

**PREDICTING FINANCIAL DISTRESS: AN EVIDENCE OF ROLLING
LOGIT MODEL IN INDONESIAN LISTED MANUFACTURE COMPANY**

By

AYUNINGTYAS, Dwi

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

MASTER OF DEVELOPMENT POLICY

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ABSTRACT

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By

Dwi Ayuningtyas

Research on financial distress has been carried out for many years. Various models have been used to explain the probability of a firm's propensity to be distressed. Given the lack of agreement on the best model to study financial distress, the paper will attempt to compare the rolling-logit model with the logit regression model. The aims of this study are to find out: 1) which variables of financial ratios, industry relative ratios, and firms' sensitivity to macroeconomic variables, are to be included as determinant variables in financial distress model; and 2) compare each model predicting ability and performance. The research is descriptive verification while the method used is a case study using cross-sectional pooled data. The sample is manufacturing companies listed in IDX period 2000-2015. The distressed company was defined as a firm that has negative book equity value in the observation period 2015. The data analysis used is descriptive analysis, Mann-Whitney U test, backward stepwise regression, logit regression, rolling-logit regression, and jackknife validation test.

The findings indicate: 1) determinant variables to predict the probability of firm's financial distress were EBIT to Sales, EBIT to total assets, current assets to total assets, net worth to sales, sales to total assets, cash to sales, cash to total assets, inventory to sales, quick assets to sales, firms' sensitivity to M2 and real exchange rates, previous bankruptcy probability; 2) rolling-logit regression model as general exhibit higher predicting ability compared to logit regression;

Keywords: *financial distress, financial ratios, industry relative ratios, macroeconomic variables, logit model, rolling-logit model, jackknife validation test*

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Hopefully, this research would enrich common knowledge, especially in the field of financial distress prediction model.

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I. INTRODUCTION

A. Introduction and Background to the Problem

The world economy will remain fragile in 2016, as it has not yet recovered from the global financial crisis and Europe's sovereign debt crisis. This unstable economic condition may lead companies to go bankrupt which, in turn, could cause a systemic risk. Similar to the world's economic condition, Indonesia is also facing an economic recession due to insufficient structural reform and deceleration in global economy. The government of Indonesia has still not thoroughly resolved food security and domestic energy issues, low competitiveness of local industries, nor the lack of long-term financing capacity. Additionally, China's slowing economy puts pressure on Indonesia's commodity prices as the export demand gradually decreases.

According to the Central Bank of Indonesia (2016), the rate of economic growth in 2015 was only 4.79% (YOY). This low economic growth can hamper the nation's economic goal, as Indonesia aims to become one of the ten largest economies by 2025. Therefore to achieve financial stability and attract more investors, the Central Bank of Indonesia set a high-interest rate at 6.5%. A high interest rate will help manage the liquidity and support financial market deepening, also ensure that the inflation rate remains under control. The Indonesian Ministry of Finance also initiated a new policy to keep a debt-to-equity ratio no more than 4¹. Through this policy, Government can help manage the liquidity of financial sector by maintaining company leverage ratio, and also

¹ Minister of Finance Regulation no.169/PMK.010/2015. This regulation was made for the purpose of tax income calculation, in which government ruled the maximum proportion of debt and equity for a company that was established and located in Indonesia in which the capital is consist of stock. Yet, some industries are exempted from this regulation, including bank, financial institutions non-bank, insurance, mining, and infrastructure.

achieve the tax revenue target. This policy will strengthen company's capital in the hope to induce domestic economic growth and obtain financial stability.

Accordingly, if companies show an indication of high debt, by the regulation of the Capital Market and Financial Institutions Regulatory Bodies (now FSA) no. 367/BL/2012, a firm which has net asset value under IDR 25 million for 90 consecutive days should stop their stock market transactions since they might lack the capacity to pay their debt and dividend. This regulation was set only as a warning, and the Government of Indonesia does not have a specific model or methodology to indicate and prevent the probability of bankruptcy or financial distress. Therefore, the Government of Indonesia should adopt a financial distress prediction model as tools for monitoring, identifying, and assessing potential risks that can threaten financial stability.

Financial distress indicates a declining stage of a company's financial condition before it bankrupts or liquidates (Platt and Platt, 2002). Such economic stage is also characterized as having a negative net income for several continuous years (Whitaker, 1999). In an attempt to prevent bankruptcy, which might trigger the collapse of nation's economy, financial distress should be identified in advance by the company's manager, investors, creditors, and also the government.

Financial distress prediction model can be used as an Early Warning System (EWS) to identify financial risk in early stages. Over the past 40 years, various literature using statistical methods have been developed to predict the probability of a firm facing financial distress and has become the domain research concern in the field of corporate finance. The debate about the suitability of which statistical method and determinant factors for predicting financial distress of firms is still ongoing.

Despite all the arguments and considering the suggestions from the previous study, financial prediction model continue to have a major role. In fact, scholars and practitioners still believe in the model's usefulness in minimizing the probability of contagion-effects and systemic risks. Then, what is the best model to predict financial distress? To provide the answer, this study will try to develop a financial prediction model that uses both internal and external factors. As the rolling-logit model offers the simplest assumptions with easy interpretation, it can capture the company's movement over time. This study will re-examine the rolling-logit method and utilize it for financial distress prediction model for the case of Indonesia.

B. Literature Review

Financial distress: Platt and Platt (2002) defined financial distress as a declining stage of a company's financial condition before it becomes bankrupt or liquidates. Whitaker (1999) characterized financial distress of a firm having a negative net income for several continuous years. Meanwhile, Rose et al. (1982) defined financial distress as a situation when the borrower has a lack of ability to pay at least one debt, and they indicated firm's financial distress stage when the firms have negative equity condition. In Indonesia, firm failure is regulated under Law no. 1 the year of 1998. The firm will be declared bankrupt by a court when the debtor (firm) has two or more creditors and not able to pay at least one debt that has matured and uncollectable.

Review of financial distress models: A vast amount of literature has been dedicated to finding a financial distress prediction model. The first financial distress prediction model was developed by Beaver (1966) using univariate discriminant analysis. Beaver (1966)

used 30 selected financial ratios which were classified into cash-flow ratio, net income ratio, debt to total asset ratio, turnover ratio, liquid asset to total assets ratio, and liquid asset to current debt ratio. Those selected financial ratios were computed to find the mean values for profile analysis, in order to outline the relationship between failed and non-failed firms or the cut-off point between them. Following this, Beaver (1966) utilized a dichotomous classification test solely based on profile analysis to classify the bankruptcy status of each firm. Beaver (1966) found that the ratio distribution of healthy firms was more stable compared to that of failed firms. Also, the cash flow to total debt ratio turned out to have the ability to classify failed and non-failed firms.

The advantage of the model is its simplicity, as it does not require any statistical knowledge since it simply compares each ratio with the cut-off point (Ooghe & Balcaen, 2004). While conducting the univariate analysis, researchers assumed that the relationship between dependent and independent variables is linear. Yet, Ooghe and Balcaen (2004) found that the variables used in this study show a non-linear relationship, leading to a biased classification of firm's failure status.

In the meantime, Altman (1968) used the multiple discriminant analysis (MDA) to find which ratios were the most important to detect bankruptcy and how much weight should be attached. The MDA considers the interaction of firms' relevant characteristics simultaneously. It transforms the individual variables into a single discriminant Z -score, which is used to identify the failure status. Furthermore, Altman (1968) successfully

found five linear combinations of variables including the suited weight for each of them, providing the best distinction model to identify failing and non-failing firms².

The MDA though applied restrictive assumptions that in turn becomes the weakness of the model itself. If researchers failed to meet group dispersion matrices and normal distribution assumption, then they could not have conducted the univariate Z-test (MDA). Group dispersion matrices assume that the variance-covariance matrix is equal within the group, both for failed and non-failed groups. While normality assumption means that data is normally distributes, in other words follows the bell shape curve distribution

Therefore, Ohlson (1980) argued that logit analysis (LA) can perform better than MDA because LA can avoid the problems associated with MDA. Logit analysis can be performed without assuming either normality distribution or group dispersion. Through LA, the fundamental prediction problem could be answered by finding the probability of occurrence of bankruptcy within a specific period, without boldly classifying firms into failed and non-failed groups. For each three years prior to bankruptcy, Ohlson developed three logit models separately. The one year before bankruptcy model possesses the higher predictive ability, which is 83.88%, while the two and three years before bankruptcy were 79.7% and 71.9%.

Similar conditional probabilistic models, such as probit analysis was also conducted by Zmijewski (1984) to estimate corporate failure. Zmijewski (1984) constructed probit analysis with three explanatory variables and found them to be strongly correlated to firm's failure. The estimated coefficient from the study cannot be directly interpreted and

² The Altman's (1968) Z-score is calculated as $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$. X_1 to X_5 respectively is working capital to total assets, retained earnings to total assets, EBIT to total assets, market value of equity to total liabilities, sales to total assets

needs to be calculated in a separate formula. Therefore, regarding conditional probability models, scholars prefer logit analysis because it offers simple interpretation in contrast to probit analysis (Zavgren, 1983; Doumpus & Zoupundis, 1999; Ooghe & Balcaen, 2004).

Nevertheless, a skeptical observer disapproved the static model used above, as it ignores the fact that most of the firm characteristics change over time (Morris, 1997; Shumway, 2001). Therefore, scholars tried to develop a dynamic or multi-period statistical model to overcome time-inconsistency problem in static models (e.g. univariate discriminant, MDA, logit, and probit). An example of dynamic or multi-period statistical models is rolling-logit analysis.

The rolling-logit model was used by Morris (1997) to capture the merits of logit analysis and to solve the static model problems. Through recall mechanism, a rolling-logit model captured both present and previous information to assess the probability of corporate bankruptcy. Morris (1997) utilized the prediction score obtained from logit model estimated at year $t-1$ as an independent variable at year t . Based on the aforementioned research, the information variable used was found to be also the most important indicator over 5-year period.

A replication study was done by Um (2001) using Korean manufacturing firms showed opposite results. Um (2001) used of Korean Manufacturing company listed in stock exchange period 1997 with sample period 1991 to 1995. The status of the firms was based on firms' insolvency condition on Q4 1997-Q3 1998 (during Asian Financial Crisis). The predictive ability of previous information was not significant for any of the 4-year periods. Um (2001) concluded that this insignificant result might suggest that indication of financial distress did not arise and the incremental information did not prove

beneficial in predicting bankruptcy. These results might emerge because the bankruptcy in Korea during Asian Financial Crisis was an abnormal case or abrupt events that hard to predict.

Meanwhile, a replication study done by Lin and Yang (2012), supports the result found by Morris (1997). They too proposed that compared to the logit model, the overall performance of rolling-logit model exhibit higher accuracies and lower misclassification errors for any 3-years period before bankruptcy.

