Source: Own calculation.

CONCLUSION

This study offers a model for predicting bankruptcy using logit regression. The model happens to be a general prediction model as the data was obtained from 18 countries across the globe, including 6 countries each from different income countries. The study, for the first time in bankruptcy prediction literature, developed a general model which have used accounting, market and macroeconomic variables. Prior research have used accounting variables to predict bankruptcy in a single country and reported that the predictors are inconsistent when tested for other countries. The same happens for the model that have tested the predictive ability of market variables and macroeconomic variables for data from various countries. The results obtained from these models were inconsistent.

The existing models have tried and tested the superiority of one type of variables over the other, which is not the case in this study. This study has estimated the affect of accounting only ratios, from the literature, on the likelihood of bankruptcy. The results for the accounting ratios are consistent when estimated in t-1 and t-2. Another model tested by including market variables with the accounting variables for the bankruptcy in time t-1 and t-2. The accounting variables are still consistent with statistically significant coefficients and the market variables also reported the estimated coefficients have more magnitude than the accounting variables and are statistically significant. Finally, the third model includes the accounting, market, and macroeconomic variables to test for bankruptcy in t-1 and t-2. The results for the model indicate that the accounting and market variables used in the study are consistent when macroeconomic variables are added to the model and using all three types of variables improve the results and predictive ability of the model. Interestingly, the model performance measures tested for the panel in t-1 and t-2 show the goodness of fit test for the logit model shows that the full model is a better fit for the given purpose than the intercept-only model.

The results of this study suggests a set of predictors for a global model incorporating all three categories of variables – accounting, market, and macroeconomic that are consistent across countries. While this study is an initial step toward developing a general bankruptcy prediction model, its scope does not include a comprehensive validation of predictive accuracy across different economies. Future studies may fill this gap by conducting additional tests to further refine and validate this model. Furthermore, this has a data limitation of lower income countries because of non-reporting of all the data.

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