The Stock Price Crash Risk Prediction by Neural Network

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Abstract

The prediction of stock price crash risk is an important and widely studied topic in both accounting and finance, since crash risk has a significant impact on shareholders, creditors, managers, investors, and regulators. In this paper, I develop a neural network crash risk prediction model that has not been explored before. In addition, I compare the performance of the neural network model with the logistic model and random forecast. I show that the neural network crash risk prediction model provides a significant improvement in prediction accuracy over logistic regression and random forecast. The results indicate that the neural network methodology is a good alternative to predict stock price crash risk.

Keywords: Stock price crash risk, Neural network

1. Introduction

Stock market returns are among the most important indicators of financial performance (Ansari & Riasi, 2016; Riasi & Pourmiri, 2015), therefore a stock price crash can have a severe negative impact on a firm's financial stability and competitiveness (Riasi, 2015; Riasi & Amiri Aghdaie, 2013). Stock price crash risk has been an important and widely studied topic, especially after the 2008 financial crisis. Investors, regulators and academics have paid a lot of attention to firm-level stock price crash risk which is defined as the experience of the extreme negative firm-specific stock returns. Typically, stock price crash implies that the firm is under a condition of high opacity, weak corporate governance and high agency cost that informed managers withhold bad news from uninformed investors. Once the negative news hoarding reaches a tipping point, all of them is released suddenly at once and results in a stock price crash. Individual investors suffer significant unexpected wealth losses (Merton, 1987) and their confidence in the equity market is jeopardized by stock price crashes.

Given the significant adverse consequences of stock price crashes, it has spurred researchers' interests to develop a sophisticated stock price crash risk prediction model for the purpose of helping investors to avoid purchasing stocks that are subject to high crash risk and helping regulators to increase the stability of financial markets. To date, intense academic research has primarily employed either the logistic regression or the OLS regression to study the determinants of future crash risk (Kim et al., 2011a, 2011b; Callen and Fang, 2013, 2015). Little attention has been paid to other methodologies, e.g., neural network, etc., which can be easily implemented by investors.

The aim of this paper is to build a neural network stock price crash risk prediction model. I started with nine financial ratios used by Hutton et al. (2009), Kim et al. (2011a, 2011b) and Kim et al. (2014), but only eight financial ratios are used in the final neural network model. To avoid the multicollinearity issue among independent variables, I drop the variable SIGMA due to its high correlation with the variable WRET (correlation coefficient -95.70%).

Table 1 presents the definitions of all variables.

Table 1. Variable Definitions

CRASH	An indicator which takes the value of 1 if a firm experience one or more crash events in a year and 0 otherwise.
NCSKEW	The negative conditional return skewness.
WRET	100 times of the previous fiscal year's average firm-specific abnormal weekly returns ($w_{j,t}$ from Model (1)).
LSIZE	Natural log of total assets (Compustat AT).
MTB	The market capitalization of shareholders' equity (Compustat PRCC_F×CSHO) divided by the book value of shareholders' equity (Compustat CEQ).
LEV	The leverage ratio, calculated as the total assets (Compustat AT) minus the stockholders' equity of common shareholders (Compustat CEQ) divided by the total assets.
ROA	Net income before extraordinary items (Compustat IB) divided by total assets (Compustat AT) at the beginning of the year.
DTURN	The average monthly share turnover for the last fiscal year minus the average monthly share turnover for the year before the last fiscal year. The total monthly trading volume ((CRSP VOL)) divided by the total monthly number of shares outstanding (CRSP SHROUT) is monthly share turnover.
OPAQUE	The moving sum of the absolute value of discretionary accruals estimated from Modified Jones (1991) model over the last three years.
SIGMA	The standard deviation of firm-specific abnormal weekly returns ($w_{j,t}$ from Model (1)).

Description: This table presents the variable definitions.

I investigate whether the neural network built on those eight ratios can discriminate between crash and non-crash firms in any given year between 1990 and 2013. Following Kim et al. (2011a, 2011b), predictors are measured at the end of year t-1 and the stock price crash is measured in year t. The results of the neural network model show an overall prediction accuracy of 73.48%, which is higher than the conventional logistic model (72.62%) and random prediction (71.81%). My study contributes to the stock price crash risk literature by providing an alternative method to logistic regression to predict the actual occurrence of crash events. My study also contributes to the neutral network literature by suggesting a new field to apply this methodology.

