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Investigating the effects of Accounting Law on the Credit Rating Models using Artificial Neural Networks: a study in Vietnam

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Abstract

Purpose: This study builds up a credit rating model for small, medium, and large firms in Vietnam in the period from 2008 to 2018 and applies the model to analyse the effect of the new accounting law on credit rating. This research has several contributions to the literature. First, this study investigates the local accounting law which significantly affects the credit rating for small, medium, and large firms in Vietnam by using Artificial Neural Networks (ANN). To illustrate, the new accounting law changes the measures in the financial reports of firms, including assets, liabilities, owner's equity, revenues, and expenses. Thus, it will affect the credit rating.

Design/ Methodology/ Approach: In this research, the dataset includes 39,162 small, medium, and large firms in Vietnam in the period 2008–2018 from the Orbis Database using Artificial Neural Networks (ANN). For the first time in the literature, this research analyses the effect of the new accounting law on credit rating for Vietnamese small, medium, and large firms by using ANN.

Findings: The result of this study shows that the new local accounting system significantly affects the credit rating in several ways: (1) by changing the inputs of the models, (2) by changing the model performance, and (3) by changing the exact values of the weights and biases of the models. This research also finds evidence that the ANN model for the period from 2008 to 2014 (before implementing Circular 200) has a better predicting power than that for the period from 2015 to 2018 (after implementing Circular 200).

Practical implication: This study investigates the new accounting system (Circular 200) implemented on 1 January 2015 in Vietnam which guides both local and foreign enterprises in accounting policies for financial years beginning 1 January 2015.

Keywords: local accounting law, Vietnamese accounting system, credit classification, credit rating, Artificial Intelligence (AI), Artificial Neural Networks (ANN), firms in Vietnam.

JEL classifications: A21, A22

1. Introduction

The Vietnamese accounting system developed significantly during the period from 1986 to 2016 when Vietnam joined ASEAN and the World Trade Organisation (WTO). There were five primary milestones during the 2006−2016 period of the Vietnamese Accounting Standards (Phan, Joshi, and Tran-Nam 2018). First, in 1988, the Ministry of Finance updated its accounting system with a new one in 2006. The fundamental goal of the 2006 accounting system is to align financial reporting obligations with International Accounting Standards (IAS). From 2006, all businesses in Vietnam were required to use the accounting system. The Ministry of Finance then formed a group with the Vietnam Association of Securities Business and 44 other members to improve the 2006 accounting system and publish new standards in 2011 that were aligned with the International Financial Reporting Standards. Following that, in 2013, the Vietnam Association of Securities Business suggested six new accounting standards, including revisions to the eight current capital market accounting standards. Then, the Ministry of Finance brought the Vietnamese accounting system closer to the International Financial Reporting Standards by replacing the previous accounting system of 2006 with the new accounting system of 2014. In 2016, the Ministry of Finance created a series of workshops to train in the implementation of the new accounting system of 2014 and also to obtain feedback from practitioners (Phan, Joshi, and Tran-Nam 2018).

Furthermore, following the global financial crisis (GFC) of 2007–2008, governments all over the world had to deal with their economic concerns. Countries are grappling with a slew of serious macroeconomic issues, including major drops in economic growth and rising credit risk. This has resulted in a huge increase in the number of defaulting businesses in a variety of industries. Vietnam is no different (Pham, Do, and Vo 2018). According to the General Statistics Office of Vietnam (GSO), there were 16,840 enterprises in Vietnam that completed default procedures in 2019, up 3.2 percent from 2018 (GSO 2020). These figures demonstrate the necessity of a dependable credit rating system that accurately forecasts and categorizes good and poor creditors. Thus, these credit ratings may help commercial banks, financial investors, and other related stakeholders make loan or investing decisions (Hao and Wong, 2021; Nhan et al., 2021).

From the literature review, the accuracy of credit rating models vary significantly based on country and time period (Altman et al., 2017; Altman and Sabato, 2007; Jones et al., 2017; Q. H. Pham et al., 2018, 2022; V. N. B. Pham et al., 2018; Tsai et al., 2009). However, most of the critical researchers build credit rating models using the US and European context (Altman and Sabato 2007; Psillaki, Tsolas and Margaritis 2010; Wu, Gaunt and Gray 2010; Giordani et al. 2014; Jones, Johnstone and Wilson 2017; Sigrist and Hirnschall 2019; Cornée 2019; Muñoz-Izquierdo et al. 2019). Besides, the Vietnamese accounting system, which is changing all the time, also affects the financial ratios and the credit rating model (Phan, Joshi, and Tran-Nam 2018) significantly. In this research area, Lantto and Sahlström (2009) investigate the effects of IFRS implementation on significant financial ratios and accounting numbers. Lantto and Sahlström (2009) state that IFRS adoption affects the measurement of the essential accounting ratios of Finnish companies significantly. Morales-Díaz and Zamora-Ramírez (2018) show that the IFRS 16 implementation significantly impacts the leverage ratios and solvency ratios in European companies. Another influential research in this field is Tran et al. (2019) who investigate the effect of IFRS adoption in the listed firms of Vietnam. These key papers look at the influence of IFRS on financial ratios, but none of them look at the impact of Vietnamese accounting law on credit rating models.

This study contributes to the current literature for several reasons. Given the circumstance of the Vietnamese accounting system, this study investigates the new accounting system (Circular 200) implemented on 1 January 2015 in Vietnam which guides both local and foreign enterprises in accounting policies for financial years beginning 1 January 2015 (Phan, Joshi, and Tran-Nam 2018). Circular 200 enhances the comparability and transparency of corporate financial statements and brings the Vietnamese accounting system and international accounting system closer. Circular 200 significantly affects the measurement of financial ratios (Phan, Joshi, and Tran-Nam 2018). This research investigates the effects of local accounting law on the credit rating for small, medium, and large firms in Vietnam in the period 2008-2018 by using Artificial Neural Networks (ANN). To illustrate, this paper compares the credit rating model for Vietnamese firms before and after implementing Circular 200. For the first time, the findings of this research contribute significantly to the literature by identifying the effects of the local accounting law on the credit rating models (Pham et al., 2022). The comparison result of the ANN model for the credit rating between the 2008 – 2014 dataset (before implementing Circular 200) and the 2015 – 2018 dataset (after implementing Circular 200). This research uses Artificial Neural Networks (ANN) which can maximise the predicting power than the other methodologies including Multiple Discriminant Analysis (MDA) and Ordered Logistics Regression (OLR) (Hamori and Kume, 2018; Pham et al., 2022). After analysis of these two sub-datasets, the results of this study are not only able to show the effects of the new local accounting law on the credit rating models, but also could build a credit rating model for small, medium, and large Vietnamese firms in the period 2008–2018.

2. Literature Review

2.1 Literature on credit rating

Using current and historical information about the credit customer, the credit rating is an analytical model that can categorize whether the credit customer can pay their loan on time or not (Altman and Sabato, 2007; Tsai et al., 2009). Although the data (the business nature of the nation and the organizations) affects the accuracy of the credit rating models differently in each study (Altman and Sabato, 2007), the models' overall accuracy has improved significantly in the forty years since Altman (1968) introduced his MDA (Z-score), which solely relied on financial ratios. Then, Ohlson (1980) proposed the updated logit model (O-score), which still solely employed financial measures and helped make Altman (1968) credit rating model successful. Altman and Sabato (2007) suggested a new logit model that includes recorded financial variables to evaluate the accuracy of MDA and the logit model. The results clearly demonstrated that the logit model with logged financial variables outperformed the MDA model and the unlogged logit model, even though Altman and Sabato (2007) still solely utilized financial indicators.

When Wu et al. (2010) proposed a novel discrete-time hazard model incorporating a variety of independent variables, such as accounting data, market and business characteristic data, and inferred probabilities from option-pricing models, they enhanced the credit rating theories. According to Wu et al. (2010) findings, the authors' novel comprehensive model outperformed MDA, logit, and probit models. Psillaki et al. (2010) proposed a two-step model that could be used as an early warning system for assessing credit default risk: (1) they used the Data Envelopment Analysis method to develop an early warning system by obtaining a measure of firm performance (technical efficiency); and (2) they used LR analysis to evaluate the significance of efficiency in predicting failure. Financial variables and company characteristics were utilized in Psillaki et al. (2010) model. Later, using accounting data, market data, and business diagnostic data, Psillaki et al. (2010) suggested a novel forward-intensity multiperiod model to forecast default risk in the future (this was incredibly accurate for a short time period of 1-3 months). Finally, a novel non-linear logistic spline model focused on the non-linear correlations between the independent variables and the company default risk was put out by Giordani et al. (2014). Data on the market and firm characteristics, accounting information, and macroeconomic indicators were all used by Giordani et al. (2014).