Inconsistency and lack of research on the rolling-logit model to predict bankruptcy encourages more research to confirm the predictive ability of the model. Based on the findings from previous studies, the rolling-logit model seems to have more advantages other models. Rolling-logit possesses the advantages of logit model and can also reflect multi-period information. Therefore, this study tries to validate the usefulness of rolling-logit model to predict financial distress, especially in the case of Indonesian corporations.

Determinant variables of financial distress model: The earliest study developed to predict firm's failure is heavily dependent on the annual financial information provided by the firms. However, the use of financial ratios as the only determinant variables for financial distress prediction models has been subject to harsh criticism. This is because solely depending on financial ratios means researchers believe that all relevant indicators regarding firm's failure or success, neither internal nor external indicators, are purely reflected through the annual financial account. Yet, financial ratios can explain limited information regarding a firm's performance (Maltz, Shenhar, & Reilly, 2003). In their study, Maltz et al. (2003) found that financial performance, customer, process, people development, and future dimensions are affecting the measurement success of a firm.

Therefore, previous authors suggested to include non-financial indicators in financial distress prediction model (Ohlson, 1980; Zavgren, 1983; Zopoudinis & Doumpus, 1999).

By taking into consideration that firm's failure might be affected by internal and external factors, this study will attempt to develop financial distress prediction model using financial ratios, industry relative ratios, and macroeconomic variables.

Internal factors (which are financial ratios): This study will use classification financial ratio done by Chen and Shimerda (1981), which was factor classification gained from previous empirical study in predicting financial distress. However, in this study ten ratios was excluded because those ratios can be explained by other ratios, as suggested by Chen and Shimerda (1981). Therefore, this study used a total of 24 financial ratios that was classified into the following 7 categories:

1. *Return on investment.* The ability of firms to effectively operate and generate higher profit in association with sales, total assets, and total equity. Ratios included in this category were funds flow to net worth, funds flow to total assets, net income to total assets, net income to net worth, earnings before interest and taxes (EBIT) to sales, and EBIT to total assets.
2. *Capital turnover.* The ability of firms in utilizing their assets to generate income. Ratios included in this category were quick assets to total assets, funds flow to sales, current assets to total assets, net worth to sales, and sales to total assets.
3. *Financial leverage.* The proportion of debt to finance firm's capital or investments. Ratios included in this category were total liabilities to total assets, long term debt to total assets, and total liabilities to net worth.

4. *Short term liquidity.* The utilization of cash and cash equivalents to finance operational expenses and other obligations that have matured. Ratios included in this category were current assets to current liabilities, quick assets to current liabilities, current liabilities to net worth, and current liabilities to total assets.
5. *Cash position.* The ability of firms to fulfill their short term obligation by using cash and cash equivalents. Ratios included in this category were cash to sales, cash to total assets, and cash to current liabilities.
6. *Inventory turnover.* The ability of firms to generate sales by utilizing current assets and equivalents. Ratios included in this category were current assets to sales, inventory to sales, and sales to working capital
7. *Receivables turnover.* The ability of firms to generate sales by using their receivables. Ratio included in this category was quick assets to sales.

Industry relative ratios: Previous studies tried to control the differences or uniqueness between industries by standardized firm's financial ratio using average industry ratios (Platt & Platt, 1990). Almilia (2004) utilize industry relative ratios as determinant variables and found that prediction the model that used industry relative ratio lead to a higher predicting ability that of the model that used financial ratios. Sayari and Mugan (2016) also attempt to develop industry specific financial ratios and the result showed that the ratios precisely predict firm's failure. This study will refer to the previous study developed by Platt and Platt (1990), by using the formula of industry relative ratios noted as:

$$\text{Ratio-Relative Industry }_{i,j} = [\text{Firm}_i \text{ Financial Ratio } (r) / \text{Mean Ratio in Industry } j] \times 100$$

Macroeconomic variables: As the business environment changes over time, macroeconomic variables are needed to control it as those indicators are usually omitted in the prediction model (Zavgren, 1983). Interest rates and inflation are the most popular macroeconomic indicators used by researchers as determinants variables which is found as significant variables to predict financial distress (Hill, Perry, & Andes, 1996; Tirapat & Nitayagasetwat, 1999; Darayseh, Waples, & Tsuokalas, 2003; Almilia, 2004). Other macroeconomic indicators used are Money Supply or M2 (Tirapat & Nitayagasetwat, 1999; Almilia, 2004), unemployment rate (Hill, Perry, & Andes, 1996), market index (Darayseh, Waples, & Tsuokalas, 2003; Almilia, 2004), business climate index (Hu & Sathye, 2015), and GNP or GDP growth (Tirapat & Nitayagasetwat, 1999; Darayseh, Waples, & Tsuokalas, 2003).

By taking the aforementioned studies into account and business environment characteristic in Indonesia, this study will utilize inflation, interest rates, market index, exchange rate, and money supply (M2) as external factors to capture systemic risk that might affect firm's failure status. As higher inflation and interest rate has a higher probability of bankruptcy. High inflation means an increase in the cost of production, while high interest rates mean an increase in the cost of borrowing, resulting in poor financial conditions. On the other hand, an increase in M2 will stimulate lower interest rates and stimulate spending. This means firms will produce more and generate more sales.

Meanwhile, the market index represents investor expectation of market in the future. If firm's return has high sensitivity to movement in the market index, firms are riskier. If market index value drops, firm's return or value will drop further. This will

affect firm's business operation, as investors or shareholders are reluctant to invest.

Moreover, most of the Indonesian company listed in the IDX has a huge export transaction. Therefore, the exchange rate has a direct impact on firm's cost of production and profit. In fact, because of depreciation of Rupiah in 2012 and 2013, the nominal value of transaction decreased up to 8%³ compared to 2011. Although there was an increase in volume of export for manufacture products up to 25% compare to 2011

Table 1.1 shown a general review of several previous empirical studies explained above. Table 1.1 indicate the main arguments of each author that used different approach to predict financial distress in different time frame.

³ Based on data from Indonesia Central Bureau of Statistic, Export volume for manufacture products on 2011, 2012 and 2013 are 523, 551 and 655 thousand tons. While, the nominal value of transaction are 162, 153, and 149 Million USD. The information can be access through <http://bps.go.id/>

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Table 1.1.

Summary of main literature review

Author (s)	Beaver	Altman	Ohlson	Mensah
Year	1966	1968	1980	1984
Model	Univariate Analysis	MDA	Logit Analysis	Logit Analysis and Factor Analysis
Data	158 companies using paired analysis. The data was obtained from Moody's Industrial Manual (USA) period of 1954-1964.	66 manufacture companies using paired analysis. The bankrupt group was based on chapter X of the USA national Bankruptcy Act period of 1946-1965	105 failed firms and 2058 non-failed firms. The data was obtained from Moody's Manual and Standard & Poors period of 1970-1978	110 firms using paired analysis. The data referred to Wall Street Journal Index period of 1972-1980
Conclusions	<ol style="list-style-type: none"> 1. Each ratio have different predictive ability 2. Out of 14 ratios, there were 6 ratios that could be best predictor for bankruptcy, which are: cash flow/total debt, net income/total assets, total debt/total assets, working capital/total asset, current asset/current liabilities, no-credit interval. 3. Cash flow/total debt ratio has the best predictive ability to distinguish failed and non-failed firms 5 years before bankruptcy 	<ol style="list-style-type: none"> 1. 5 ratios were used as final discriminant, and ratios retained earnings/total assets contributes the most on explaining the model. 2. Firms with Z-score smaller than 1.81 were classified as failed, while firms with Z-score greater than 2.99 were healthy. 3. MDA showed better predictive ability than Univariate analysis. 	<ol style="list-style-type: none"> 1. Firm size appeared as an important variable to classified firm's bankruptcy status. 2. Logit analysis showed better predictive ability. 3. Logit model offered more simple interpretation and more practical applications 	<ol style="list-style-type: none"> 1. The used of factor analysis on financial ratios shown better normality distribution. 2. Depending on sectors and economic environments, the model showed different predictive ability.

Table 1.1. (Continued)

Summary of main literature review

Author (s)	Year	Model	Data	Conclusions
Morris	1997	Rolling-Logit	140 firms using paired analysis. Listed in UK stock exchange period of 1973-1983	1. Firm's previous year's bankrupt probability was an important predictor throughout all observation period (5 years) 2. The rolling-logit model was able to capture incremental information over time, which can convey more information to assess firms' financial status
Um	2001	Rolling-Logit, Entropy Analysis	385 manufacturing firms listed on stock exchange from 1991-1997	3. The firm's debt level (Total debt/total assets) was a significant predictor of bankruptcy 4. Incremental information and degree of uncertainty cannot predict firm's bankruptcy ahead of time, cause the symptoms did not appear even two years before bankruptcy
Lin and Yang	2012	Rolling-Logit, Component Analysis, Jackknifing Method	104 firms using paired analysis. Sample was a TSE listed companies period of 1999-2005	1. Component earnings, liquidity, and leverage were significant indicators across all period for both model 2. Variable of previous bankruptcy probability had positive and significant relation with present bankruptcy probability 3. Rolling-logit model exhibited higher predictive ability than logit model
Platt & Platt	1990	Logit Analysis	114 firms using paired analysis. Data was obtained from NYSE and AMEX	1. The prediction model that used industry relative ratios has higher classification ability than financial ratios. 2. Type II error of model that used only financial ratios is higher, which means the model predict that firms will bankrupt but they are healthy

Table 1.1. (Continued)

Summary of main literature review

Author (s)	Tirapat & Nittayagasetwat	Almilia	Hu & Sathye	Chen & Shimerda
Year	1999	2004	2015	1981
Model	Logit Analysis (Backward Stepwise)	Logit Analysis (Backward Stepwise)	Logit Analysis and Jackknife Method	Literature study and Component Analysis
Data	396 firms listed on TSE period of 1995-1997	60 firms using purposive sampling method. Data was obtained from IDX period of 1993-2002	150 firms of Hong Kong Growth Enterprise Market period of 2000-2010	1053 firms
Conclusions	<ol style="list-style-type: none"> 1. Macroeconomic factors were important indicators to classify firms' status. 2. The higher the firms' sensitivity to inflation the higher chance to be exposed to financial failure 	<ol style="list-style-type: none"> 1. Industry relative ratios, auditor's reputation, and firm's sensitivity to macroeconomic conditions were factors that affected firms' financial distress condition. 2. The firms' sensitivity analysis using direct method (coefficient regression of multifactor model) have a better predictive ability. 	<ol style="list-style-type: none"> 1. The model that use financial ratios, auditor opinion, and macroeconomic variables showed better predictive ability. 2. As companies may window-dress their financial statement, non-financial and distressed macroeconomic variables can assess the probability of firm's bankruptcy better. 	<ol style="list-style-type: none"> 1. A total of 34 ratios were found as significant variables for predict firms' failure. 2. Financial ratios to predict failure in previous studies can be classified and reduced substantially by using component analysis, as several ratios might have high correlation that leads to misleading

C. Research Question

Post the analysis of literature above, this study poses some important questions, which are:

1. What determinant variables are significant in predicting firm's financial distress level?
2. Which model that can perform better on predicting firm's financial distress?