The remainder of this paper is organized as follows. Section 2 is the literature review and section 3 describes the sample, the measurement of variables, and the methodology. Section 4 presents my analysis results. Section 5 concludes this paper.

2. Literature Review

Prior research in the crash risk area mainly focuses on finding predictors associated with the crash risk. Chen et al. (2001), for instance, find that firms that have high past returns, past return skewness, and high differences in investors' opinions are likely to experience more crash risk than otherwise similar firms without these characteristics. Hutton et al. (2009) document that opaque earnings are associated with higher stock price crash risk, and conclude that transparency in reported earnings is important for the stability of capital markets. They also find that firms with high market-to-book (MTB) exhibit more crash risk. Kim et al. (2015) and Callen and Fang (2015) both find a positive association between a firm's profitability (ROA) and its crash risk. Kim et al. (2014) document that big firms are more likely to crash, whereas firms with high leverage are less likely to crash. In all of the above research, the prediction of stock price crash risk is based on the conventional approach (logistic model for stock price crash occurrence). No research, however, has been done using the neural network model to examine the occurrence of stock price crash risk. In this study, I explore neural network in predicting stock price crash risk.

The neural network approach has gained increasing popularity among accounting and finance society in recent years. For example, Hwang & Lin (2000), Lin et al. (2003) and Lin et al. (2004) examine the use of neural networks for detecting fraudulent financial reporting and management fraud. In addition, the neural network has been widely applied to predict bankruptcy (e.g., Odom & Sharda, 1990; Altman et al., 1994; Hu et al., 1999; Yang et al., 1999; Shah & Murtaza, 2000; Lee, 2001; Alam et al., 2005; Hu & Tseng, 2010; Kim & Kang, 2010). Recently, Brédart (2014) develops a neural network model that predicts bankruptcy using three financial ratios for small and medium Belgian firms. Overall, better classification rates are reported in the literatures for the neural network approach when compared to the conventional logistic regression approach.

3. Methodology

3.1 Sample and Data

In order to construct crash risk measure and control variables, I obtain data from Compustat and CRSP for the period of 1990 to 2013. I choose the period of 1990 to 2013 as my sample period because there are various stock market crashes occurred during the period, e.g., the dot-com bubble collapsed in 2000 and the financial crisis occurred during 2007 to 2008. After subtracting the firm years that are in financial (SIC codes 6000-6999) and utilities industries (SIC codes 4000-4999) and eliminating observations with insufficient data to calculate all variables, the final sample consists of 60,614 firm-year observations with 10,459 crash firm-years and 50,155 non-crash firm-years. The total sample is randomly divided into two subsamples: 80% of the total sample is used for training and 20% is used for testing. The training data has 48,592 firm-year observations (8,368 crash observations versus 40,224 non-crash observations) and the test sample consists of 12,022 firm-year observations (2,091 crash observations versus 9,931 non-crash observations).

3.2 Measurement of Stock Price Crash Risk

I follow previous literature in defining the measurement of stock price crash risk: specifically, CRASH is an indicator which equals to 1 if a firm has at least one week in the fiscal year with an abnormal return that is 3.2 standard deviations lower than the average firm-specific abnormal weekly return during that fiscal year (Hutton et al., 2009; Kim et al., 2011a, 2011b) (Note 1). The firm-specific abnormal weekly return, W, is computed using the following model:

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-2} + \beta_{2,j} r_{m,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{m,t+1} + \beta_{5,j} r_{m,t+2} + \varepsilon_{j,t}, \tag{1}$$

In Model (1), $r_{j,t}$ is the return on stock j in week t (CRSP RET), and $r_{m,t}$ is the market index weighted by value from CRSP in week t (CRSP VWRETD). I include two-week-prior and two-week-post market returns in Model (1) to account for microstructure noise, consistent with Dimson (1979). The firm-specific weekly return is calculated as follows:

$$W_{j,t} = ln(1 + \varepsilon_{j,t}) \tag{2}$$

3.3 Methodology

The neural network is a pattern recognition method designed to simulate the behavior of biological neural network, which is typically organized in layers. Figure 1 shows the neural network for stock price crash risk model. There are three big layers consisting of a number of neurons in a typical neural network. Layers are connected through neurons. The first layer (labeled as I1-I8) is the input layer, the last layer (labeled as O1) is the output layer, and the hidden layer (labeled as H1-H14) is the layer in the middle of the input and output layers. Similar to intercept terms in a regression model, bias layers (B1 and B2) adjust the nodes through constant values. The number of neurons in the input layer is the number of variables considered in the network (e.g., eight financial ratios). The output layer is the crash risk of the company in consideration. The output neuron takes values between 0 and 1, which indicates the likelihood of stock price crash occurrence. To be consistent with logistic regression, I choose the output to have a probability value between 0 and 1, instead of being an indicator of 0 or 1. Synaptic weights link neurons and are gradually estimated during the training phase.