In conclusion, there are two main ways that credit rating models' accuracy rises. The first step is to enhance the independent variables, which are divided into four groups: financial indicators, market indicators, firm-specific indicators, and macroeconomic indicators. The other approach, which is based on technological advancement, is to improve procedures. Additionally, a dependent variable with default and non-default values is used in practically all credit rating literature (two classes). Only Chai et al., (2019) research divided the dependent variable's credit rating into nine classes, which are more illuminating and have superior credit ratings than the dependent variable's two classes.

2.2 Literature on the variables that influence credit rating models

Macroeconomic variables

According to Giordani et al. (2014) and Le (2018), three of the most important determinants of the average level of firm failure are macroeconomic variables, such as the GDP annual growth rate, annual real interest rate, and inflation rate. These variables also shift the mean of the default risk distribution over time. The Central Bank reduces its real interest rate to encourage businesses to borrow so they may expand and to increase the total demand of a nation in order to illustrate this in broad terms, assuming all other factors are equal Mankiw (2020). The outcome is a rapid expansion of the economy. Most organizations experience an improvement in profitability when the GPD growth rate rises, which helps them be better able to pay off debt (Adebayo et al., 2022). As a result, the risk of default will gradually decrease. However, when the economy is in a downturn, the GDP growth rate (annual percentage) drops, companies become less profitable, and default risk increases. In other words, real interest rates are positively correlated with credit ratings, but GDP growth rates are negatively correlated with credit ratings (Jacobson et al., 2013; Le, 2018).

Another macroeconomic factor that affects credit rating quality is the annual rate of inflation. What effect the yearly inflation rate has on credit quality is not obvious from the studies. Let's use an expanding economy as an example where, with all else being equal, increasing aggregate demands can lead to greater GPD growth rates and inflation rates (Aye and Odhiambo, 2021; Mankiw, 2020). It follows that the inflation rate has a negative relationship with credit rating because most firms may earn more money and improve their credit rating during an expansionary period. However, according to Schechtman and Gaglianone (2012), there is a correlation between credit rating and inflation rate. For instance, the central bank may raise interest rates in response to an increase in the rate of inflation, which will boost the cost of loans. The businesses must pay greater interest expenses as a result. From a contrary perspective, Washington (2014) asserts that the inflation rate has no influence on credit ratings in the near term since firms may ignore its negative consequences if they can plan for the predictable rate of inflation. In summary, this study extends the range of financial measurements by three macroeconomic elements in order to capture the critical time-varying mean of the failure risk distribution: annual percentage growth rate of the GPD, annual real interest rate, and inflation rate.

Market variables

Most typically, three key variables are used as market indicators in the literature (Doumpos et al., 2019). As a market-based measure of leverage, Campbell et al. (2008) employed the TLMTA model (Total Liabilities to the Market value of Total Assets). These writers contend that the traditional book value-to-leverage ratio is inferior to a measure of leverage based on the market. In any instance, if a firm has a large amount of debt relative to the market value of all of its assets, this will increase both its ability to repay debt and its credit rating. As a result, the TLMTA benefits the company's credit rating. The log of a business's share price at the end of the prior year is the second variable of the market indicators since share prices frequently have a positive relationship with company size (LogPL). For instance, the share price of a corporation with greater recognition will be higher, and vice versa. The share price and liquidity may be favourably connected. To be clear, businesses with incredibly low stock prices often have lower average liquidity, making it hard for them to pay their debts off and putting their credit rating in peril (Wu et al., 2010). LogPL, therefore, has a positive effect on the company's credit rating.

The third component is the market-to-book total assets ratio (MBTA), a combined indication of market misevaluation and potential future development (Lok et al., 2022). The forward default severity of the market-to-book assets ratio will increase as the market miss-valuation impact does. If not, the coefficients ought to show negative values. Their results showed that, for the vast majority of the forecast horizons, the projected future intensities in the market-to-book assets ratio were consistent with the expanding control of an additional covariate (Campbell et al., 2008). Simply said, a higher MBTA shows that the company's assets have been valued more favourably, allowing it to pay off its debt more quickly and keep a higher credit score. LogPL, therefore, has a positive effect on the company's credit rating.

2.3 Literature on the new accounting system that affects the credit rating model

Lantto and Sahlström (2009) investigate the effects of International Financial Reporting Standards implementation on significant financial ratios and accounting numbers. The authors make two essential contributions to the literature (Adebayo et al., 2022; Barth et al., 2008; Bartov et al., 2005; Daske and Gebhardt, 2006; Ding et al., 2007; Hope et al., 2006). First, Lantto and Sahlström (2009) show evidence of how seminal financial ratios change after implementing the International Financial Reporting Standards in Finland. Second, their paper explains the reasons for fluctuations in these ratios in their sample. The research further demonstrates differences between the local accounting system and International Financial Reporting Standards in more detail in Finland compared with Ding et al. (2007). Lantto and Sahlström (2009) state that the International Financial Reporting Standards adoption affects the measurement of essential accounting ratios of Finnish companies significantly. The results suggest a sharp increase in the profitability ratios, a moderate increase in gearing ratios, and a slight decrease in the PE ratio and equity and quick ratios. To illustrate, International Financial Reporting Standards adoption leads to an increase in Net Profit, then increases the profitability ratios and decreases the PE ratio, which is consistent with Jones and Higgins (2006). Lantto and Sahlström (2009) indicate that changes in the financial leverage ratios are because of the increase in debt and the decrease in equity. Besides, an increase in current liabilities leads to a reduction in liquidity ratios.

Morales-Díaz and Zamora-Ramírez (2018) investigate leverage ratios, profitability ratios, and the interest coverage ratio before and after IFRS 16 implementation and then analyse the differences. The results show that the IFRS 16 implementation significantly impacts leverage ratios and solvency ratios in European companies in their sample. However, profitability ratios do not deliver consistent results across sectors with the effect magnitude based on the business sector of the company. To illustrate, there is a significant increase in total assets, total liabilities, and leverage ratios, while the interest coverage ratio decreases. Besides, the results of each sector are significantly different for most cases in the dataset (Morales-Díaz and Zamora-Ramírez 2018).

Another influential study in this field is Tran et al. (2019), which investigates the factors affecting International Financial Reporting Standards adoption in the listed firms of Vietnam. The results show that ROE (Return on Equity), QMD (Firm Size), and CLK (Audit Quality from Big 4) significantly affect International Financial Reporting Standards adoption in the listed firms of Vietnam. These results are consistent with the previous literature (Dumontier and Raffournier 1998; Affes and Callimaci 2007). Besides, Tran et al. (2019) state that companies with higher ROE, QMD, and CLK are more likely to adopt International Financial Reporting Standards (Leuz and

Verrecchia 2000; Affes and Callimaci 2007; Carmona and Trombetta 2008). On the other hand, there is no evidence that TLN (Debt to Equity) or NYN (Foreign Operations) affects International Financial Reporting Standards adoption in Vietnamese-listed firms (Tran et al., 2019). These results do not support the findings of Dumontier and Raffournier (1998), Murphy (1999), El-Gazzar, Finn, and Jacob (1999), and Cuijpers and Buijink (2005) and suggest a positive relationship between foreign operations and International Financial Reporting Standards adoption. These mixed results are evident because of different research contexts and sample sizes (Tran et al., 2019).

Florou, Kosi, and Pope (2017) use the dataset including 202 firms in the period 2000-2009 from 17 countries to test the effect of International Financial Reporting Standards (IFRS) on the credit rating model. Florou, Kosi, and Pope (2017) show that the new accounting system adoption (IFRS) will significantly change the credit rating model, including increasing the explanatory power of the credit rating model because IFRS provides more reliable and informative financial statements. Furthermore, by following the recommendations of Florou, Kosi, and Pope (2017), this research compares the credit rating models before and after the implementation of Circular 200. Thus, we conjecture the following hypothesis:

H1: The change in the accounting system (Circular 200) leads to a significant change in the credit rating model for small, medium, and large firms in Vietnam during the sample period.

2.4 Literature on the Artificial Neural Networks (ANN)

ANNs, sometimes referred to as Neural Networks (NN), are a type of Artificial Intelligence (AI) system that attempts to learn and mimic the behavior of the nerve cells in the human brain (Farhadieh 2011). To illustrate, ANNs learn and create a memory by adjusting the interconnected nodes Parker (2006) in which ANNs build a network with inputs and outputs that connect each other by specific weights. The most accurate model may be created by ANN by finding the best-fit output depending on the input by modifying the node weights (Wang et al., 2022). In reality, by learning from the data inputs and outputs, ANNs may resolve financial issues, specifically credit rating and default prediction. Five exceptional capabilities of ANNs—learning, adaptation, flexibility, explanation, and discovery—can be used to tackle financial issues (Farhadieh, 2011; Goonatilake and Treleaven, 1995; Mahmood et al., 2022; Safi et al., 2022; TajMazinani et al., 2022; Xu et al., 2017).