All of these questions will be answered by developing research that compares the models using systematic and unsystematic factors, such as unadjusted financial ratios, industry relative ratios, and firm's sensitivity to macroeconomic variables. These variables would be analyzed by using rolling-logit analysis as a benchmark and logit analysis as a comparison. This study will use a total of 114 Indonesia's manufacturing companies listed on IDX from 2000-2014 as a sample. A total of 8 companies are grouped as distress firms, while 106 companies are recognized as healthy firms.

D. Purpose of the Study

Seeing divergence in the previous studies, this study attempts to re-examine the existing predicting models using independent variables used in previous research that can indicate firm's financial distress. The independent variables are financial ratio, industry relative ratio, and firm's sensitivity to macroeconomic variables that are calculated separately in a regression equation, which is mention in the literature review above. This study also tries to revisit the rolling-logit model for predicting financial distress and comparing the results with those from the logit regression. Furthermore, the specific purposes of this study are to:

1. Select the determinant variables to be included in financial distress model;

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2. Compare each model's predicting ability and performance

This study intended to utilize existing financial distress model and modifies it into 4 types of financial distress prediction models that uses different combination of independent variables to predict firm's probability of financial distress. These are:

- 1) Model that only uses financial ratios as independent variable;
- 2) Model that only uses industry relative ratios as independent variable;
- 3) Model that use financial ratios and firm's sensitivity to macroeconomic as independent variables;
- 4) Model that use industry relative ratios and firm's sensitivity to macroeconomic as independent variables.

All models will be calculated using both rolling-logit and logit regression. Given the models, the hypotheses of this study are:

1. Some of the variables from financial ratios, industry relative ratios, and firm's sensitivity to macroeconomic variables are significant in predicting financial distress;
2. Previous bankruptcy predicted score is a determinant factor to predict firms' financial distress status.
3. Models that use external factors, which are firm's sensitivity to macroeconomic variables, indicate a higher accuracy level than models that only use internal factors;

II. RESEARCH METHOD

A. Research Design

A quantitative, non-experimental, predictive and secondary research design was conducted to assess whether the rolling-logit prediction model can exhibit higher ability to predict bankruptcy, especially for Indonesia manufacture companies listed in IDX. The rolling-logit model was chosen because it has several advantages compare to other models. First, as rolling-logit model carry the same characteristic with logit model, the analysis can be performed without assuming either normality distribution or group dispersion (Ohlson, 1980; Zavgren, 1983; Doumpus & Zoupundis, 1999). Second, the rolling-logit model offers simple interpretation because the occurrence of financial distress lies on percentage distribution between 0-100% (Zavgren, 1983; Doumpus & Zoupundis, 1999; Ooghe & Balcaen, 2004). The last advantage is the use of previous information as predictor variable which was able to capture the change in firm's characteristics over the year (Morris, 1997; Lin & Yang, 2012).

Furthermore, in this study, the model will utilize both unsystematic and systematic factors as determinant variables that affect the occurrence probability of firm's financial distress. The unsystematic factors will be represented using firm's financial ratios, while the systematic factors will be captured by firm's sensitivity toward macroeconomic variables using multifactor model. Meanwhile, the dependent variable of this study is in the form of a binary variable. A binary variable was preferred to designate the firm's financial distress status. The value of 0 indicates the status of healthy firms, while the value of 1 will indicates financially distress firms.

B. Sample and Data Collection

Sample method: This study used a non-probability, purposive sampling plan to collect data for bankrupt and non-bankrupt companies. The information about the firms will be collected from the manufacture companies listed in the IDX from 2000-2014. The reason the study choose those specific samples was because manufacture companies in Indonesia contribute more than 20% to the GDP⁴ (BPS, 2016) and employs large number of workers. If the industry faces financial distress, then it will have a systematic impact for Indonesian Economy. Further criterions for sample selection in this study were:

- a. Listed in Indonesia Stock Exchange (IDX) and categorized as manufacture companies from 2000-2015
- b. Firms with complete financial statement for the fiscal year 2000-2014

Based on criteria mention above, samples are grouped as distress and non-distress or healthy firms. Following Ross and Westerfield (pp. 885-856, 1993), distress firms are firms that have negative net worth or negative book equity value. While healthy firms are firms that have positive book equity value. As this study will predict firm's bankruptcy probabilities in the fiscal year 2015, therefore firms with negative equity value in 2015 are distress firm and vice versa for the non-distress firm. Hence, from the total population of 528 companies listed in Indonesia Stock Exchange in 2015, only 114 companies have published their complete financial statement for the fiscal year 2000-2014. A total of 8 companies are grouped as distress firms, while 106 companies are grouped as healthy firms.

⁴ <http://bps.go.id/linkTabelStatis/view/id/1199>

Data collection: The data for this study is secondary data collected from the balance sheet, income statement, and shares traded performance of each manufacture's firms listed in IDX period of 2000-2015. Whereas the macroeconomic variables, which were inflation, interest rate, market index, foreign exchange rate, and M2, will be collected from the website of Central Bank of Indonesia and Indonesia Central Bureau of Statistic, in the form of monthly data (time series data). The corresponding data for financial ratios and industry relative ratios were obtained from the firm's yearly financial statement from Indonesian Capital Market Directory, published by the IDX and official website of each company. The type of data for financial ratios and industry relative ratios are pooled cross-sectional data.

C. The Operational Definition of Variables

Dependent variable (Y) in this study was a binary variable that represents the status of distress and non-distress firm during the observation period. According to financial distress criteria of this study, a distressed company was indicated as 1 if during the observation period (the fiscal year 2015) have negative book equity value. Then a non-distress firm was represented as 0 if during observation period have positive book equity value.

Meanwhile, the independent variables consisted of financial ratios, industry relative ratios, and macroeconomic variables. Financial ratios and industry relative ratios are firms' specific risk or firms' unsystematic risk. The classification of financial ratios used in this study followed the study done by Chen and Simerda (1981). Based on their study 34 ratios were found to be significant to predict financial distress. However, based on

factor loadings result, 10 ratios can be represented by other ratios. Therefore this study will only use 24 ratios, classified into 7 factors. Moreover, industry relative ratios were calculated using financial ratios of each firm divided by the average value of each industry ratios. Below is the formula to calculate industry relative ratios:

$$\text{Industry Relative Ratios}_{i,j} = \frac{\text{Firms' } i \text{ ratio } (X_{i,j})}{\text{Average ratio } \bar{X}_j} \times 100$$

Moreover, for the macroeconomic variables (F_k), this study used the annual growth rate of inflation, market index, risk-free rate of Indonesian' Government obligation, real effective exchange rate of USD to IDR, and money supply (M2), which will be computed as follow:

$$\text{Growth rate of } \hat{F}_k = \frac{F_{k,t} - F_{k,t-1}}{F_{k,t-1}} \times 100$$

The computed macroeconomic conditions above will be used to estimate firms' systematic risk, which will be obtained through multifactor model according to the following equation:

$$\hat{R}_i = \beta_{0,i} + \sum_k \beta_{k,i} \hat{F}_k + e_i$$

\hat{R}_i is the estimated monthly stock return of firm i , $\beta_{k,i} \hat{F}_k$ or the coefficient of regressions is the estimated firms' i sensitivity to macroeconomic variables \hat{F}_k , which represent the systematic risk of the firm i . The last independent variable, which is previous bankruptcy probability (PBP), was the predicted bankruptcy probability value that calculated from the previous period. Table 2.1 below show the summary of the operational definition for each variable.

Table 2.1*Operationalization variable*

Variable	Sub-Variable	Criteria / Classification	Measurement	Scale
Y	Y=1	Distress firms	Negative net worth ⁵	Nominal
	Y=0	Healthy firms	Positive net worth	Nominal
X _{i,j}	X _{1,i}	Return on investment	Funds flow ⁶ / net worth	Ratio
	X _{2,i}		Funds flow / total assets	Ratio
	X _{3,i}		Net income / total assets	Ratio
	X _{4,i}		Net income / net worth	Ratio
	X _{5,i}		Earnings before interest and taxes / sales	Ratio
	X _{6,i}		Earnings before interest and taxes / total assets	Ratio
	X _{7,i}	Capital turnover	Quick assets ⁷ / total assets	Ratio
	X _{8,i}		Funds flow / sales	Ratio
	X _{9,i}		Current assets / total assets	Ratio
	X _{10,i}		Net worth / sales	Ratio
	X _{11,i}		Sales / total assets	Ratio
	X _{12,i}	Financial leverage	Total liabilities / total assets	Ratio
	X _{13,i}		Total liabilities / net worth	Ratio
	X _{14,i}	Short-term liquidity	Current assets / current liabilities	Ratio
	X _{15,i}		Quick assets / current liabilities	Ratio
	X _{16,i}		Current liabilities / net worth	Ratio
	X _{17,i}		Current liabilities / total assets	Ratio
	X _{18,i}	Cash position	Cash ⁸ / sales	Ratio
	X _{19,i}		Cash / total assets	Ratio
	X _{20,i}		Cash / current liabilities	Ratio
	X _{21,i}	Inventory turnover	Current assets / sales	Ratio
	X _{22,i}		Inventory / sales	Ratio
	X _{23,i}		Sales / working capital ⁹	Ratio

⁵ Net worth was calculated by subtracting total liabilities from total assets

⁶ Funds flow was calculated from change in net working capital ($WC_t - WC_{t-1}$)

⁷ Quick assets was calculated by subtracting inventory from current assets

⁸ Cash was estimated using account cash and cash equivalents in balance sheet statement of each firms

	$X_{24,i}$	Receivable turnover	Quick assets / sales	Ratio
$M_{i,j}$	$M_{i,j}$	Industry relative ratios	Each measurement in variable $X_{i,j}$ divided by the average value of X_j	Ratio
$\beta_{k,i}\hat{F}_k$	$\beta_i\hat{F}_1$	Firms' sensitivity to macroeconomic factor	β_i of Inflation growth	Ratio
	$\beta_i\hat{F}_2$		β_i of time deposit rate growth	Ratio
	$\beta_i\hat{F}_3$		β_i of money supply growth	Ratio
	$\beta_i\hat{F}_4$		β_i of real effective exchange rate growth	Ratio
	$\beta_i\hat{F}_5$		β_i of market index growth	Ratio
PBP_t	PBP_t	Previous bankruptcy probability (P_{t-1})	$\ln \frac{P_{t-1}}{1 - P_{t-1}}$	Ratio

D. Method of Data Analysis

According to sample and collected data, this study analyzed a research design to predict financial distress by using the programs of Microsoft Excel version 2010, SPSS version 13.0, and STATA version 13.0. Several statistical procedures, such as descriptive statistics, Mann-Whitney U test, independent t-test, the backward stepwise logit regression, and jackknife validation method were used to examine research questions and test the hypotheses.