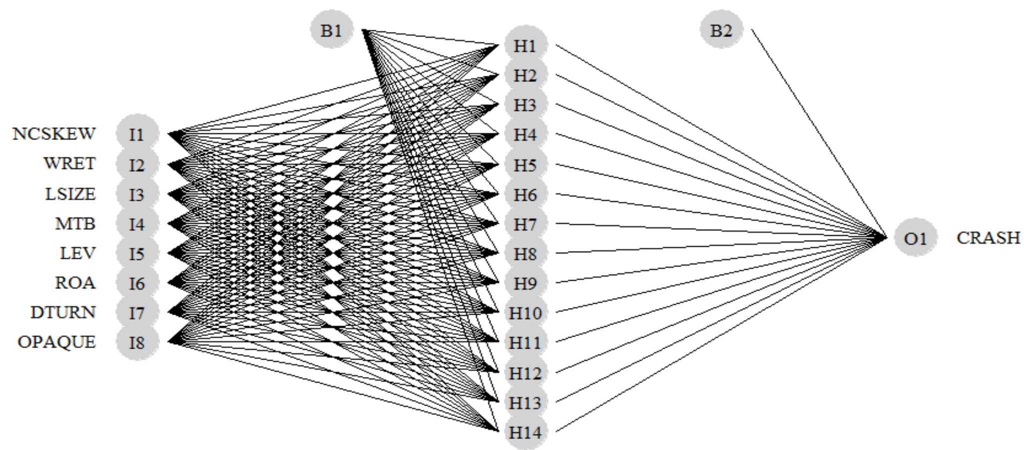

Figure 1. neural network architecture with one hidden layer

Description: This figure shows the neural network architecture used in building the neural network model to predict crash risk.

The neural network model is trained by using the R package carat and nnet. The optimal parameters of decay (weight decay) and size (number of hidden units) are chosen based on the training dataset by using the caret train () function. The final size chosen for hidden neurons is 14, and the decay parameter is 0.001.

4. Results

4.1 Correlations and Descriptive Statistics

Table 2 presents the Variance Inflating Factors (VIF) and the correlation coefficients between the variables used in the neural network. I find that all VIFs are under the value of 5 and all correlation coefficients are under 0.55, suggesting that multicollinearity issue is unlikely to be a problem among explanatory variables.

Table 2. VIF and correlation coefficients between explanatory variables

	Variable	VIF	1	2	3	4	5	6	7
1	NCSKEW	1.043							
2	WRET	1.451	0.116***						
3	LSIZE	1.422	0.204***	0.534***					
4	MTB	1.168	0.013***	0.069***	0.422***				
5	LEV	1.004	-0.007*	0.098***	0.044***	-0.115***			
6	ROA	1.265	0.083***	0.369***	0.337***	0.251***	-0.112***		
7	DTURN	1.035	0.017***	-0.074***	0.055***	0.102***	0.024***	0.066***	
8	OPAQUE	1.021	-0.006	-0.228***	-0.061***	0.110***	-0.139***	-0.108***	-0.014***

Description: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Variables are defined in Table 1.

Table 3 presents the descriptive statistics regarding the eight ratios used in the model. The descriptive statistics are generated based on the entire sample, for the group of crash firms, and the group of non-crash firms. I also conduct statistical tests comparing the firm characteristics between the crash group and the non-crash group.