Studies on the use of NNs for bankruptcy prediction began in 1990 and continue to be active today (Atiya, 2001). For two main reasons, a non-linear approach is better than a linear approach. Firstly, the relationship between the financial ratios and the prediction of default has saturation effects. For example, if earnings/total assets changes by 0.2, from -0.1 to 0.1, it will have a much more significant effect (in the default forecast) than if the ratio changes from 1.0 to 1.2 (Atiya, 2001). Secondly, it can also be argued that multiple factors exist. For example, if it has significant liabilities, a firm's credit rating with a negative cash flow becomes more serious. The reason is that it is more difficult for highly leveraged companies to borrow money for their debts. Generally, NNs have outperformed existing methods (Atiya, 2001).

Angelini, di Tollo and Roli (2008) present two borrowers' classifications of neural architectures in two separate classes: non-default and default. The system was trained and tested for data relating to small Italian enterprises. One of the research systems was based on a classic feed-forward NN,

while the other had a particular feed-forward architecture. Results in both cases show that the approach was very efficient and led to a system capable of classifying inputs correctly with less error. The overall performance of the networks developed can be regarded as state-of-the-art. A careful analysis of the available data is one of the reasons for this performance. Real data are often noisy and incomplete; therefore, the analysis aimed to reduce misleading values and replace empty values with meaningful ones. Data normalisation also played a significant role in the final performance, Angelini, di Tollo and Roli (2008) investigated specific standardisation procedures to keep as much information as possible in the network feed inputs. This empirical work shows, on the one hand, the actual applicability of NNs in credit risk applications, in particular as non-linear black-box systems, to be used in conjunction with a classical rating and rating systems. In contrast, this research also showed that the critical issues in the system are data analysis and processing.
The research uses the Neural Network Training algorithm by MATLAB R2019a to solve the fitting problems, in which the NN will map the input dataset to the output dataset. The Neural Network Training algorithm can help in selecting data, creating and training the network, and evaluating its performance based on Mean Square Errors (MSE) and regression analysis.

2.5 Research Model

This research applies the independent variables, including 30 variables which are organized into four main groups: financial, market, macroeconomic, and firm characteristics (Figure 1) (Altman & Sabato, 2007; Chai et al., 2019; Doumpos et al., 2019; Giordani et al., 2014; Q. H. Pham et al., 2022; V. N. B. Pham et al., 2018; Psillaki et al., 2010; Tsai et al., 2009; Wu et al., 2010). This research investigates the effects of local accounting law on the credit rating for small, medium, and large firms in Vietnam in the period 2008-2018 by using Artificial Neural Networks (ANN). To illustrate, this paper compares the credit rating model for Vietnamese firms before and after implementing Circular 200 (Phan, Joshi, and Tran-Nam 2018). The comparison result of the ANN models for the credit rating between the 2008 – 2014 dataset (before implementing Circular 200) and the 2015 – 2018 dataset (after implementing Circular 200). By using ANN, this research can maximise the predicting power of the credit rating models and effectively investigate the effects of local accounting law on the credit rating model.

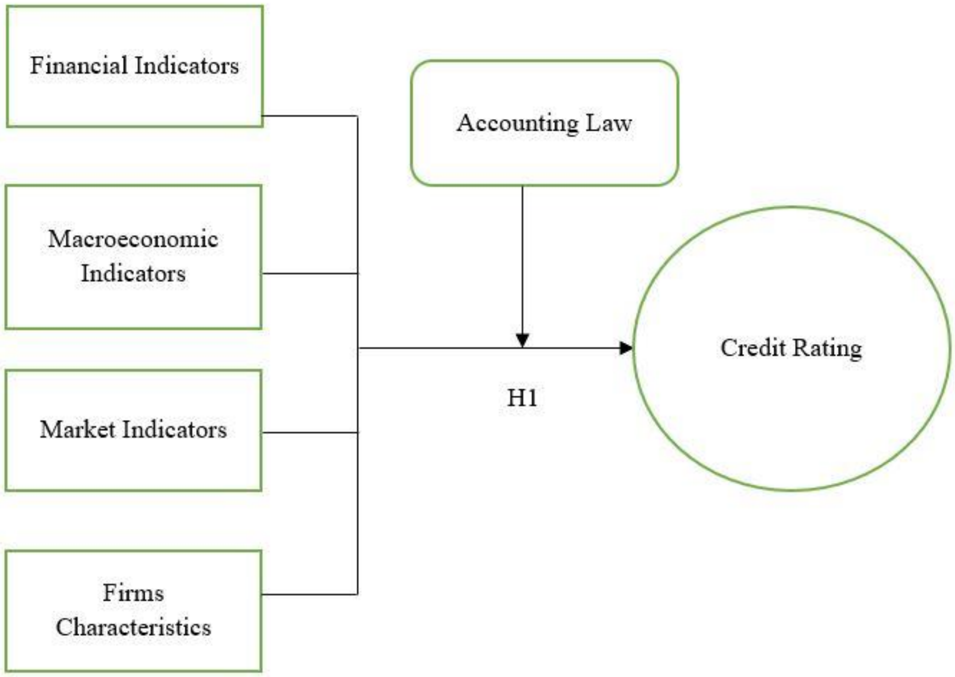


Figure 1. The proposed research model

3. Research Methodology

3.1 Data processing

In this research, the large dataset collected includes 39,162 firms from the Orbis database over the years 2008–2018. Each set of firm data includes 30 Independent Variables (IVs) and a Dependent Variable (DV) (credit rating – 10 classes). The training data use 70% of the data, the validating data uses 15% of the data and the testing data uses the remaining 15% of the data. In this research, the dataset is separated into two sub-datasets to test for the effects of the issuing of Circular 200 in Research Question 3, so there are two sub-datasets from before and after the issuing of Circular 200:

- Before the issuing of Circular 200: dataset 2008–2014
- After the issuing of Circular 200: dataset 2015–2018

3.2 Neural network fitting model performance

This research builds 31 testing models for dataset 2015–2018 and 19 testing models for dataset 2008–2014 to identify the significant factors that affect the credit rating models. The input for each ANN testing model is set following the forward elimination variable selection of Blanchet, Legendre, and Borcard (2008). The testing models add one variable at a time step by step. For example, in the first test, the research uses only the EBITTA as the input and ScoreG10 as the target to build the model using ANN via MATLAB R2019a. The result of the testing model contains two leading figures, the MSE, and regression ratio (R) for the training dataset, validating dataset, and testing dataset.

The default performance function of ANNs using MATLAB R2019a is the MSE, which is the average square of the difference between the network's proposed output and the actual target output t (MATLAB 2019f). The closer MSE is to zero, the better the ANN's performance. Another significant result of the ANN model is the regression plot (the value of the R-squared) validating the network, which visualises the relationships between the predicted outputs from the network and the actual targets. In the optimal situation of the training process, the predicted outputs from the network and the actual targets are completely equal. However, this ideal relationship rarely happens in practice (MATLAB 2019a). To explain, the R-squared is calculated to represent the relationship between the outputs and targets where if the R-squared equals 1, then it is a precisely direct linear relationship between the outputs and targets and vice versa. If the R-squared is approximately zero, then there is no linear relationship between the outputs and targets (MATLAB 2019a). In this research, MSE and R-squared are used as the main criteria for evaluating the ANN performance.

According to advice from Blanchet et al. (2008), the forward elimination variable selection IVs, in which the model will add one variable at a time step by step, is the input for the ANN. This study determined that 30 hidden layers for ANN models were the ideal number based on the criteria provided. To begin with, many hidden layers will increase the model's accuracy. According to MATLAB 2019a's guidelines, this study reduces the number of hidden layers to 25 or 20, which causes a steep increase in the MSE of the models and a considerable fall in the regression ratio. On the other hand, the MSE and regression ratio of the models do not significantly improve if the number of hidden layers is increased in this research to 40 hidden layers or 50 hidden layers, but the time required increases noticeably. As a consequence, 30 hidden layers were found to be the optimum amount in this study for maximizing model correctness, satisfying the computational capacity, and satisfying the technical criteria of MATLAB 2019a.

Table 1. ANN testing models for the number of hidden layers (Pham et al., 2022).