There are two research questions that will be answered through this study. The first question is to find out what are the determinant variables that are significant in predicting firms' financial distress level. In order to answer those question two hypothesis will be tested, with null hypothesis written as $H_0: X_{i,j}, M_{i,j}, \beta_{k,i}\hat{F}_k, PBP_t = 0$ (there are no significant variables on predicting firms' financial distress level); and alternative hypotheses written as $H_a-1: X_{i,j}, M_{i,j}, \beta_{k,i}\hat{F}_k \neq 0$ (at least one variables from financial

⁹ Working capital was calculated by subtracting current liabilities from current assets

ratios, industry relative ratios, firms' sensitivity to macroeconomic variables is significant in predicting firms' financial distress level); Ha-2: $PBP_t \neq 0$ (previous bankruptcy probability is significant on predicting firms' financial distress level, thus rolling-logit model is useful to predict the probability of firm's financial distress).

The second research question is to seek which model can perform better on predicting firms' financial distress by comparing the predictive ability of each model. Based on the previous scholarship, this study wants to reconfirm that model which use external factors will perform better compared to models that only use internal factors (financial ratios or industry relative ratios), with hypothesis notate as H0:

$$P_{it}[X_i|\beta_{k,i}\hat{F}_k] = 0, \text{ and Ha: } P_{it}[X_i|\beta_{k,i}\hat{F}_k] \neq 0.$$

Therefore, to answer research questions above, this study will conduct the following step to test the hypothesis:

1. Define dependent variable from the list of distress and non-distress firms in the IDX on the period of 2015. Dependent variable (Y) equal to 1 for distress firms and 0 for non-distress firms;
2. Analyze the profile characteristics of distress and non-distress sample by using descriptive statistic procedure and Mann-Whitney U test: Descriptive statistic provides an overview of the sample allowing the identification of presence of systematic difference between distress and non-distress groups. The mean comparison test using Wilcoxon rank sum test (called Mann-Whitney-U test) will also perform to reaffirm the systematic difference of groups. The Mann-Whitney U test is similar to the independent t-test, which was able to analyze whether two independent groups that gathered from the same population have equal means or

not. This method does not require the sample to be normally distributed. The profile characteristic will be conducted based on calculated firm's financial ratios from period of 2000-2014;

3. Calculate the prediction model using stepwise backward on logit regression:

(Tirapat and Nittagayasetwat, 1999; Almilia, 2004). By using backward stepwise on logit regression, will allow the analysis to eliminate insignificant variables based on researcher's acceptable confidence level. This study will use 95% confidence level, so variables that are insignificant at the minimum significant level 0.05 will be automatically dropped from the logit regression. The standard formula for logit regression is $Prob (Y_i = 1) = \frac{1}{1 + e^{-Z_i}}$, whereas Z_i will be defined in 4 different equation as follow:

$$Z_i = a + \sum_j b_j X_{j,i} + e_i \quad (\text{equation 1})$$

$$Z_i = a + \sum_j b_j M_{j,i} + e_i \quad (\text{equation 2})$$

$$Z_i = a + \sum_j b_j X_{j,i} + \sum_k C_{k,i} \hat{F}_k + e_i \quad (\text{equation 3})$$

$$Z_i = a + \sum_j b_j M_{j,i} + \sum_k C_{k,i} \hat{F}_k + e_i \quad (\text{equation 4})$$

4. Calculate the prediction model using backward stepwise on rolling logit

regression. The regression uses a logit regression formula, but adds the previous predicted probability value (P_{t-1}) as an additional independent variable in order to capture previous information. The main formula of rolling-logit regression is similar with logit regression, which is $Prob (Y_i = 1) = \frac{1}{1 + e^{-Z_i}}$, but the component variables will be different. The following 4 equations to be tested will be as follow:

$$Z_i = a + \sum_j b_j X_{j,i} + \widehat{Z_{i,t-1}} + e_i \quad (\text{equation 5})$$

$$Z_i = a + \sum_j b_j M_{j,i} + \widehat{Z_{i,t-1}} + e_i \quad (\text{equation 6})$$

$$Z_i = a + \sum_j b_j X_{j,i} + \sum_k C_{k,i} \widehat{F}_k + \widehat{Z_{i,t-1}} + e_i \quad (\text{equation 7})$$

$$Z_i = a + \sum_j b_j M_{j,i} + \sum_k C_{k,i} \widehat{F}_k + \widehat{Z_{i,t-1}} + e_i \quad (\text{equation 8})$$

5. A validation test to obtained significant variables using jackknife method:

Jackknife method is a cross validation technique by an iterative process. This method is useful because by using a relatively small sample, researchers can obtain the parameters. The method will first estimate from the whole sample, then do partial estimation by dropping each element (iterative). This method will provide unbiased prediction estimators of predicted Y values from the set of independent variables for each model;

6. Compare the predictive ability of each equation by using the cut-off point 0.5:

When performing a logit regression, cut-off point 0.5 is a general rule assuming that both classification errors have symmetric loss function. It means the cost of predicting the associated event (distress and healthy) is the same. The comparison of overall predictive ability will be conducted as far back as 6 years before bankruptcy for logit regression. Then, as rolling-logit regression used estimated probability information from previous year, the comparison will perform up to 5 years before bankruptcy. This result will help to examine the significances of previous information and the usefulness of rolling-logit regression to predict bankruptcy for manufacture companies listed on the IDX.

III. EMPIRICAL RESULTS

This paper wants to develop an empirical analysis to answer the research questions and to test the hypotheses. Therefore, this chapter is organized into two sections. The first part is the descriptive analysis of the sample firms in order to determine the characteristics of distressed and healthy firms. The second section concentrates on hypothesis testing to find out the determinant variables to predict the firm's financial distress. It reconfirms if the utilization of macroeconomic variables will lead to better predicting ability, and also validate if the previous bankruptcy information is one of determinant factor to predict firm's financial distress.

A. Characteristic of Distress and Healthy Firms

Based on the dataset collected from Indonesia Capital Market Directory, there were 8 companies that were declared distressed and 106 companies were recognized as healthy. The determinant factor that classified firms' status is based on their net worth value. According to Ross and Westerfield (pp. 885-856, 1993), distress firms are those that have negative net worth or book equity value, and vice versa for healthy firms. This study used the negative net worth value of the fiscal year 2015 to define bankrupt firms. Thereafter the mean average of each ratio is calculated for each observation by using the financial statement period of 2000 to 2014.

Table 3.1 presents the general characteristics of each group of the firm based on average and standard deviation value of each financial ratio, including the *p-values of* Mann-Whitney-U test. Based on the outcome of Mann-Whitney-U test all ratios were having a statistically significant difference between bankrupt and healthy firms. Ratio

funds flow to sales and current assets to sales were significant at 10 percent significant level. The ratio funds flow to net worth, funds flow to total assets, and inventory to sales was significant at 5 percent significant level. While the rest of ratios were significant at 1 percent significant level.

Table 3.1

The characteristic of distress and healthy firms based on internal factors

Classification	Variable		Total Sample		Distress		Healthy		M-W Test (p-value)
			Mean	SD.	Mean	SD	Mean	SD	
Return on Investment	X _{1,i}	ffnw	1.53	61.89	-0.91	9.74	1.71	64.12	0.027
	X _{2,i}	ffta	0.03	0.64	0.04	0.38	0.03	0.66	0.034
	X _{3,i}	nita	0.05	0.19	-0.06	0.15	0.06	0.19	0.000
	X _{4,i}	ebits	0.19	5.13	-0.20	4.42	0.22	5.19	0.000
	X _{5,i}	ninw	0.06	0.30	-0.07	0.25	0.07	0.30	0.005
	X _{6,i}	ebitta	0.09	0.14	-0.01	0.10	0.10	0.14	0.000
Capital Turnover	X _{7,i}	qata	0.34	0.33	0.26	0.16	0.34	0.34	0.000
	X _{8,i}	ffs	0.03	0.83	0.01	1.24	0.04	0.79	0.090
	X _{9,i}	cata	0.55	0.40	0.44	0.21	0.55	0.41	0.000
	X _{10,i}	nws	0.41	1.60	-1.14	2.92	0.53	1.38	0.000
	X _{11,i}	sta	1.18	0.95	1.03	0.70	1.19	0.97	0.003
Financial Leverage	X _{12,i}	tlta	0.64	0.59	1.49	0.90	0.58	0.50	0.000
	X _{13,i}	tlnw	2.93	50.57	14.66	161.4	2.04	28.09	0.001
Short Term Liquidity	X _{14,i}	qacl	2.63	13.17	1.21	1.97	2.74	13.65	0.000
	X _{15,i}	qacl	1.80	10.78	0.72	1.53	1.88	11.17	0.000
	X _{16,i}	clnw	1.51	28.49	9.37	105.3	0.92	6.19	0.000
	X _{17,i}	clta	0.43	0.43	0.90	0.77	0.39	0.38	0.000
Cash Position	X _{18,i}	cashs	0.09	0.15	0.03	0.03	0.10	0.16	0.000
	X _{19,i}	cashta	0.09	0.13	0.03	0.05	0.10	0.13	0.000
	X _{20,i}	cashcl	0.50	2.37	0.07	0.15	0.54	2.45	0.000
Inventory Turnover	X _{21,i}	cas	0.59	0.68	0.60	0.67	0.59	0.68	0.056
	X _{22,i}	invs	0.23	0.32	0.24	0.16	0.23	0.33	0.017
	X _{23,i}	swc	3.30	184.1	9.90	124.26	2.81	187.84	0.000
Receivables Turnover	X _{24,i}	qas	0.36	0.47	0.38	0.61	0.36	0.45	0.002

Source: Author computation

Moreover, if we consider the results from descriptive statistics (mean and standard deviation value), and analyze the difference of the average magnitude of each ratio from each group, there were two classification categories that have high deviation between a healthy firm and distressed firm. Healthy firms have a higher value in cash position classification, while a bankrupt firm has higher a value in their financial leverage ratio. As observed in table 3.1, the average value of total liabilities to net worth of distressed firms was seven times larger, which is 14.66 point, while average value of the same ratio for healthy firms were only 2.04 points. Table 3.1 also indicated that the average value of ratio current liabilities to net worth of healthy firms was ten times smaller compared to distress firms, with results 0.92 points and 9.37 points respectively.

On the other hand, the mean value of ratio cash to current liabilities of healthy firms was seven times larger than distress firms, which is 0.54 points, while the value of the same ratio for bankrupt firms were only 0.007 points. The mean value of cash to sales and cash to total asset of healthy firms also appeared to be three times higher compare to distress firms. Additionally, the average value of EBIT to total assets ratios of healthy firms was positive and twelve times larger compared to distress firms with value of 0.10 points and negative 0.01 points respectively.

Furthermore, the computed results of the average value of financial ratios for healthy firms, as general, more represents the value of manufacturing industry (total sample), as the results showed that the value was almost similar compared to the mean value generated by bankrupt firms. In this context, it can be sid that healthy firms are better able to raise cash and finance their operational expenses, also short term obligations by

utilizing their assets, especially liquid assets (cash). Meanwhile, bankrupt firms have difficulty in generating cash and profits, as they have lower cash position and negative earnings ratios. Moreover, distress firms mostly finance their activities through a high proportion of debt. Therefore, the results of mean and standard deviation statistics clearly reveal that distress firms exhibited lower performance in managing their assets and have a huge proportion of debt, which leads to lower ability to generate profit and cash.