Table 3. Descriptive Statistics

Variable	Total Sample (N=60,614)			Non-Crash (N= 50,155)			Crash (N=10,459)			Difference (Crash-NonCrash)	
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Mean	Median
NCSKEW	-0.118	-0.145	0.788	-0.134	-0.155	0.775	-0.045	-0.090	0.842	0.089***	0.065***
WRET	-0.266	-0.160	0.305	-0.273	-0.165	0.313	-0.228	-0.142	0.261	0.046***	0.023***
LSIZE	5.429	5.348	2.076	5.332	5.201	2.096	5.891	5.943	1.912	0.559***	0.742***
MTB	3.041	2.013	3.341	2.979	1.950	3.331	3.339	2.322	3.377	0.361***	0.372***
LEV	0.188	0.155	0.177	0.190	0.158	0.177	0.175	0.137	0.174	-0.015***	-0.021***
ROA	0.003	0.042	0.189	-0.001	0.039	0.190	0.025	0.055	0.183	0.026***	0.016***
DTURN	0.004	0.000	0.126	0.003	0.000	0.124	0.010	0.002	0.134	0.007***	0.002***
OPAQUE	0.555	0.296	0.794	0.546	0.291	0.785	0.598	0.323	0.836	0.052***	0.031***

Description: *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively. Variables are defined in Table 1.

I find from Table 3 that crash firms have higher negative conditional return skewness (NCSKEW), higher average weekly return (WRET), bigger size (LSIZE), higher market-to-book ratio (MTB), lower leverage ratio (LEV), higher return on assets (ROA), higher stock turnover (DTURN), and are more opaque in financial reporting (OPAQUE). The significant differences of these firm characteristics between crash firms and non-crash firms indicate these variables are good predictors of stock price crash risk.

4.2 Neural Network

The neural network is like a "black-box," with no clear relationship among variables provided. Recent studies have tried to make the black-box more transparent. For instance, Özesmi and Özesmi (1999) propose a neural interpretation diagram (NID) to plot parameters in a neural network model. The importance of covariates given their relative influence on response variables is illustrated in the diagram. The causation is inferred from model weights. Basically, the diagrams link between layers through the lines: line width corresponds to magnitude, and line color represents the direction of each weight. Thicker connections imply highly influential variables. Positive weights are represented in black color, and negative weights are in gray color.

Figure 2 plots the neural interpretation diagram for a neural network crash risk model. The weights in a neural network, which describe the relationships between variables, are similar to coefficients in a regular regression model. In other words, the relative influence is reflected by the weights. If a variable is not relevant to a response variable, it will be suppressed by the weights. If a variable has a strong correlation with a response variable, it will be reflected by the weights. A neural network has a higher number of weights than the number of coefficients in a standard regression model, which makes neural network easier when modeling non-linear relationships between dependent variable and independent variables. However, one can barely draw any conclusion based on Figure 2 since there are too many lines in between the input layer and the output layer. The neural interpretation diagram provides a clearer picture under the condition that the number of the input layer and hidden layer is small. Thus, I need a simple measure that is only one number, but can inform us the whole story for each independent variable as described in the next paragraph.

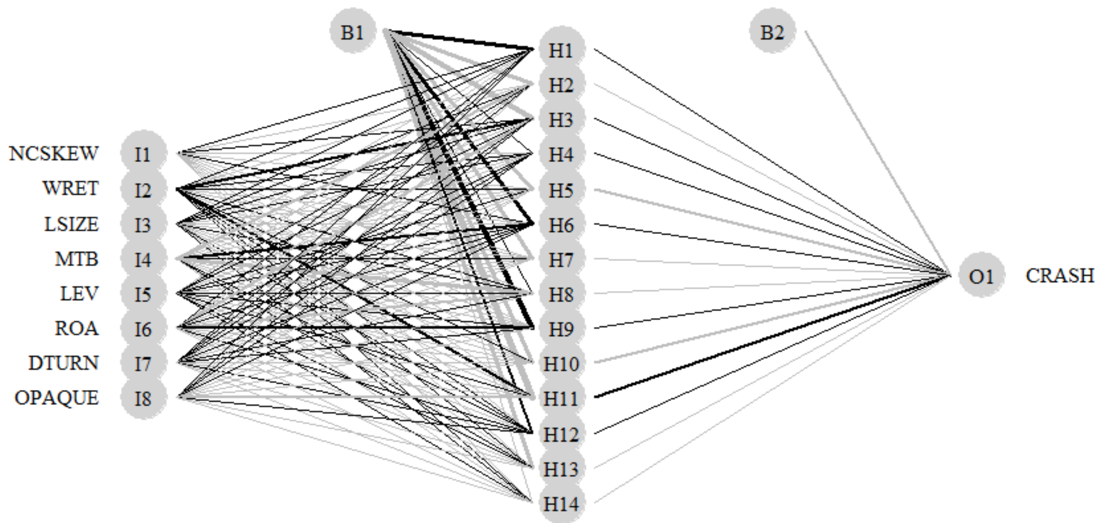

Figure 2. Neural interpretation diagram of neural network crash risk model

Description: This figure shows neural interpretation diagram in which connection weights are visualized.