Hidden Layers	**Training Algorithm**	**Time Consumed in minutes**	**Min MSE**	**Max MSE**	**Min R percent**	**Max R percent**
20	Bayesian Regularisation	02:51	0.36443	0.36586	84.29	84.30
25	Bayesian Regularisation	04:11	0.36465	0.38566	83.43	84.29
30	Bayesian Regularisation	03:17	0.35460	0.36338	84.28	84.50
40	Bayesian Regularisation	08:28	0.36330	0.37996	83.53	84.43
50	Bayesian Regularisation	10:42	0.36495	0.37615	83.28	84.42

4. Data Analysis

In this study, secondary data analysis of the credit rating system's default prediction for Vietnamese companies is done using information from two large databases, including the Orbis database. Data were gathered from 39,162 companies in Vietnam with Multi-Objective Rating Evaluation (MORE) credit scores given by ModeFinance from the Orbis database because this study primarily focuses on the financial industry. The research chose businesses from the dataset that met five criteria: (1) they were based in Vietnam; (2) they had MORE credit scores; (3) they had data from the period 2008-2018 and were small, medium, or large enterprises that adhere to the definition of Vietnamese SMEs in Decree 56/2009/ND-CP of 2009; (4) they had at least ten employees in the last year of the data; and (5) they had total assets in the last year of the data of at least $450,000 (approximately) (The development of SMEs in Vietnam 2011). The World Bank provided a second dataset that covers three macroeconomic indicators for Vietnam from 2008 to 2018: real interest rate, inflation, and GDP growth (RIR).

4.1 Distribution of the observations

The Vietnamese MoF issued Circular 200 to improve the comparability and transparency of corporate financial statements and to bring the Vietnamese accounting system closer to the international accounting system. Circular 200 provides guidelines on accounting policies for both local and foreign enterprises in Vietnam from the financial year beginning 1 January 2015. The research investigates the effects of Circular 200 on credit rating. As a result, the primary dataset is divided into two sub-datasets:

- Before the issuing of Circular 200: Dataset 2008–2014
- After the issuing of Circular 200: Dataset 2015–2018

The researchers divided the dataset into two sub-datasets, as shown in both Tables 2 and 3 in the following:

Table 2. Data distribution in different years from 2008 to 2014

		Frequency	**Percentage**	**Valid Percentage**	**Cumulative Percentage**
Validity	2008	639	3.0	3.0	3.0
	2009	1107	5.2	5.2	8.2
	2010	2514	11.8	11.8	20.0
	2011	3103	14.6	14.6	34.6
	2012	3196	15.0	15.0	49.7

	2013	836	3.9	3.9	53.6
	2014	9859	46.4	46.4	100.0
	Total	21254	100.0	100.0	

The total number of yearly data points in the dataset 2008–2014 (before the issuing of Circular 200) is 21,254, which is 46.4% (2014), 3.9% (2013), 15.0% (2012), 14.6% (2011), 11.8% (2010), 5.2% (2009) and 3% (2008). The research uses the dataset 2008–2014 to investigate the effect of Circular 200 on the predicting model for the credit rating of firms in Vietnam. The credit rating model using the dataset 2008–2014 will be compared with the credit rating model using the dataset 2015–2018. The result of this comparison will illustrate the effects of Circular 200 on credit rating for firms in Vietnam.

Table 3. Data distribution in different years from 2015 to 2018

		Frequency	Percentage	Valid Percentage	Cumulative Percentage
Validity	2015	23105	29.9	29.9	29.9
	2016	26199	33.9	33.9	63.8
	2017	27134	35.1	35.1	99.0
	2018	790	1.0	1.0	100.0
	Total	77228	100.0	100.0	

The total number of observations is 77,228, which includes 23,105 (29.9%) in 2015, 26,199 (33.9%) in 2016, 27,1343 (5.1%) in 2017, and 790 (1%) in 2018. The dataset was collected from the Orbis database, which includes the credit score from ModeFinance. As a result, based on time consumption and financial resources, this research uses a dataset from 2008 to 2018 to investigate the effects of the new accounting law 'The circular 200' in 2014 and started to apply in 2015. The observations in the nearest years 2015, 2016, and 2017 can be considered the most effective observations to show the effects of 'The circular 200'. Thus, the dataset 2015-2018 still effectively represents the effects of 'The circular 200'.

4.2 Dependent variables

According to the credit rating issuance procedure by ModeFinance, one of the first steps is to obtain credit scores using the MORE framework for the regulated entity by collecting publicly available information. ModeFinance developed the MORE method to evaluate industrial companies' level of distress using information included in financial statements. It primarily offers a creditworthiness opinion (assessment) according to a predefined scale through a risk class (MORE class) (ModeFinance, 2017). The model's basic idea is to evaluate a series of financial and economic ratios in a predictive model of corporate restructuring in order to create a basic model of credit scoring. Results are obtained by applying newly developed quantitative methodologies, integrating financial theory, data mining and design methodologies. MORE's core is a multidimensional and multi-objective algorithm that produces the company classifications by taking into consideration all attributes (such as industry and country) that characterise a company (ModeFinance, 2017).

Table 4. Score G10 frequency statistics for the 2015–2018 period

		Frequency	Percentage	Valid Percentage	Cumulative Percentage
Valid	1	131	0.2	0.2	0.2
	2	65	0.1	0.1	0.3
	3	2548	3.3	3.3	3.6

4	9454	12.2	12.2	15.8
5	23133	30.0	30.0	45.7
6	26438	34.2	34.2	80.0
7	11523	14.9	14.9	94.9
8	3345	4.3	4.3	99.2
9	542	0.7	0.7	99.9
10	49	0.1	0.1	100.0
Total	77228	100.0	100.0	

ScoreG10 is a representation of the DV credit rating in ten classes, including AAA, AA, A, BBB, BB, B, CCC, CC, C, and D (table 4). For credit rating purposes, the ScoreG10 serves as the DV. The DV ScoreG10 has a 0.005-slightly negatively skewed distribution. The top three greatest frequency values are seven occurrences of CCC with 14.9%, six occurrences of B with 34.2% of the entire dataset, and five occurrences of BB with 30.0%. The three lowest frequency values, however, are ten instances of D (0.1% of the entire sample), two instances of AA (0.1%), and one instance of A (0.2%). With a mean of 5.61 and a standard error of 0.004, the ScoreG10 frequency histogram for the dataset 2015-2018 (Figure 2) demonstrates that ScoreG10 is fairly normally distributed. ScoreG10 - Descriptive statistics for the dataset 2015–2018 are shown in both Figures 2 and 3.