B. Hypothesis Testing Results

As mentioned in Chapter II, this study will analyze eight equations using different combination of independent variables applying logit prediction model and rolling-logit prediction model. The general formula for both logit regression and rolling-logit regression are $Prob (Y_i = 1) = \frac{1}{1 + e^{-z_i}}$. As rolling-logit regression is a method to capture previous information, the model will add a unique additional variable which notates as “ $\ln \frac{P_{t-1}}{1-P_{t-1}}$.” In order to generate variables that have confidence level higher than 95%, a backward stepwise regression technique was conducted, as had been done in the previous study (Tirapat & Nittayagasetwat, 1999; Almilia, 2004).

The analysis result that answered research question 1 was illustrated in Table 3.2 and Table 3.3. As observed in Table 3.2, there are 17 variables that are significant in determining firms' bankruptcy status with confidence level higher than 95%¹⁰. Therefore this study accepts alternative hypothesis which said, there are determinant factors from financial ratios, industry relative ratios, and firm's sensitivity to macroeconomic variables that are statistically significant to predict firm's financial distress.

¹⁰ For detail of coefficient regression results see Appendix A1 to A8

There were 6 variables that exhibit a significant positive relationship, including total liabilities to total assets, cash to total assets, inventory to sales, quick assets to total assets, firm's sensitivity to money supply (M2), and previous year bankruptcy probability. A positive relationship that is to say an increased value of those specific ratios will lead to a higher likelihood to be classified as distressed firms. Meanwhile, the rest of the variables have shown an inverse relationship, which includes EBIT to sales, EBIT to total assets, funds flow to net worth, current assets to total assets, net worth to sales, sales to total assets, current liabilities to total assets, cash to sales, current assets to sales, quick assets to current liabilities, and firm's sensitivity to real exchange rate. This inverse relationship means that the likelihood of firms' being classified as distressed decreases as the value of those financial ratios increases.

Moreover, as each equation was regressed as far as 6 years before bankruptcy, there were variables that appeared to be significant only in one period for a specific equation, such as EBIT to total assets, funds flow to net worth, current assets to total assets, sales to total assets, total liabilities to total assets, current liabilities to total assets, cash to total assets, current assets to sales, inventory to sales, quick assets to sales, quick assets to current liabilities, firm's sensitivity to money supply (M2), and firm's sensitivity to real exchange rates.

Meanwhile some variables exhibited consistent appearance throughout the years for some equation, which is EBIT to sales (eq. 5), net worth to sales (all eq.), cash to sales (all eq.), current assets to sales (eq. 1 to 4), and previous year bankruptcy probability (eq. 5 to 8). Variable EBIT to sales, performed a consistent significant result for the entire equation, although not the entire year for all equations. Additionally, three of previous

variables mentioned had shown consistency not only as far as 6 years before bankruptcy, but also on the entire equation. Those variables were net worth to sales, cash to sales, and previous year bankruptcy probability. Also, the variable current asset to sales was significant through the year for the equation that used logit regression. The highlighted column was indicating that the specific variables exhibited constant significant results for every year.

Table 3.2

Summary of significant variables

Ratios	Equation							
	1	2	3	4	5	6	7	8
EBIT to sales	***	***	***	***	**	***	***	***
EBIT to total assets							**	
Funds flow to net worth					**		**	
Current assets to total assets							***	
Net worth to sales	***	***	***	***	***	***	***	***
Sales to total assets	**	**	**	**		**		**
Total liabilities to total assets	***	***	***	***				
Current liabilities to total assets	**	**	**	**				
Cash to sales	***	***	***	***	***	***	***	***
Cash to total assets		***		**		**	***	**
Current assets to sales	***	***	***	***	**	**	***	***
Inventory to sales	**	**	**	**		***	**	**
Quick assets to sales	**	**	**	**		**	**	**
Quick assets to current liabilities	**	**	**	**			**	**
Firms' sensitivity to M2			**	**			**	***
Firms' sensitivity to real exchange rate			**	**				
Previous Bankruptcy Probability					***	***	***	***

Note: “***” resemble 95% confidence, while “****” resemble 99% confidence level. Highlight color showed a consistent appearance up to 6 years before bankruptcy

Furthermore, to validate the results from Table 3.2, a jackknife validation method was conducted to obtain unbiased predictor of Y (bankruptcy probability). Table 3.3 present the result of same variables after validation process. Based on Table 3.3, there were 5

variables that become insignificant, which are EBIT to sales, funds flow to net worth, total liabilities to total assets, current liabilities to total assets, and quick assets to current liabilities

Additionally, another surprising outcome was found after validation process. Ratio EBIT to sales, which exhibited consistency throughout the equation, turned out to be insignificant in equation 4, 5, 6, 7, and 8. Similar results were seen with the variable ratio funds flow to net worth, total liabilities to total assets, current liabilities to total assets, quick assets to current liabilities. However, ratios that performed consistently significant up to 6 years before bankruptcy throughout entire equation displayed the same outcomes.

In conclusion, refer to Table 3.2 and Table 3.3, there were only 3 variables that showed a high reliability, which are variable net worth to sales, cash to sales, and previous year bankruptcy probability, as it's exhibited constant performance not only throughout the entire equation but also significance as far as 6 years before bankruptcy; and even after the jackknife validation process was conducted. This study can also conclude that the symptoms of distress firms can be shown from their previous internal performance as far back as 6 years before bankruptcy.

Table 3.3

Results of jackknife validation test

Ratios	Equation							
	1	2	3	4	5	6	7	8
EBIT to sales	*	*	*					
EBIT to total assets							*	
Funds flow to net worth								
Current assets to total assets							**	
Net worth to sales	***	***	***	***	***	***	***	***
Sales to total assets	*	*	*	*		**		**
Total liabilities to total assets								

Current liabilities to total assets									
Cash to sales	***	***	***	***	***	***	***	***	***
Cash to total assets				*		*	***	**	
Current assets to sales	***	***	***	***			***	***	
Inventory to sales	***	***	***	***		***	***	***	
Quick assets to sales	**	***	***	***		***	**	**	
Quick assets to current liabilities									
Firms' sensitivity to M2			**	**			***	***	
Firms' sensitivity to real exchange rate			**	**					
Previous Bankruptcy Probability						***	***	***	***

Note: “***” resemble 95% confidence, while “****” resemble 99% confidence level.

Highlight color showed a consistent appearance up to 6 years before bankruptcy

Following the general cut-off point 0.5¹¹ in standard logit estimation, table 3.4

displayed the summary of the predicting ability of both logit regression and rolling-logit regression. The use of cut-off 0.5 means that the observations which have $P(Y=1)$ value estimation equal to or higher than 0.5, will be declared as distress firm. Then, if $P(Y=0)$ value estimation lower than 0.5, the observations will be declared as healthy firm. As observed in table 3.4, the equation that was calculated by rolling-logit regression exhibited a little higher predicting ability compared to logit regression. Therefore, this study successfully reassesses the utilization of rolling-logit regression, in the case of manufacture companies listed in IDX using observation period 2000-2015.

Table 3.4.

Summary of predicting performance of each model

Logit	T-6	T-5	T-4	T-3	T-2	T-1	Average	Type 1	Type 2
Eq. 1	0.9395	0.9410	0.9423	0.9399	0.9398	0.9427	0.9409	0.0515	0.0076
Eq. 2	0.9368	0.9402	0.9423	0.9399	0.9405	0.9427	0.9404	0.0517	0.0079
Eq. 3	0.9386	0.9410	0.9423	0.9399	0.9405	0.9427	0.9408	0.0516	0.0076
Eq. 4	0.9421	0.9402	0.9423	0.9399	0.9398	0.9421	0.9411	0.0518	0.0072

¹¹ Author has tried different cut off point, ranging from 0 to 1 with scale 0.1, and the best results was using the cut-off point 0.5

Rolling-logit									
Eq. 5		0.9439	0.9450	0.9437	0.9413	0.9417	0.9431	0.0499	0.0070
Eq. 6		0.9430	0.9418	0.9423	0.9413	0.9424	0.9421	0.0496	0.0083
Eq. 7		0.9412	0.9450	0.9437	0.9420	0.9430	0.9430	0.0498	0.0073
Eq. 8		0.9430	0.9418	0.9423	0.9399	0.9436	0.9421	0.0499	0.0080

Moreover, the model that appeared to have the highest performance was equation 5, which only used financial ratios as an independent variable with a predicting ability of 94.31 percent that was calculated through the rolling-logit regression. Meanwhile, the model that showed the lowest predicting ability, with only 94.04 percent, were equation 2, which only used industry relative ratios as an independent variable, calculated through logit regression. Thus financial ratios or firm's specific risk with previous bankruptcy information were preferable in predicting bankruptcy probability as the ratios might already capture and represent the industry and macroeconomic condition.

This study was unable to successfully reaffirm the argument from previous research which said the model that use financial ratios and macroeconomic variables were able to perform better than models that apply only financial ratios (Tirapat & Nittayagasetwat, 1999; Almilia, 2004; Hu & Sathye, 2015). As observed in table 3.4, the equation that included the firm's sensitivity to macroeconomic variables exhibited a lower performance compared to the equation that only uses internal factors, which is financial ratios and industry relative ratios. Furthermore, as this study found a positive association of PBP variables to firms' probability of financial distress and the rolling-logit regression in general performed better. Therefore it was able to reaffirm previous research carried out by Morris (1997) and Lin and Yang (2012) and proved the usefulness of rolling-logit model to predict financial distress.

Additionally, it is also important to consider percentage error of each model performance, which is including type 1 and type 2 errors. Type 1 error indicates that the observation was predicted to be healthy firm, but the actual status was bankrupt firm. While type 2 error indicates that the observation was predicted as bankrupt firm, but the actual status was healthy firm. In this regard, type 1 error appeared to be more costly as it can lead to a potential lawsuit and negatively impact stakeholders, especially creditors and investors. However, type 2 error will have more negative impact on firms as it will harm the firm's reputation, as the result of accused healthy firms as bankrupt.

According to table 3.4, model that used rolling-logit regression not only exhibited a general higher predicting ability, but also lower type 1 error compare to model that used logit regression. Model 6, which used rolling-logit regression and industry relative ratios as independent variables, exhibited the smallest percentage of type 1 error, which only 4.96 percent. This means that model 6 was only 4.96 percent falsely accused default firm as healthy firm. Meanwhile, model that use industry relative ratios and firm's sensitivity to macroeconomic variables through logit regression (equation 4) shown the highest value of type 1 error, which is 5.18 percent

Whereas, as for type 2 error, the model that used only financial ratios, calculated by rolling-logit regression (equation 5), exhibited the lowest value, around 0.70 percent. This means that the model was only 0.70 percent falsely accused healthy firm as default firm. In addition, although model 6 has lowest type 1 error, but it has the highest type 2 error, 0.83 percent. In general, the model with logit regression and rolling-logit regression, in average exhibited low type 2 error, which was less than 1 percent.