Garson (1991) and Goh (1995) suggest another method to shed light on the neural network black box—the relative importance of independent variables. The relative importance of independent variables is calculated by decomposing the model weights in a neural network. Essentially, the relative importance of an independent variable for the dependent variable can be traced by weighted connections, since all weights linked to the input variable can be followed. This can be done for all input variables. The final importance number of an input variable is relative to all other inputs in the neural network model (see Goh, 1995 for details). Garson (1991) proposes the first version of the algorithm to calculate the relative importance, which varies from zero to one, but the signs cannot be determined. In this paper, I employ the version developed by Goh (1995) to show both the value and the sign of the independent variables.

Figure 3 shows the relative importance of the predictors on stock price crash risk in the neural network model. I find that LEV has a negative relationship with one-year ahead crash risk, while other variables have positive relationships with stock price crash risk. The variable DTURN has a relative importance close to zero, which indicates it has a marginal contribution to predict crash occurrence. Note that the bar values indicate the relative importance of the predictor. Therefore, MTB has the highest impact on crash risk, followed by ROA and LSIZE.

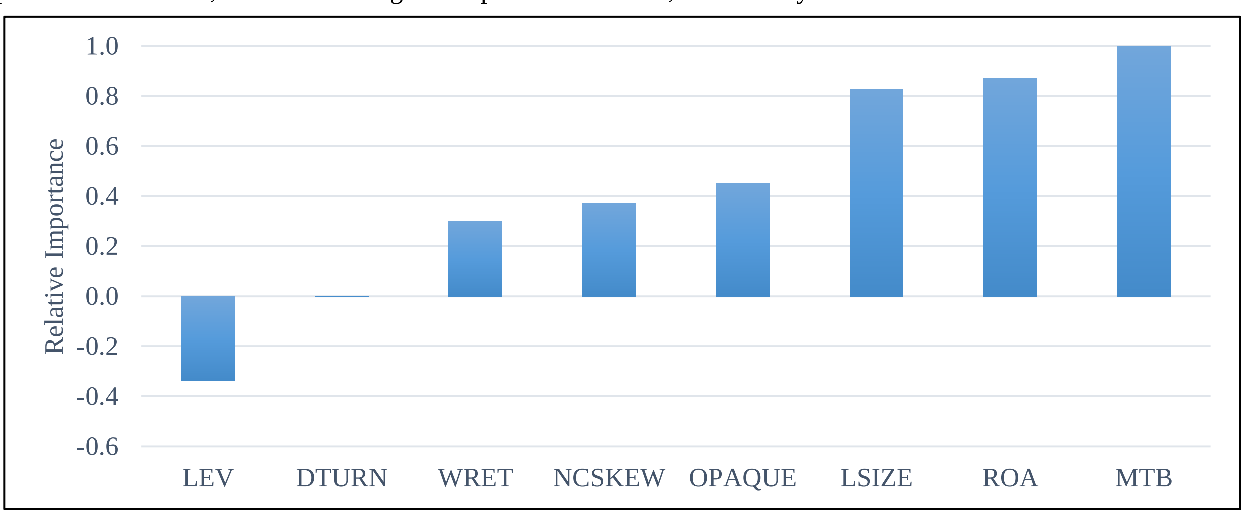

Figure 3. Relative importance of the independent variables for crash risk in the neural network model

Description: This figure shows the relative importance of the independent variables in the neural network model.

Next, I check whether these relative importance values provide a directional relationship between the independent variables and the dependent variable. I find that the signs in relative importance support the findings in Table 3 and are consistent with the signs of the coefficients from logistic regression (Hutton et al., 2009; Kim et al., 2011a, 2011b; Callen and Fang, 2013, 2015), indicating that relative importance values correctly measure the directional relationship between the predictors and the response variable.

Table 4 shows the classification results of the neural network model. For comparison purposes, I also present the results from the logistic model (based on the same variables used in neural network model) in Table 5, and the results from a random forecast in Table 6. The logistic and random predictions only suggest the likelihood of an observation belonging to the class coded as 1 (crash group) given all explanatory variables. For classification, one needs to find a threshold, which in some sense is optimal for the specific problem. Thus, the threshold could be affected by monetary costs or ethical boundaries. Since I don't have any of these costs or boundaries (i.e., a cost function), I choose such a cutoff point of the predicted score that the predicted crashes are equal to the observed crashes based on the training sample for each model. The cutoff is firstly derived based on training data for each model and is then applied to test data. Consistent with logistic and random prediction, the neural network model predicts the likelihood of a firm to experience a crash for a given year. Cutoff for the neural network is derived the same way as that of the logistic regression and random forecast.