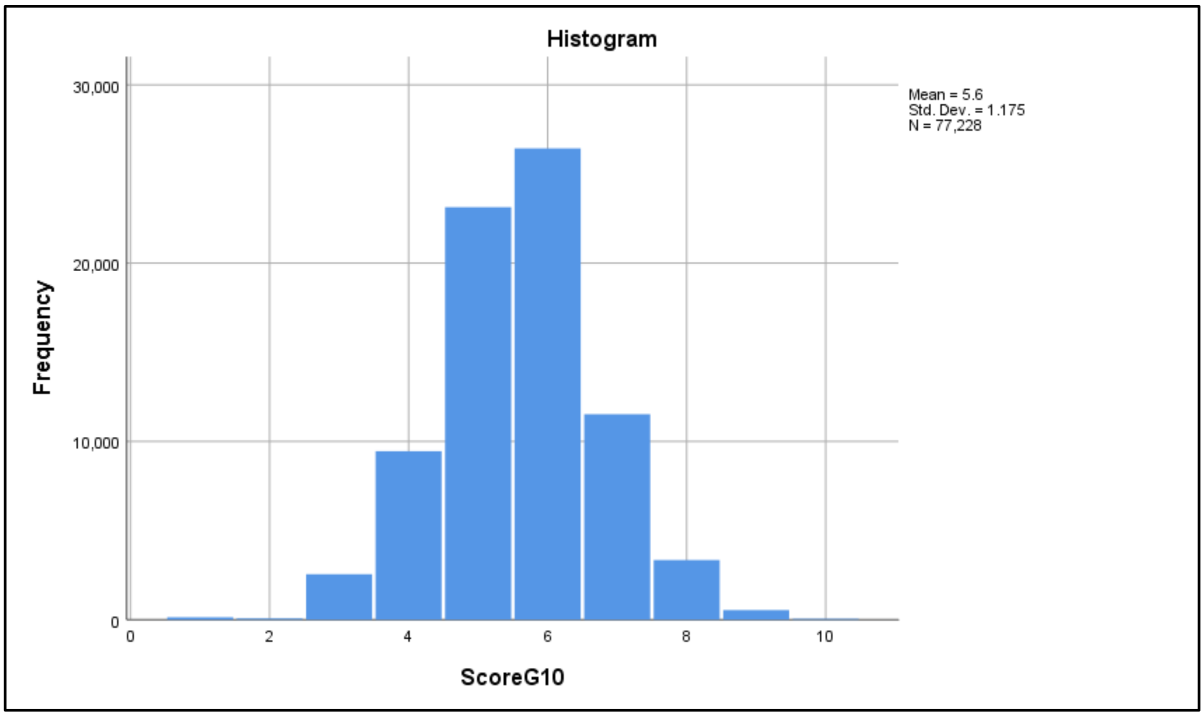


Figure 2. Score G10 frequency histogram for the 2015–2018 period

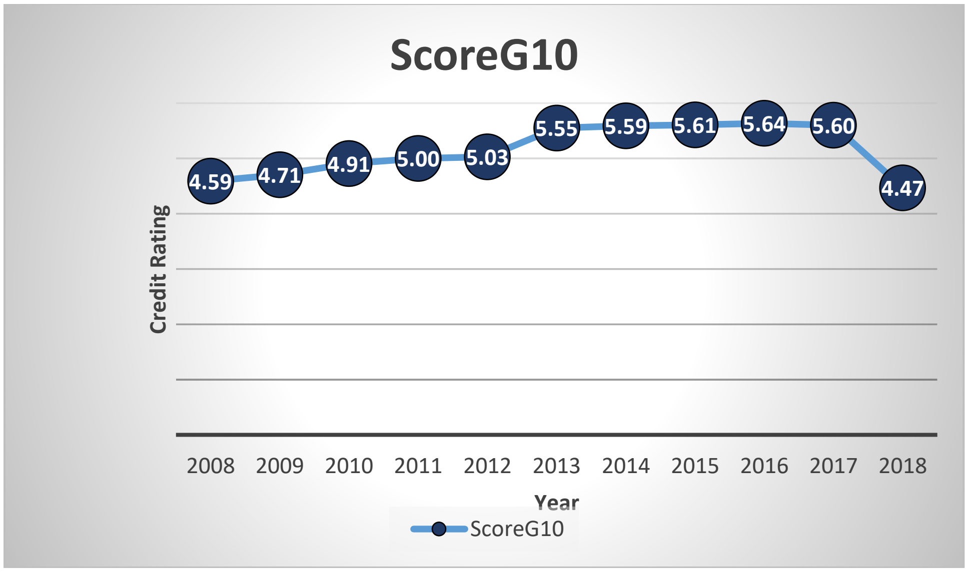


Figure 3. Average Score G10 for the 2008–2018 period

The average ScoreG10 increased from 4.59 to 5.60 from 2008 to 2017 (increased by 22%), but it decreased to 4.47 in 2018 (Figure 2). The increase in average credit score means that the Vietnamese firms had a lower credit rating from 4.59 (between BBB and BB) to 5.60 (between BB and B) in the period 2008–2017. In other words, the lower credit rating means that Vietnamese firms had higher credit risk as a result of the GFC in 2008 affecting Vietnam. However, in 2018 the average ScoreG10 decreased from 5.6 to 4.47 (decreased by 20%), which indicates a higher credit rating. This is a good sign that Vietnamese firms had lower credit risk and recovered from the GFC. However, the dataset only contains 910 data points in 2018 (0.8% of the total dataset) that represent the average ScoreG10 of 2018. The average ScoreG10 of 2018 is probably biased based on the small sample size.

4.3 Independent variables

The IVs include 30 variables that are categorised into four main groups, financial indicators, market indicators, macroeconomic indicators and firm characteristic indicators (Figure 3). However, the dataset also contains incomplete data, which can lead to unavailable measurements and analysis. Following the recommendations of Angelini, di Tollo and Roli (2008), Langkamp, Lehman and Lemeshow (2010) and Dias (2013), the research deleted IVs with more than 10% of their data missing. However, some variables are still considered to be retained based on the suggestion of influential papers discussed, such as NITA (ROA), ROE (using EBT), current ratio (current assets/current liability), solvency ratio, macroeconomic indicators such as GDPG (GDP growth) and firm characteristic indicators such as SIZENENE (Log10 of the number of employees). The formula and explanation of the IVs are provided in Table 5 below:

Table 5. The independent variables

Code	Explanation
EBITTA	Earnings Before Interest and Tax / Total Assets
NITA	Return of Assets

ORTA	Operating Revenue /Total Assets
PM	Profit Margin
ROE	Return of Equity using Earnings Before Tax
ORLG10	Size of the company calculated by Operating Revenue
CR	Current Ratio
SolvencyR	Solvency Ratio using Assets Based
ORSE	Operating Revenue / Share Equity
GDPG	Annual GDP Growth
INF	Annual inflation rate
RIR	Annual real interest rate
SIZELNNE	Size of the firm calculated by number of employees

5. Research Findings

5.1 An artificial neural network model for dataset 2015-2018

The research builds 33 testing models to build the credit rating model for Vietnamese firms in the period 2015–2018. The dataset 2015–2018 represents the latest current business environment for Vietnamese firms. The final ANN model for the dataset 2015–2018 is built using a similar procedure as for the testing models. This research aims to build a model with the highest ANN performance for Vietnamese firms for the datasets 2008–2014 and 2015–2018. Consequently, the research applies the Bayesian regularisation training algorithm. Bayesian regularisation consumes more time, but it can create better generalisations for complicated, small and noisy inputs where the training process will stop according to adaptive weight minimisation. In this research, the Bayesian regularisation training algorithm can produce ANN models that have better performance than using the Levenberg–Marquardt (LMA) training algorithm.

This section analyses the credit rating model performance of Vietnamese firms for the dataset 2015–2018. The summary characteristics of the model are given below:

- Dataset: 2015–2018 = 77,228 observations
- Training dataset: 70% dataset = 54,060 observations
- Validating dataset: 15% dataset = 11,584 observations
- Testing dataset: 15% dataset = 11,584 observations
- Number of hidden layers: 30
- Output: ScoreG10
- ✓ Inputs: NITA, ROE, solvency ratio, current ratio and GDPG
- ✓ Training algorithm: Bayesian regularisation

Results

	Samples	MSE	R
Training:	54060	3.63338e-1	8.44992e-1
Validation:	11584	0.00000e-0	0.00000e-0
Testing:	11584	3.54601e-1	8.42784e-1

Figure 4. Result for the 2015–2018 period by using the ANN credit rating model

Figure 4 presents the summary results of the ANN model for the dataset 2015–2018. The MSE for the training dataset is 0.36334, while the MSE for the testing dataset is 0.35601. The R-squared for the training dataset is 84.50%, while the R-squared for the testing dataset is 84.28%. Comparing the result for this final model using the Bayesian regularisation training algorithm with testing model 25 using LMA (Table 6), it is clear that the ANN performance improves slightly (MSEs decrease and the values of the R-squared increase). Also, Bayesian regularisation minimises a linear combination of the network squared errors and weights, as well as Bayesian regularisation, which modifies this linear combination. Consequently, the training process of the network produces a high generalisation. By the nature of Bayesian regularisation, the validation data consisting of 15% are employed to observe and tune the model weights throughout estimation, also maintained at the minimum (MATLAB 2019b).

Table 6. Comparison results from the 25th testing model and the final model for the 2015–2018 period.

Model	Training Algorithm	Result 1	Result 2	Result 3	Result 4	Result 5	Result 6
		Training MSE	Validation MSE	Testing MSE	Training R	Validation R	Testing R
No. 25	Levenberg-Marquardt	0.36682	0.37910	0.38104	0.8426	0.8351	0.8361
Final	Bayesian Regularisation	0.36334	0.00000	0.35460	0.8450	0.0000	0.8428

The final ANN model has the specified value of each layer displayed in the Simulink of the ANN model. The final ANN model uses five significant IVs: NITA (ROA), ROE using EBT, current ratio, solvency ratio and GDPG. The output is ScoreG10. In the final model, this research uses 30 hidden layers, as visualised in Figure 2 below.

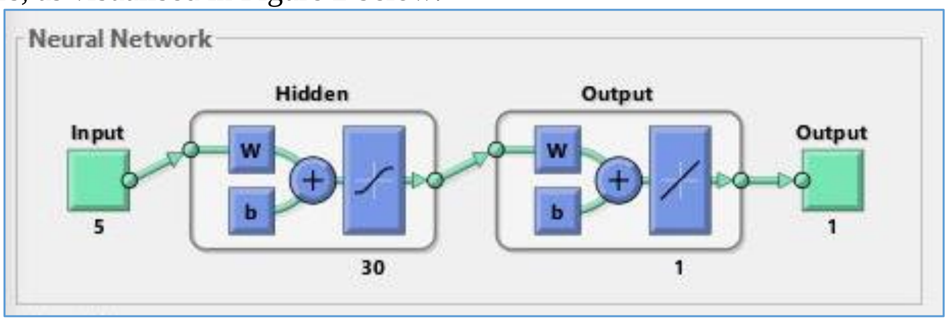
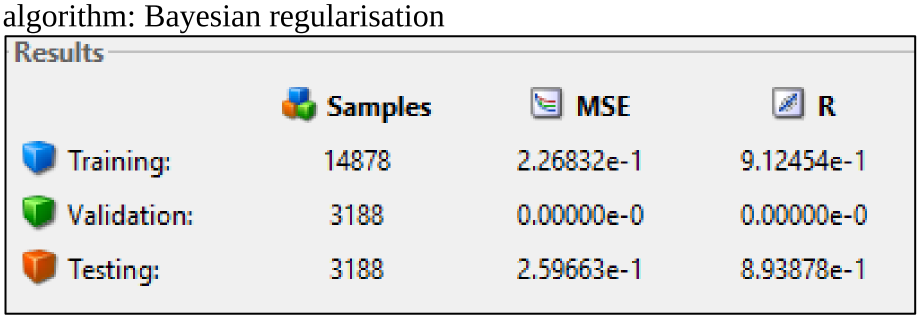