In conclusion, as it observed in Table 3.4, all equations did not show a big difference either in predicting ability, type 1 error, and type 2 error. Nonetheless, all models showed a steady result on predicting ability as far as 6 years before bankruptcy, unlike the results of the previous study.

IV. DISCUSSION

The purposes of this study is to re-examine the existing predicting models by utilizing independent variables used in the previous studies, which are financial ratios, industry relative ratios, and firm's sensitivity to macroeconomic variables. This study also attempts to investigate the usefulness of previous bankruptcy probability information through rolling-logit regression, and thereafter compare the overall performance with logit-regression. All of those processes were conducted by using 114 Indonesia listed manufacture companies during the period 2000-2015, which were divided into 8 distress firms and 106 healthy firms.

According to empirical results in Chapter III, 17 variables were found to be significant as determinant factors to predict the probability of firm's financial distress. The variable firm's sensitivity to macroeconomic variables exhibited bias results, as it only appeared to be significant in 2 years before bankruptcy. Meanwhile, the overall predicting ability of rolling-logit regressions, in general, were slightly higher than logit regression, where equation 5 that used financial ratios as independent variables had shown the highest predicting ability. In addition, variable net worth to sales, cash to sales, and previous year bankruptcy probability showed a reliable result as it exhibits significantly across the model and up to 6 years before bankruptcy. This chapter provides the interpretations and implications of the empirical study, which cover the finding on determinant factors and prediction model; the limitation of this study and recommendation for the future research.

A. Determinant Factors

As observed in the results from Mann-Whitney U test, all financial ratios displayed a significant difference between bankrupt and healthy firms, with at least 90 percent confidence level. According to model regression results, as displayed in Table 3.2 and 3.3, there were 17 significant variables to predict firms' financial distress probability, which were 14 ratios out of 24 ratios financial ratios (industry relative ratios), two firm's sensitivity to macroeconomic variable (money supply and real exchange rate), and previous year's bankruptcy probability.

Financial ratios and industry relative ratios. As observed in Chapter III, 14 ratios have shown significant results based on logit regression and rolling-logit regression. Post the validation test through jackknife method, only 10 variables remained significant. Those variables were EBIT to sales, EBIT to total assets, current assets to total assets, net worth to sales, sales to total assets, cash to sales, cash to total assets, current assets to sales, inventory to sales, and quick assets to sales.

The variable that had a positive association with default risk probability is cash to total assets, inventory to sales, and quick assets to total assets. In accordance with the inventory to sales ratios, it means that the longer it takes for the company to sell their inventory and turned it into sales, the higher chance the company to face financial distress risk. In fact, the high value of inventory to sales ratio is known as common recession indicators because as the idle inventory increases, it will lead to a decrease in the number of sales.

Furthermore, in terms of ratio cash to total assets and quick assets to sales, the results imply that the more efficient the firm generates cash and short-term liquid assets from

operations or their sales activity, the higher probability of financial distress. Yet, these positive associations are uncommon¹². The more liquid and the higher ability of the firm to generate liquid assets, the lower probability of financial distress. The contrary relationship might happen because too much cash holdings receivables showed that there is a probability that management has run out of investment opportunities or they might be unable to decide how they should effectively spend their liquid assets (idle assets). This uncommon scenario can happen because up to a particular level, a ratio can indicate financially healthy firms, but after some points, that sign might diminish (Sayari & Mungan, 2016).

Furthermore, the rest seven ratios exhibit a negative association with firm's probability of financial distress, which inferred that the higher the value of that ratio the lower the probability of financial distress. With regards to EBIT to sales, EBIT to total assets, and sales to total assets ratio, the results can be judged as the higher the ability of the company to generate earnings or profit from their business operation, the lower the chance of the company to face default risk. With respect to cash to sales and current assets to sales, the outcome might be defined as the higher the firms' ability to turn sales into cash or liquid assets (current assets), the lower the probability of financial distress. Moreover, the ratio of net worth to sales revealed an adequate proportion between investment (net worth – equity) and sales activity. Thus the better the ability of the company to obtained more sales with a thin margin on their investment, the likelihood of the company to suffer financial distress will decrease. Lastly, in terms of current assets to

¹² Previous study done by Sayari and Mungan (2016), Daekin (1972) had shown similar results, i.e.. an increase in ratio cash to total assets and quick assets to sales will increase the likelihood of firm's financial distress. Unfortunately, both studies were unable to explain in more details why these outcomes arose.

total assets ratio, the larger proportion of current assets, the lower probability of financial distress. All ratios mentioned is classified as return on investment

All mentioned ratios above are classified as return on investment, capital turnover, cash position, inventory turnover, and receivables turnover. Accordingly, the previous study which was done by Mensah (1984) advocate that ratios related to capitalization, cash flow, inventory intensiveness, and receivable intensiveness, were the most useful to predicting financial distress, especially in the recession. Meanwhile, most of the studies support the importance of profitability or return on investment ratios as predictor of financial distress (Altman, 1968; Daekin, 1972; Ohlson, 1980; Shumway, 2001; Liang, 2016)

In conclusion, this study can infer that the higher the ability of the firm to generate earnings, cash, and liquid assets from their business activity will decrease the chance of financial distress risk. As higher profit and liquid assets will assure the continuity of firms, thus they will able to pay their debt and other obligations. Meanwhile, the company that mismanages their assets or hold a huge number of inventories will have a higher probability of financial distress. There is also a possibility where a firm with large amount of cash, who does not invest or seek out investment opportunity, also run the risk of financial distress

Macroeconomic factors. Previous studies suggested the use of external factor such as macroeconomic variables to be put in financial distress regression model. The reason is the external factor might able to capture the movement of environment or firm's systematic risk (Balcaen & Ooghe, 2004). Following that suggestion, this study develops a model that used firm's sensitivity to macroeconomic variables, which was calculated

through equation 3, 4, 7, and 8. The outcome from the previous chapter has shown that the firm's sensitivity to money supply (M2) have significant result with positive association, while the firm's sensitivity to real exchange rate exhibit significant result with a negative association.

In regards to firm's sensitivity to money supply, the results indicate that an increasing supply of money in the market will lead to a higher chance of firm to face distress risks. In the short term, an increasing amount of money supply is to increase aggregate demand and reduce the interest rate. However, in the long run, as aggregate demand increases, private consumption will increase the demand for more money which in turn will result in high demand for borrowing. An increasing demand of borrowing will bring about in an increase in interest rate (dampening effect). Therefore that might be the reason why the significant results were exhibited at 1 year and 2 years before bankruptcy for logit regression, and only 2 years before bankruptcy for rolling-logit regression model, which is because of lack effect. This result showed a possibility that the policy related to money supply not directly affecting firms after several years.

Moreover, in term of firm's sensitivity to real exchange rate, the negative association means that the firm will face an increasing probability of financial distress when real exchange rate decrease, in other words when the domestic currency depreciates. Yet, as it observed from table 3.4 in the previous chapter, those variable only showed a significant result in 6 years before bankruptcy, which was only in logit regression. This outcome might be because the effect of the global financial crises in 2008 that caused a sudden rise in the real exchange rate in Indonesia. As the sample used manufacture industry, a sudden increase in the real exchange rate will negatively affect a firm's earning because the

depreciation of domestic currency will raise the cost of production. Also, as the rolling-logit regression did not regress the results up to 6 years before bankruptcy (2009), real exchange rate did not reflect a significant result. It may be said that a sudden hike in macroeconomic factors, which is real exchange rate, can lead to the higher probability of firm's financial distress. Yet, a normal or stable increase of real exchange rate might not have any effect on firm's probability of financial distress.

B. Evaluation of Prediction Model Ability

This paper attempted to revisit the rolling-logit regression as the prediction model for firm's financial distress by using the sample of 114 manufacture companies listed in the Indonesia stock exchange. The empirical result successfully proved that the rolling-logit model, in general, exhibits a slightly higher predicting ability and lower type 1 error compared to the logit model. It was also able to verify the significant result of previous year bankruptcy probability (PBP) as the determinant factor to predict firm's financial distress¹³. Therefore, this study validated the usefulness of rolling-logit model to predict financial distress as have been done in the previous study (Morris, 1997; Lin & Yang, 2012). In summary, the evidence or symptoms of bankruptcy appears not only one year before bankruptcy, but up to 5 years before bankruptcy, as the significant of PBP was found up to T-5. Moreover, this study can also conclude that higher distress risk faced by

¹³ Author did additional regression to validate the significant of PBP variable when using different year of prediction status, which mean not only to predict bankruptcy in year 2015 but also for the year 2014, 2013, 2012, and 2011. The results had shown that PBP was statistically significant as one of the determinant factor, except for the year 2012. As PBP exhibit significant result, it affected the predicting ability of the rolling-logit model, which become slightly higher than the logit model.

the firms in previous period would reduce the firm's ability to post earnings and pay their debts, which in turn will increase the present probability of financial distress.

Additionally, although empirical results revealed the usefulness of rolling-logit model, but the predicting ability was not significantly higher compared to logit model. This might be due to the utilization of backward stepwise regression. The methodology allows the model equation to only select variable that is statistically significant. Therefore the selected variables in the logit regression and rolling-logit regression have almost similar explanatory power. Thus making the predicting ability of the logit and rolling logit regression not significantly different.

Nonetheless, the stable predicting ability up to 6 years before bankruptcy was also the outcome of the backward stepwise in logit and rolling-logit regression model. As the backward stepwise methodology will automatically drop independent variables that have significant level higher than five percent, the statistical power of model as a whole can be similar to other years. Consequently, the independent variable that was found to be significant can be different in every year, as the number of observation change and some ratios might have a temporary effect. The previous research that applied backward stepwise method (Tirapat & Nittayagestwat, 1999; Almilialia, 2004) was only predicted one year before bankruptcy. Therefore, there was no evidence of difference determinant factor at a different year.

Moreover, the model that acquired the highest predicting ability was the one that used only financial ratios as independent variables (equation 5). As it observed in appendix B.5, the determinant factors after jackknife validation method were the same through the years. Those factors were variables that exhibited consistency in all equation

at each year, which includes net worth to sales, cash to sales, and previous year bankruptcy probability. Yet, this study failed to prove that information from macroeconomic variables, in the forms of firm's sensitivity to macroeconomic variables, in average, did not lead to better predicting ability compared to the equation that only used firm's internal indicators (financial ratios and industry relative ratios).

This empirical result was parallel with earlier research (Liou & Smith, 2002; Lu, Lee & Chang, 2008; Iramani, 2008; Veronica & Anantadjaya, 2014). According to a study done by Lu, Lee, and Change (2008) financial indicators and corporate governance have a better explanatory power to explain the episode of financial distress event compared to macroeconomic variables. Meanwhile, Veronica & Anantadjaya (2014) also indicate that the addition of macroeconomic indicators into prediction model did not exhibit substantial impact. In the same economic condition, a firm might face different financial situations depending on how efficiently a firm can manage their business activity and financial performance (Brahmana, 2007; Sandin & Porporato, 2007). Nonetheless, both studies revealed that the macroeconomic indicators were significant factors that contribute to the determination of firm's status (distress or healthy), although the model did not perform a better predicting ability.