Table 4. Neural Network Results.

Panel A: Training Sample (N=48,592)

Status	Non-Crash	Crash	Hit ratio
Predicted Non-Crash	34,061	6,163	84.68%
Predicted Crashed	6,163	2,205	26.35%
Accuracy	84.68%	26.35%	74.63%

Panel B: Test Sample (N=12,022)

Status	Non-Crash	Crash	Hit ratio
Predicted Non-Crash	8,332	1,589	83.98%
Predicted Crashed	1,599	502	23.89%
Accuracy	83.90%	24.01%	73.48%

Description: This table presents the prediction results using neural network method.

Table 5. Logistic Model Results

Panel A: Training Sample (N=48,592)

Status	Non-Crash	Crash	Hit ratio
Predicted Non-Crash	33,775	6,449	83.97%
Predicted Crashed	6,449	1919	22.93%
Accuracy	83.97%	22.93%	73.46%

Panel B: Test Sample (N=12,022)

Status	Non-Crash	Crash	Hit ratio
Predicted Non-Crash	8,253	1,614	83.64%
Predicted Crashed	1,678	477	22.13%
Accuracy	83.10%	22.81%	72.62%

Description: This table presents the prediction results using logistic model.

Table 6. Random Forecast Results

Panel A: Training Sample (N=48,592)

Status	Non-Crash	Crash	Hit ratio
Predicted Non-Crash	3,3314	6,910	82.82%
Predicted Crashed	6,910	1,458	17.42%
Accuracy	82.82%	17.42%	71.56%

Panel B: Test Sample (N=12,022)

Status	Non-Crash	Crash	Hit ratio
Predicted Non-Crash	8,271	1,729	82.71%
Predicted Crashed	1,660	362	17.90%
Accuracy	83.28%	17.31%	71.81%

Description: This table presents the prediction results using random forecast method.

On the training subsample, Table 4 shows that the percentage of good predictions of neural network reaches 26.35% for the crash firms; in other words, 26.35% of actual crash firms are correctly predicted as crash firms. The percentage of good predictions is 22.93% (Table 5) for logistic regression and 17.42% for random forecast (Table 6) on the training subsample, respectively. The accuracy is higher using neural network than the other two methods for the training subsample. These results are verified on the testing subsample. Specifically, the percentage of good predictions is about 24.01% for the crash firms (i.e., about 24.01% of the crash firms are correctly classified as so by a neural network method). This number is also higher than those numbers for logistic (22.81% in Table 5) and random prediction (17.31% in Table 6). The overall prediction accuracy rate is 73.48% in the testing subsample, and 74.63% in the train subsample for the neural network method. The results in Tables 4 through 6 indicate that the neural network method is more accurate than the logistic model and random forecast to predict one-year ahead crash risk. As expected, both the neural network and logistic model provide more accurate predictions than random forecast.

5. Discussion and Conclusion

Crash risk prediction has gained much interest from shareholders, creditors, managers, investors, and regulators. Aiming to predict the crash risk probability of U.S. firms over the period of 1990 to 2013, I develop a neural network utilizing variables constructed from Compustat and CRSP. Because my objective is to use neural network to forecast crash risk, I choose eight widely used financial ratios as explanatory factors. The results show that LEV has a negative relationship with crash risk, while other variables have positive relationships with stock price crash risk. The overall prediction accuracy rate for neural network is 73.48%, which is higher than the logistic model of 72.62% and random prediction of 71.81% on the testing sample. This study may be of interest to investors, such as short-sellers who may want to short stocks with higher crash risk, while risk-averse investors may try to avoid stocks with higher crash risk. Scholars may also be interested in this paper because the methodology is unexplored in crash risk literature.

The study is not free from limitations. First, the neural network model only includes eight financial ratios. More predictors could be included to achieve higher prediction accuracy. Second, the cutoff is chosen based on development data for all years during 1990 to 2013, year-specific cutoffs could be used to get higher prediction accuracy.

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Notes

Note 1. 3.2 is chosen to generate a frequency of 0.1% in the normal distribution.