Figure 5. ANN model 2015–2018

5.2 An Artificial neural network model for dataset 2008-2014

This research builds the ANN model for the dataset 2008–2014, in which this research builds 19 testing models to build a credit rating model for Vietnamese firms in the period 2008–2014. The final ANN model for the dataset 2008–2014 is built using a similar procedure as the ANN model for the period 2015–2018. The summary characteristics of the model are given below:

- Dataset: 2008–2014 = 21,254 observations
- Training dataset: 70% dataset = 14,878 observations
- Validating dataset: 15% dataset = 3,188 observations
- Testing dataset: 15% dataset = 3,188 observations
- Number of hidden layers: 30
- Output: ScoreG10
- Inputs: NITA, ROE, Solvency, CR and SIZELNNE
- Training algorithm: Bayesian regularisation


Results

	Samples	MSE	R
Training:	14878	2.26832e-1	9.12454e-1
Validation:	3188	0.00000e-0	0.00000e-0
Testing:	3188	2.59663e-1	8.93878e-1

Figure 6. Result for ANN model 2008–2014

Figure 6 presents a summary of the results of the ANN model for the dataset 2008–2014. The MSE for the training dataset is 0.226832, while the MSE for the testing dataset is 0.259663. The R-squared for the training dataset is 91.25%, while the R-squared for the testing dataset is 89.39%. Comparing the result for this final model using the Bayesian regularisation training algorithm with testing model 19 using LMA, it is clear that the ANN performance improves slightly (MSEs decrease and the values of the R-squared increase). Bayesian regularisation minimises a linear combination of the network squared errors and weights, as well as Bayesian regularisation, which modifies this linear combination. Consequently, the training process of the network produces a high generalisation. By the nature of Bayesian regularisation, the validation data consisting of 15% are employed to observe and tune the model weights throughout estimation, also maintained at the minimum (MATLAB 2019b).

Table 7. Comparison results from the 19th testing model and the final model for the 2008–2014 period

Model	**Training Algorithm**	**Result 1**	**Result 2**	**Result 3**	**Result 4**	**Result 5**	**Result 6**
		Training MSE	**Validation MSE**	**Testing MSE**	**Training R**	**Validation R**	**Testing R**
No. 19	Levenberg-Marquardt	0.25140	0.26163	0.23228	0.9007	0.8905	0.9029
Final	Bayesian Regularisation	0.22683	0.00000	0.25966	0.9125	0.0000	0.8939

The final ANN model summary is given in Figure 7, while the specified value of each layer is displayed in the Simulink of the ANN model. The final ANN model uses five significant IVs: NITA (ROA), ROE using EBT, current ratio, solvency ratio and SIZELNNE. The output is ScoreG10. In the final model, this research uses 30 hidden layers, as visualised in Figure 7 below.

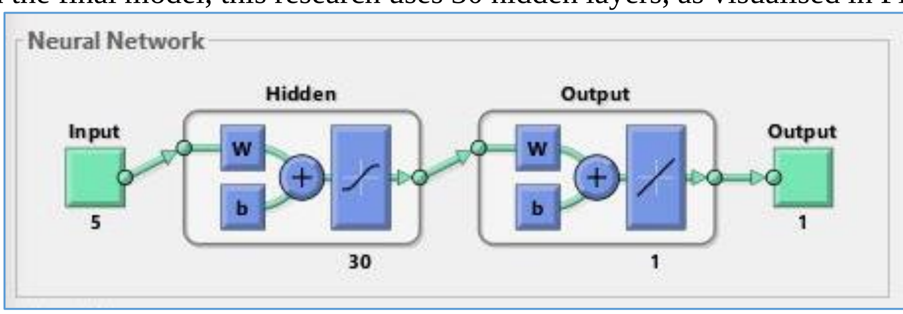


Figure 7. ANN model 2008–2014

5.3 ANN model comparison

In order to answer Research Question: 'Is there any significant difference before and after the implementation of Circular 200 to the credit rating of small, medium, and large firms in Vietnam?', this research needs to compare the credit rating model of firms in Vietnam before and after the implementation of Circular 200. Table 8 presents the comparison result for the ANN credit rating model for the 2008–2014 dataset (before the implementation of Circular 200) and the 2015–2018 dataset (after the implementation of Circular 200).

Table 8. Comparison of the results for the 2008–2014 period and 2015–2018 period by using the ANN credit rating model

	2008–2014 period	2015–2018 period
Output	ScoreG10	ScoreG10
Input 1	NITA (ROA)	NITA (ROA)
Input 2	ROE using EBT	ROE using EBT
Input 3	Solvency Ratio	Solvency Ratio
Input 4	Current Ratio	Current Ratio
Input 5	SIZE Number of Employee	GDP Growth Rate
AVG MSE	0.233	0.362
ALL R value	90.94 percent	84.45 percent
Weight and Bias Value	Appendix 1	Appendix 2

Table 8 presents the comparison result for the ANN model for the dataset 2008–2014 and the dataset 2015–2018. For both datasets, the dependent variable is the credit rating ScoreG10. The four main inputs are similar between both models: NITA, ROE, solvency ratio and current ratio. On the other hand, SIZELNNE is a significant input in the 2008–2014 model but is an insignificant input in the 2015–2018 model. In other words, the size of the company is significant in the 2008–2014 model but is insignificant in the 2015–2018 model. GDPG is a significant input in the 2015–2018 model but is an insignificant input in the 2008–2014 model. This means that the annual GDP growth rate of Vietnam is significant in the 2015–2018 model but is insignificant in the 2008–2014 model.

Another significant comparison result is that the ANN model of 2008–2014 has better predicting power than the 2015–2018 model. To illustrate, the average MSE of the 2008–2014 model is 0.233, which is lower than the average MSE of the 2015–2018 model of 0.362. Also, the R-squared of the entire period from 2008 to 2014 is 90.94 percent, which is also higher than the R-squared of the period from 2015 to 2018 with a value of 84.45 percent. The exact values of the weights and biases from both models are entirely different. In short, before the implementation of Circular 200, the credit rating model is more robust and affected by NITA, ROE, solvency ratio, current ratio and SIZELNNE. However, after the implementation of Circular 200, the credit rating model is less effective and affected by NITA, ROE, solvency ratio, current ratio and GDPG. Based on this conclusion, for the current business context (2015–2018), the annual GDP growth rate in the country is a significant predictor, while the SIZE of the company does not affect the credit rating model.

6. Discussion and Conclusion

This research investigates the effects of local accounting law on the credit rating for small, medium, and large firms in Vietnam in the period 2008-2018 by using Artificial Neural Networks (ANN) to compare the credit rating for Vietnamese firms before and after implementing Circular 200. As far as we know, our paper is the first paper to obtain findings that contribute to the literature by identifying the effects of the local accounting law on credit rating (Pham et al., 2022). To do so, we first apply the ANN model to compare the credit rating between the period from 2008 to 2014 (before implementing Circular 200) and the period from 2015 to 2018 (after implementing Circular 200). For both periods, we find that the four main inputs for the model are similar, including NITA, ROE, Solvency Ratio, and Current Ratio. In other words, NITA, ROE, Solvency Ratio, and Current Ratio are significant Independent Variables in the models before and after implementing Circular 200. On the other hand, there are several significant differences in determining the credit rating before and after implementing Circular 200. First, SIZELNNE is a substantial input in the 2008 – 2014 model but it is insignificant input in the 2015 – 2018 model. To illustrate, the size of the company measured by the number of employees is significant in the credit rating model for Vietnamese small, medium, and large firms in the period 2008 – 2014. Second, GDPG is a significant input in the 2015 – 2018 model but it is insignificant input in the 2008 – 2014 model. It means that the GDP growth of Vietnam in the year is significant in the 2015 – 2018 model but it is insignificant in the 2008 – 2014 model. Moreover, we find that the ANN model for the 2008 – 2014 period has a better predicting power than that for the 2015 – 2018 period. It is because the average MSE of the 2008 – 2014 period is 0.233, which is smaller than the average MSE for the 2015 – 2018 period with a value of 0.362. Further, the R-squared for the entire period from 2008 to 2014 is 90.94 percent which is higher than that for the 2015 – 2018 period with a value of 84.45 percent. Finally, the exact values of Weight and Bias for both periods presented in Appendices 1 and 2 are different. In short, the credit rating is more robust and affected by NITA, ROE, Solvency Ratio, Current Ratio, and SIZELNNE before implementing Circular 200. However, after implementing Circular 200, the credit rating is only affected by NITA, ROE, Solvency Ratio, Current Ratio, and GDPG. These findings can help not only the related stakeholders of financial markets but also the commercial banks which will be discussed in the next part.