C. Limitation of Study and Practical Implication

Limitation of study. In the previous empirical results, some ratios and macroeconomic variables only exhibited significant outcome in one specific year but were insignificant in a different period. As an example, ratio EBIT to total assets and current assets to total assets were only significant in equation 7 at two years before

bankruptcy (see appendix B.7). Also, some variable that should reveal a negative association, surprisingly exhibited a positive association with financial distress risk probability. Those issues might be due to pooling data problems, measurement errors, and temporary effect.

This study used cross-sectional pooled observations over a different period in order to see the predictive ability before the occurrence. Therefore, there might be a possibility that errors were not independent and nonrandom across observations. Errors might portray some causal heterogeneity within units, time, or both, as the association of dependent and independent variables tend to diverge across firms and periods (Hicks, 1994 in Podesta, 2000). Hence, that causal heterogeneity can affect the relationship between dependent and independent variables, which in turn can also affect the significant power of the variables.

Moreover, measurement error can also take place on account of the secondary data. This is because it was gathered from the Indonesia Capital Market Directory, which only summarizes the financial statement and does not provide a detailed annual report. Hence, the author is unable to reconfirm some of the unexplained strange values published in the financial statement. Furthermore, there is also the possibility that some ratios have only temporary effect, while some ratios have longer time effect, resulting in a steady outcome. In addition, this study only used the sample from manufacturing company listed in the IDX, the findings may not be applicable to different situations. Therefore there will be limitation on the usefulness of rolling-logit regression and determinant factors found in this study.

Practical implication. The outcome and finding can provide practical implication to the stakeholders of corporations, especially manufacturing companies in Indonesia. First, the profile characteristics revealed the mean value of financial indicators used; are statistically different between healthy and distress firms, especially in term of magnitude on cash and leverage position. Therefore, the management of the company should put more effort to maintain their cash position and a modest level of leverage. Moreover, the findings in regression results also suggested that management should efficiently manage their business activity, so they will be able to generate more earnings and other liquid assets, while maintaining low level of inventory.

Additionally, referring to the Government of Indonesia policy about the proportion of debt to equity ratio¹⁴, less or equal to 4 points, the profile analysis outcome also displayed supporting evidence. The profile analysis showed that distress firms have an average 14.66 points, while healthy firms have an average 2.04 points only. However, this ratio was not a determinant factor to predict firms' financial distress. This results might be because of heterogeneity effect, which end up resulting the effect to be canceled out each other within the group.

Secondly, the empirical results also proved that the rolling-logit model exhibit higher predicting ability to distinguish the distress status of Indonesia's manufacture companies. Thus, rolling-logit model is an appropriate approach for stakeholders to measure the distress risk of company. Furthermore, as previous year bankruptcy probability shows a consistent appearance up to five years before bankruptcy, stakeholders can objectively assess the company distress risk based on incremental

¹⁴ in this study similar to total liabilities to net worth ratio

information from previous years. Subsequently they can apply for appropriate return or risk premiums based on estimated distress risk from the model.

V. CONCLUSION

This study was able to show the systematic difference between healthy and distress firms through profile analysis. The descriptive analysis in profile analysis displayed that all 24 ratios were significantly different between healthy and distress firms with 90 confidence level. Meanwhile, ratios that showed a high deviation between healthy and distress firms were classified in cash position and financial leverage group. Moreover, the computed descriptive analysis of healthy firms, in general, represented the value of whole sample (manufacturing industry).

In addition, this study also successfully demonstrated the usefulness of rolling-logit regression to predict the probability of a firm's financial distress, although the predicting power was not significantly higher. In other words, a company's history and previous performance is a useful indicator of its tendency to financial distress. There were 17 significant determinant factors found, which consist of 14 ratios (financial ratios and industry relative ratios), firm's sensitivity to money supply (M2), firm's sensitivity to real exchange rate, and previous year bankruptcy probability. Yet, after the utilization of jackknife validation method, 4 ratios become insignificant. Those ratios were funds flow to net worth, total liabilities to total assets, current liabilities to total assets, and quick assets to current liabilities. Furthermore, some variables had shown a consistent appearance in entire equation up to six years before bankruptcy, including net worth to sales, cash to sales, and previous year bankruptcy probability.

Based on empirical results in this study, it implies that company which efficiently manages their assets and their business activities were able to generate higher profits and

liquid assets, thus decrease the probability of financial distress. Whereas, firms that inefficiently managed their inventory and other assets had a higher chance to face distress risk. The paper also found that a sudden change in macroeconomic factors (real exchange rate) might increase the probability of financial distress. Adding macroeconomic factor in prediction model, though, do not have a huge impact on model predicting ability.

Nevertheless, as this study will limit the sample only on manufacture companies listed in the IDX, the findings might not be applicable in different sample and observation. The sample of firms was also not randomly selected and unable to match-paired between healthy and distress firms, thus this data may have external validity issue. Moreover, the selected financial ratios and macroeconomic variables were gathered from 2000-2014, which is not publicly accessible. Therefore, some future researchers might face difficulties in replicating this study, if they do not have private access to some data.

Therefore, future studies could try to attempt to try the model in a different sample and under different economic conditions. As this study able to reconfirm the usefulness of rolling-logit model for manufacturing firms listed in the IDX with selected variables, future studies can extend the research in different industry sector with other predictor variables, such as audit and governance indicators. It is also suggested to use different indicators to define the status of the firms, because this study does not define distress firms based on firms that actually filed for bankruptcy. Yet, different indicators to define the status of the firms can lead to higher balance or lower balance number between healthy and distress firms.

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APPENDICES

Appendix A

Equity Status

Equity	Year															
	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000
ARGO	1	1	0	0	0	0	0	0	0	1	1	1	0	1	1	1
BIMA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
JKSW	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MYTX	1	1	1	0	0	0	0	0	0	0	0	1	0	1	1	0
POLY	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
RMBA	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SCPI	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
SULI	1	1	1	1	0	0	0	0	0	0	0	0	1	1	1	0
ADES	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
ADMG	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
AISA	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
AKPI	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
AKRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ALMI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AMFG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
APLI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ARNA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ASGR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ASII	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AUTO	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Equity	Year															
	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000
BATA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BRAM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BRNA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BRPT	0	0	1	1	1	0	0	0	0	0	0	1	1	0	1	0
BTON	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
BUDI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CEKA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CNTX	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CPIN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CTBN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DLTA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DPNS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DVLA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EKAD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ERTX	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
ESTI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ETWA	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
FAST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FASW	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FPNI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GDYR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GGRM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
GJTL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
HDTX	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0

Equity	Year															
	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000
HEXA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HMSP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IGAR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IKAI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
IKBI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
IMAS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
INAF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INAI	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
INCI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INDF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INDR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INDS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INKP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INTA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
INTP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
JECC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
JPFA	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
JPRS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KAEF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KBLI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
KBLM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
KDSI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KICI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KKGI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
KLBF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Equity	Year															
	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000
LION	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LMPI	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
LMSH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LPIN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MERK	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MLBI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
MLIA	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MRAT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MTDL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
MYOR	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
NIPS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PBRX	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PICO	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
PRAS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
PSDN	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
PYFA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RDTX	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
RICY	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SCCO	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
SIMA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SIPD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
SKLT	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
SMCB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
SMGR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SMSM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Equity	Year															
	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000
SOBI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
SPMA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
SQBI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
SRSN	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0
SSTM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
STTP	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
TBMS	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TCID	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TFCO	0	0	0	1	1	0	1	1	1	1	0	0	0	0	0	0
TIRA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TIRT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TKIM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TOTO	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
TRST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TSPC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
TURI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ULTJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UNIC	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UNIT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UNVR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
VOKS	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1

Appendix B

Regression Results Equation 1

Logit (Equation 1)	sta	invs	tlta	qas	ebits	qacl	clta	cashs	cas	nws	Chi-square value	Prediction Ability
T-1 Coefficient	-0.45	5.27	0.84	5.50	-2.02	-0.28	-0.80	-14.50	-6.69	-1.01	270.4	94.27%
Std. Err.	0.17	2.07	0.31	2.01	0.47	0.13	0.33	3.72	2.07	0.22		
p-value	0.01	0.01	0.01	0.01	0.00	0.03	0.02	0.00	0.00	0	0.000	
T-2 Coefficient	-0.42	5.62		4.81	-2.00			-15.13	-6.55	-1.20	233.1	93.98%
Std. Err.	0.19	1.82		1.77	0.41			3.75	1.80	0.13		
p-value	0.02	0.00		0.01	0.00			0.00	0.00	0.00	0.000	
T-3 Coefficient	-0.38	5.17		4.70	-2.00			-15.13	-6.33	-1.12	211.3	93.99%
Std. Err.	0.19	1.91		1.85	0.43			3.84	1.89	0.13		
p-value	0.05	0.01		0.01	0.00			0.00	0.00	0.00	0.000	
T-4 Coefficient		4.99		4.2368	-1.809			-15.53	-5.765	-1.086	189.3	94.23%
Std. Err.		2.07		2.02	0.43			3.97	2.05	0.13		
p-value		0.02		0.04	0.00			0.00	0.01	0.00	0.000	
T-5 Coefficient					-1.864			-15.41	-1.251	-1.006	168.2	94.10%
Std. Err.					0.44			3.98	0.39	0.12		
p-value					0.00			0.00	0.00	0.00	0.000	
T-6 Coefficient		5.65		6.46	-0.57			-14.14	-7.35	-0.94	163.34	93.95%
Std. Err.		1.68		2.42	0.24			4.13	2.49	0.15		
p-value		0.00		0.02	0.02			0.00	0.00	0.00	0.00	

(continued-jackknife validation)