6.1 *Potential implementations*

Using reliable credit rating models is helpful for both the Vietnamese financial markets and commercial banks because an essential instrument for the bond market is the credit rating. It is a helpful tool to analyze issues with different information between lenders and borrowers (Kumar and Bhattacharya 2006; Benmelech and Dlugosz 2009). The credit rating methodology used in this study is helpful for investors in analyzing their investment risks to make the best possible investment decisions based on the company's credit rating which can categorize businesses into their credit classes. Additionally, using a better credit rating approach could enhance a company's brand and image. Companies with good credit ratings could obtain cheaper loans with lower interest rates from creditors, is easier to obtain bank loans, and raise capital in the financial markets (Kumar and Bhattacharya 2006; Benmelech and Dlugosz 2009). The credit rating model could be implemented as a regulatory instrument in the financial markets from a macroeconomic perspective. As a result, obtaining better rankings will promote and support a nation's economic progress. Applying a better credit rating model could minimize information gaps between businesses and investors in the capital markets, which is helpful in solving problems among scattered investors (Kumar and Bhattacharya 2006; Benmelech and Dlugosz 2009).

Last but not the least, Vietnamese Commercial Banks could apply the credit rating model used in this study in determining a specific number of credit rating problems for borrowers, allowing the bank to offer an appropriate credit policy, and setting different interest rates for different clients with their risk levels. In order to reduce subjective errors made by credit officers while evaluating consumers, the model offers Vietnamese Commercial Banks comprehensive credit rating information. The effectiveness of the company's management system or the relationship between the company and the Commercial Banks are qualitative factors that credit officers rate more highly than financial factors for the company when determining the internal credit rating of Vietnamese Commercial Banks (Pham et al., 2018).

6.2 Research limitations

Our study has a number of limitations. First, the application of fair value accounting is one of the factors to be taken into account when implementing credit rating models. Certain assets and liabilities must be revalued at fair value to account for changes in economic worth. Variations from carrying amounts are recognized in the period's net income or other comprehensive income according to this accounting technique. Due to its complicated and contentious character, fair value accounting has been drawing significant attention from academics, practitioners, and politicians (Laux and Leuz 2009; Hodder, Hopkins, and Schipper 2014). The viability and superiority of fair value accounting in the comparison with historical cost accounting have been hotly contested. Numerous studies have shown that fair value accounting is preferable to historical cost accounting by highlighting both the relevance and utility of fair value to decision-makers and adhering to the fundamental goals of the conceptual framework for financial reporting (Barth 1994; Barth, Beaver, and Landsman 1996; Aboody, Barth, and Kasznik 1999). Fair value accounting is currently widely used in the accounting standards of several organizations that develop standards, such as the Financial Accounting Standards Board and the International Accounting Standards Board. Fair value accounting is widely used in the financial reporting standards put out by both of these standard-setters, which shows that it has established itself as a workable measurement base in industrialized countries (Nguyen, 2019).

The approval of the Accounting Law 2015, which allows for the revaluation of both assets and liabilities by using fair value, demonstrates the Vietnamese government's commitment to adopting international accounting standards and international financial reporting standards. Fair value is described as "the price suitable to the market price that would be obtained for the sale of an asset or paid for the transfer of an obligation at the measure date" by the Accounting Law of 2015. The Accounting Law of 2015, Article 6, Paragraph 1 states that "assets and liabilities are first recognized at cost." However, in the real world, asset and liability values constantly change based on market prices and must be measured accurately at the conclusion of the financial reporting period using fair value. Accounting Law 2015 differs significantly from Accounting Law 2003 in this regard, which states that assets are valued at cost and that an accounting entity is not permitted to revalue its assets unless specifically permitted by other laws and regulations (Nguyen, 2019). Vietnam's adoption of the Accounting Law 2015, which permits the issuance of fair value-related accounting standards for items like financial instruments, fixed assets, and investment properties, is seen as a significant step in the country's transition to the International Financial Reporting Standards. The fair value notion did not make sense to Vietnam's National Assembly members, who often lack accounting experience because Vietnam is a rule-based centrally controlled economy, which made the process of having the Accounting Law 2015 enacted challenging (Nguyen, 2019).

The Accounting Law of 2003 only permitted the implementation of the cost model, which was leading accounting standards to fall behind those of other nations. The National Assembly was informed of this. The fair value idea was a significant difficulty for the majority of National Assembly members since it gave companies too much discretion that they might use to avoid paying taxes. The highest legal document that gives support for later accounting practice guidelines is the law. Since fair value accounting was prohibited by the 2003 Accounting Law, the Vietnamese accounting standards have not been revised. Members of the National Assembly seem to find it too difficult to accept giving managers a lot of discretion, which runs counter to Vietnam's normal institutional structure. Earnings management is said to be becoming more prevalent for a variety of reasons, including tax evasion (Nguyen, 2019).

The use of fair value accounting is still a contentious topic, particularly in the context of emerging economies. When national peculiarities are not taken into account, adopting a perceived high-quality standard does not always benefit the adopting countries and may even become negative (Nguyen, 2019). In the case of Vietnam, a complex transitional environment with state participation and the possibility that officeholders' personal interests might affect regulatory processes. This study implies that the current business climate in Vietnam is less favourable for implementing fair value accounting, at least until these deficiencies are adequately addressed, given the numerous hurdles mentioned. Although the independence and professionalism of auditors in Vietnam are not investigated in this research, these worries have fueled the literature's discussion on fair value accounting, with Enron and Arthur Andersen being two well-known worldwide incidents (Benston, 2006). Future study in this area is merited (Nguyen, 2019). The value of some company assets and obligations may alter if the Vietnamese accounting system implements fair value accounting. Fair value accounting may therefore have an impact on a company's financial numbers. The credit rating models may be adversely impacted if this were to occur.

6.3 Recommendations for future research

Based on the research's limitations, this study suggests three key paths for further study, including data and variable improvement, methodological improvement, and performance measure improvement. The data and variables input is the first area for research improvement. Credit rating models are an example of how large volumes of data may be processed and how intricate interactions between independent variables can be analyzed. Additionally, credit rating algorithms may look into different circumstances and pinpoint the actions and choices made by creditors and borrowers alike (Doumpos et al., 2019). The inputs of credit rating models might differ from the conventional datasets in financial models, which only comprise financial and market-based data, due to the enormous relevant datasets from multiple sources. The data intake may, for instance, contain details from social media and other internet sources that could improve credit risk analysis and offer more thorough credit rating projections. Therefore, new data management systems may offer many inputs for creating and evaluating credit rating models (Doumpos et al., 2019).

Big data analytics, which combines classic research analysis procedures with computer science methodologies, might be the focus of future research on methodological improvement (Doumpos et al., 2019). The modelling and analysis of complex data inputs, such as systemic hazards and bankruptcy correlations, are given new chances in this direction. But it's important to keep in mind that more complex models may result in a lack of clarity and transparency. To elaborate, the lack of comprehensibility and transparency for the end users prevents many of the most effective models from being used in reality (Doumpos et al., 2019). Top management, auditors, supervisors, and other external authorities may be concerned with machine learning models that have a "black box" in the analytical process. Additionally, it is challenging to modify these advanced procedures to meet the needs of end users. These restrictions could make people worry about how well these sophisticated models would work in the long run (Doumpos et al., 2019). To improve the model's interpretive power, this study uses the Simulink tool of MATLAB R2019a to unlock the ANN's "black box." To give an example, the Simulink tool offered by MATLAB R2019a can visualize the ANN model's "black box," allowing this research to successfully interpret the processing data and model output and circumvent the "black box" problem. Evaluation of credit rating model performance is the last improvement direction. An acceptable and well-understood analytical performance metric is utilized in the literature to assess the prediction ability of credit rating models. But the pertinent literature is paying more attention to the connections between statistical prediction capability and financial performance standards (Doumpos et al., 2019). The main issue with this strategy is that financial criteria need unique data for each company, such as allowing for expenditures related to bad credit or rejecting expenses related to excellent loans, which are typically subjective and fluctuate over time. Additional research is required in this area of study (Doumpos et al., 2019).

Author Contributions

All authors contributed equally.

Conflict of Interest

The authors declare that there is no conflict of interests regarding the publication of this manuscript. Additionally, the authors have adhered strictly to all ethical standards, which include plagiarism, informed consent, misconduct, data fabrication and/or falsification, duplicate publishing and/or submission, and redundancy.

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Appendix

Appendix 1. Detailed weights and block parameters of ANN model for dataset 2015-2018.

Weights IW{1,1}(1,;)’	[1.1686; 3.5209; 2.1149; 3.0353; 9.2623]
Weights IW{1,1}(2,;)’	[7.2998; 1.9749; 0.2026; −2.3859; −6.5558]
Weights IW{1,1}(3,;)’	[15.5659; −5.0439; 1.3815; 2.8883; 2.90283]
Weights IW{1,1}(4,;)’	[75.8377; 29.35095; −0.1079; −0.1329; 0.01831]
Weights IW{1,1}(5,;)’	[−1.5213; −0.7766; 33.3051; 0.3101; 0.0148]
Weights IW{1,1}(6,;)’	[−28.0306; −30.1237; −0.3607; −2.6723; −27.8430]
Weights IW{1,1}(7,;)’	[9.7682; 7.9503; −0.0169; −3.3458; −1.4902]
Weights IW{1,1}(8,;)’	[13.0186; 6.2206; −0.5615; −0.1092; −0.0321]
Weights IW{1,1}(9,;)’	[6.2667; 2.2999; −0.1390; 0.8893; −9.4037]
Weights IW{1,1}(10,;)’	[−2.1059; −3.3798; 1.5028; 1.6013; −13.4482]
Weights IW{1,1}(11,;)’	[−6.1805; 2.8076; −3.7622; −13.1043; −0.15287]
Weights IW{1,1}(12,;)’	[1.4011; 0.7243; −36.0069; −0.2549; −0.0166]
Weights IW{1,1}(13,;)’	[−74.3196; −27.8977; 0.0951; 0.0044; −0.0188]
Weights IW{1,1}(14,;)’	[−12.0992; 4.2855; −1.4262; −0.0513; 0.4429]
Weights IW{1,1}(15,;)’	[−29.5073; −30.9439; −0.3903; −2.7094; −27.7822]
Weights IW{1,1}(16,;)’	[−1.1657; 15.0269; 0.3296; 2.5365; −0.0933]
Weights IW{1,1}(17,;)’	[75.8564; 27.4546; −0.0896; 0.0958; 0.0186]
Weights IW{1,1}(18,;)’	[9.1422; 3.7245; 3.0179; 2.5514; −0.7948]
Weights IW{1,1}(19,;)’	[−9.1862; −15.1469; −0.1819; −1.6042; 3.6933]
Weights IW{1,1}(20,;)’	[97.4872; 35.8821; −0.1210; −0.0067; 0.0217]
Weights IW{1,1}(21,;)’	[1.4227; 0.7227; −33.5110; −0.2740; −0.0158]
Weights IW{1,1}(22,;)’	[−5.0575; −7.9424; 1.5243; 0.9934; −0.8783]
Weights IW{1,1}(23,;)’	[−9.2971; −12.7844; −17.7480; −13.3286; −11.3054]
Weights IW{1,1}(24,;)’	[5.0802; −2.1760; 3.3954; 3.9644; −3.5997]
Weights IW{1,1}(25,;)’	[−1.5450; −0.0041; −0.0181; 0.2566; 1.9590]
Weights IW{1,1}(26,;)’	[9.6894; 7.4685; 0.0039; −3.2869; −1.3712]
Weights IW{1,1}(27,;)’	[−0.0137; −1.7613; −0.4360; −2.4747; 0.2224]
Weights IW{1,1}(28,;)’	[9.5824; 3.3902; 2.7194; −7.7278; 1.3797]
Weights IW{1,1}(29,;)’	[−1.4410; −10.7516 ; −0.03085; 2.4037; 0.1332]
Weights IW{1,1}(30,;)’	[75.7804; 28.5725; −0.0993; 0.0082; 0.0200]
Constant B	[−6.7623; 11.1027; 11.9702; 43.0645; 31.1739; 13.4379; 7.65395; 7.4972; −0.6954; 11.0512; −4.2468; −34.2803; −41.9400; −6.6383; 12.6739; −2.0172; 43.1104; 5.6287; −0.4891; 55.4150; −31.6402; −0.4130; −10.4582; 6.7038; 0.0230; 7.6127; 1.0034; 8.6650; 0.5269; 43.4386]
IW{2,1}(1,;)’	[0.8058; 0.5150; 0.1391; 16.8265; −5.4322; 6.0039; 1.7913; −0.2136; −2.0227; −0.7065; −0.0308; 6.0221; 16.8102; 0.1533; −5.5615; −0.8392; 23.1933; −0.1140; 0.1773; −11.8322; −11.3345; 0.5204; −0.0226; −0.3670; −3.0953; −1.8666; −0.8636; −0.0604; −1.3558; −11.4742]

Appendix 2. Detailed weights and block parameters of ANN model for dataset 2008-2014.

Weights IW{1,1}(1,;)'	[2.5250; 3.4369; 2.3544; −1.2072; −0.7214]
Weights IW{1,1}(2,;)'	[−0.3568; 0.2246; −0.2105; 0.3513; −0.1361]
Weights IW{1,1}(3,;)'	[−2.7379; 2.8213; 0.9751; −0.1783; 1.8416]
Weights IW{1,1}(4,;)'	[6.0935; −0.0194; 1.1689; 2.7134; 1.9173]
Weights IW{1,1}(5,;)'	[1.7619; 3.8112; −1.6258; 3.4431; 5.0424]
Weights IW{1,1}(6,;)'	[1.6639; 2.8054; −3.0223; −2.6744; 3.4259]
Weights IW{1,1}(7,;)'	[−0.3573; 0.2255; −0.2126; 0.3514; −0.1355]
Weights IW{1,1}(8,;)'	[1.5945; −0.8197; 8.9670; 0.1751; −0.2897]
Weights IW{1,1}(9,;)'	[0.3567; −0.2244; 0.2100; −0.3512; 0.1363]
Weights IW{1,1}(10,;)'	[−1.2775; −6.8303; −0.4097; −3.7054; 0.4549]
Weights IW{1,1}(11,;)'	[−4.0657; −0.0493; −1.4204; −2.3171; 2.8520]
Weights IW{1,1}(12,;)'	[0.3562; −0.2238; 0.2086; −0.3510; 0.1367]
Weights IW{1,1}(13,;)'	[1.0677; −1.5726; −4.2263; 1.5961; 1.9274]
Weights IW{1,1}(14,;)'	[−1.3218; −1.4259; −2.0981; 2.1265; 2.8796]
Weights IW{1,1}(15,;)'	[0.0491; 3.9597; −5.6127; 1.8383; 2.3237]
Weights IW{1,1}(16,;)'	[−0.4493; 3.5601; −1.1784; 1.4216; −3.3991]
Weights IW{1,1}(17,;)'	[0.8778; −0.8052; 3.2671; −2.6277; −0.7414]
Weights IW{1,1}(18,;)'	[0.7682; −0.8088; 4.4793; 1.3258; −2.5908]
Weights IW{1,1}(19,;)'	[−2.7311; −5.2151; 1.5173; 1.6824; −0.6585]
Weights IW{1,1}(20,;)'	[−2.3368; 3.2627; 1.2748; −3.1636; −2.4912]
Weights IW{1,1}(21,;)'	[−0.6638; −0.6905; −1.1396; 0.8834; 0.2564]
Weights IW{1,1}(22,;)'	[1.1737; 7.5059; −1.5487; 1.7215; 1.3508]
Weights IW{1,1}(23,;)'	[−0.6903; 1.4319; −6.2454; 0.8674; 0.5837]
Weights IW{1,1}(24,;)'	[12.0182; 8.8728; 0.0328; −0.1321; −3.1463]
Weights IW{1,1}(25,;)'	[5.8161; 8.1874; 0.1506; 0.2145; −2.2586]
Weights IW{1,1}(26,;)'	[3.0423; −1.6870; −3.9683; −0.8924; 2.0932]
Weights IW{1,1}(27,;)'	[0.3558; −0.2230; 0.2068; −0.3509; 0.1372]
Weights IW{1,1}(28,;)'	[−0.3566; 0.2242; −0.2097; 0.3512; −0.1364]
Weights IW{1,1}(29,;)'	[−0.0935; 0.0792; 2.3620; −1.2871; 0.0866]
Weights IW{1,1}(30,;)'	[75.7804; 28.5725; −0.0993; 0.0082; 0.0200]
Constant	[2.0748; −0.2639; 2.0351; −0.0898; −0.3422; 3.1641; −0.2658; 8.3140; 0.2634; 0.4376; 3.4473; 0.2620; −1.1600; −0.1903; −3.2914; −4.3563; 1.2900; 0.3840; 0.6258; −1.4378; −0.1163; −0.3202; −6.4631; −2.8225; −1.7880; 0.0955; 0.2604; −0.2631; −0.2092; −0.3955]
IW{2,1}(1,;)'	[−4.1341; 0.7276; −3.5556; 4.5574; −3.2875; 2.7834; 0.7293; 3.9045; −0.7273; −1.5074; 3.9399; −0.7259; 2.8321; −3.3137; 3.5685; −4.4960; −2.6155; 3.3211; −1.5226; 3.5933; 1.4443; −4.5768; 7.4151; −2.9587; 5.8463; −6.2156; −0.7245; 0.7270; −1.9255; 0.8322]