Logit (Equation 1)	sta	invs	tlta	qas	ebits	qacl	clta	cashs	cas	nws	Chi- square value	Prediction Ability
T-1												
Coefficient	-0.45	5.27	0.84	5.50	-2.02	-0.28	-0.80	-14.50	-6.69	-1.01	270.4	94.27%
Jackknife S.E	0.20	1.69	0.55	1.81	1.18	0.23	0.62	4.99	1.94	0.37		
<i>p</i> -value	0.02	0.00	0.13	0.00	0.09	0.23	0.20	0.00	0.00	0.01	0.000	
T-2												
Coefficient	-0.42	5.62		4.81	-2.00			-15.13	-6.55	-1.20	233.1	93.98%
Jackknife S.E	0.22	1.52		1.47	1.20			4.97	1.59	0.21		
<i>p</i> -value	0.06	0.00		0.00	0.10			0.00	0.00	0.00	0.000	
T-3												
Coefficient	-0.38	5.17		4.70	-2.00			-15.13	-6.33	-1.12	211.3	93.99%
Jackknife S.E	0.22	1.55		1.49	1.13			5.17	1.58	0.20		
<i>p</i> -value	0.08	0.00		0.00	0.08			0.00	0.00	0.00	0.000	
T-4												
Coefficient		4.99		4.24	-1.81			-15.53	-5.77	-1.09	189.3	94.23%
Jackknife S.E		1.49		1.47	1.08			5.50	1.50	0.20		
<i>p</i> -value		0.00		0.00	0.09			0.01	0.00	0.00	0.000	
T-5												
Coefficient					-1.86			-15.41	-1.25	-1.01	168.2	94.10%
Jackknife S.E					0.70			5.27	0.40	0.17		
<i>p</i> -value					0.01			0.00	0.00	0.00	0.000	
T-6												
Coefficient		5.65		6.46		-0.57		-14.14	-7.35	-0.94	163.3	93.95%
Jackknife S.E		1.68		2.33		0.62		6.03	2.02	0.28		
<i>p</i> -value		0.00		0.01		0.35		0.02	0.00	0.00	0.000	

Appendix C

Regression Results Equation 2

Logit (equation 2)	sta	invs	cashts	qas	ebits	qacl	clta	tlta	cas	nws	cashta	Chi-square value	Prediction Ability
T-1													
Coefficient	-0.53	1.24	-1.42	2.00	-0.13	-0.50	-0.35	0.54	-3.95	-0.42		272.1	94.27%
Std. Err.	0.20	0.48	0.35	0.72	0.03	0.23	0.14	0.20	1.21	0.09		0.000	
<i>p</i> -value	0.01	0.01	0.00	0.01	0.00	0.03	0.01	0.01	0.00	0.00		0.000	
T-2													
Coefficient	-0.49	1.33	-1.45	1.75	-0.13				-3.88	-0.49		235.0	94.05%
Std. Err.	0.22	0.43	0.35	0.63	0.03				1.05	0.05		0.000	
<i>p</i> -value	0.02	0.00	0.00	0.01	0.00				0.00	0.00		235.0	94.05%
T-3													
Coefficient	-0.45	1.23	-1.43	1.72	-0.12				-3.77	-0.45		213.2	93.99%
Std. Err.	0.23	0.45	0.35	0.66	0.03				1.11	0.05		0.000	
<i>p</i> -value	0.05	0.01	0.00	0.01	0.00				0.00	0.00		0.000	
T-4													
Coefficient		1.18	-1.48	1.55	-0.11				-3.42	-0.42		190.7	94.23%
Std. Err.		0.48	0.37	0.73	0.03				1.21	0.05		0.000	
<i>p</i> -value		0.02	0.00	0.03	0.00				0.01	0.00		0.000	
T-5													
Coefficient			-1.49		-0.107				-0.743	-0.386		169.7	94.02%
Std. Err.			0.38		0.03				0.24	0.05		0.000	
<i>p</i> -value			0.00		0.00				0.00	0.00		0.000	

Appendix D

Regression Results Equation 3

Logit (equation 3)	tlt	cashs	qas	qacl	ebits	clta	invs	cas	nws	sta	$\beta_i F3$	$\beta_i F4$	Chi-square value	Prediction Ability
T-1														
Coefficient	0.82	-15.07	5.03	-0.30	-1.88	-0.69	4.72	-6.07	-0.93	-0.44	0.29		275.1	94.27%
Std. Err.	0.31	3.80	2.03	0.13	0.47	0.34	2.09	2.10	0.22	0.17	0.13		0.000	
p-value	0.01	0.00	0.01	0.02	0.00	0.04	0.02	0.00	0.00	0.01	0.03			
T-2														
Coefficient		-15.40	4.25		-1.94		5.03	-5.94	-1.16	-0.41	0.30		238.4	94.05%
Std. Err.		3.80	1.79		0.40		1.84	1.82	0.13	0.18	0.13		0.000	
p-value		0.00	0.02		0.00		0.01	0.00	0.00	0.03	0.02			
T-3														
Coefficient		-15.13	4.70		-2.00		5.17	-6.33	-1.12	-0.38			211.3	93.99%
Std. Err.		3.84	1.85		0.43		1.91	1.89	0.13	0.19			0.000	
p-value		0.00	0.01		0.00		0.01	0.00	0.00	0.05				
T-4														
Coefficient		-15.53	4.24		-1.81		4.99	-5.77	-1.09				189.3	94.23%
Std. Err.		3.97	2.02		0.43		2.07	2.05	0.13				0.000	
p-value		0.00	0.04		0.00		0.02	0.01	0.00					
T-5														
Coefficient		-15.41			-1.86			-1.25	-1.01				168.2	94.10%
Std. Err.		3.98			0.44			0.39	0.12				0.000	
p-value		0.00			0.00			0.00	0.00					

Appendix E

Regression Results Equation 4

Logit(equation 4)	gas	cashs	cas	qacl	ebits	clta	tlta	invs	nws	sta	cashta	$\beta_i F3$	$\beta_i F4$	Chi-square value	Prediction Ability
T-1															
Coefficient	1.83	-1.48	-3.58	-0.53	-0.12	-0.30	0.52	1.11	-0.39	-0.52		0.29		276.9	94.21%
Std. Err.	0.72	0.36	1.23	0.23	0.03	0.14	0.20	0.49	0.09	0.21		0.14		0.000	
p-value	0.01	0.00	0.00	0.02	0.00	0.04	0.01	0.02	0.00	0.01		0.03			
T-2															
Coefficient	1.55	-1.47	-3.52		-0.12			1.19	-0.48	-0.48		0.30		240.4	93.98%
Std. Err.	0.64	0.35	1.06		0.03			0.43	0.05	0.22		0.13		0.000	
p-value	0.02	0.00	0.00		0.00			0.01	0.00	0.03		0.02			
T-3															
Coefficient	1.72	-1.43	-3.77		-0.12			1.23	-0.45	-0.45				213.2	93.99%
Std. Err.	0.66	0.35	1.11		0.03			0.45	0.05	0.23				0.000	
p-value	0.01	0.00	0.00		0.00			0.01	0.00	0.05					
T-4															
Coefficient	-1.55	-1.48	-3.42		-0.11			1.18	-0.42					190.7	94.23%
Std. Err.	-0.73	0.37	1.21		0.03			0.48	0.05					0.000	
p-value	-0.03	0.00	0.01		0.00			0.02	0.00						
T-5															
Coefficient		-1.49	-0.74		-0.11				-0.39					169.7	94.02%
Std. Err.		0.38	0.24		0.03				0.05					0.000	
p-value		0.00	0.00		0.00				0.00						
T-6															
Coefficient	3.44	-2.41	-6.10	-1.25		-0.37		1.79	-0.48	-0.66	1.03		-0.71	173.6	94.21%
Std. Err.	0.96	0.69	1.57	0.43		0.18		0.57	0.09	0.33	0.46		0.30	0.000	
p-value	0.00	0.00	0.00	0.00		0.04		0.00	0.00	0.05	0.03		0.02		

(continued-jackknife validation)

Logit(equation 4)	gas	cashs	cas	qacl	ebits	clta	tlta	invs	nws	sta	cashta	$\beta_i F3$	$\beta_i F4$	Chi-square value	Prediction Ability
T-1															
Coefficient	1.83	-1.48	-3.58	-0.53	-0.12	-0.30	0.52	1.11	-0.39	-0.52		0.29		276.9	94.21%
Jackknife S.E	0.72	0.36	1.23	0.23	0.03	0.14	0.20	0.49	0.09	0.21		0.14			
p-value	0.01	0.00	0.00	0.02	0.00	0.04	0.01	0.02	0.00	0.01		0.03		0.000	
T-2															
Coefficient	1.55	-1.47	-3.52		-0.12			1.19	-0.48	-0.48		0.30		240.4	93.98%
Jackknife S.E	0.64	0.35	1.06		0.03			0.43	0.05	0.22		0.13			
p-value	0.02	0.00	0.00		0.00			0.01	0.00	0.03		0.02		0.000	
T-3															
Coefficient	1.72	-1.43	-3.77		-0.12			1.23	-0.45	-0.45				213.2	93.99%
Jackknife S.E	0.66	0.35	1.11		0.03			0.45	0.05	0.23					
p-value	0.01	0.00	0.00		0.00			0.01	0.00	0.05				0.000	
T-4															
Coefficient	-1.55	-1.48	-3.42		-0.11			1.18	-0.42					190.7	94.23%
Jackknife S.E	-0.73	0.37	1.21		0.03			0.48	0.05						
p-value	-0.03	0.00	0.01		0.00			0.02	0.00					0.000	
T-5															
Coefficient		-1.49	-0.74		-0.11				-0.39					169.7	94.02%
Jackknife S.E		0.51	0.24		0.04				0.07						
p-value		0.00	0.00		0.01				0.00					0.000	
T-6															
Coefficient	3.44	-2.41	-6.10	-1.25		-0.37		1.79	-0.48	-0.66	1.03		-0.71	173.6	94.21%
Jackknife S.E	0.96	0.69	1.57	0.43		0.18		0.57	0.09	0.33	0.46		0.30		
p-value	0.00	0.00	0.00	0.00		0.04		0.00	0.00	0.05	0.03		0.02	0.000	

Appendix F

Regression Results Equation 5

Rolling Logit (equation 5)	cas	cashs	nws	ebits	ffnw	pbp	Chi-square value	Prediction Ability
T-1								
Coefficient	-0.88	-15.92	-0.89	-1.73		2.86	255.0	94.17%
Std. Err.	0.36	4.05	0.16	0.40		0.80		
<i>p</i> -value	0.01	0.00	0.00	0.00		0.00	0.000	
T-2								
Coefficient	-0.80	-15.49	-0.83	-1.59		2.97	229.5	94.13%
Std. Err.	0.36	4.07	0.16	0.41		0.83		
<i>p</i> -value	0.03	0.00	0.00	0.00		0.00	0.000	
T-3								
Coefficient		-17.79	5.89	-0.85	-0.04	4.51	211.5	94.37%
Std. Err.		4.02	0.11	0.28	0.02	0.83		
<i>p</i> -value		0.00	0.00	0.00	0.04	0.00	0.000	
T-4								
Coefficient		-19.46	-0.55	-0.83		3.72	182.0	94.50%
Std. Err.		4.21	0.11	0.33		0.84		
<i>p</i> -value		0.00	0.00	0.01		0.00	0.000	
T-5								
Coefficient		-18.93	-0.53	-0.80		4.14	169.5	94.39%
Std. Err.		4.22	0.11	0.34		0.87		
<i>p</i> -value		0.00	0.00	0.02		0.00	0.000	

(continued-jackknife validation)

Rolling Logit (equation 5)	cas	cashs	nws	ebits	ffnw	pbp	Chi-square value	Prediction Ability
T-1								
Coefficient	-0.88	-15.92	-0.89	-1.73		2.86	255.0	94.17%
Jacknife S.E	0.77	5.14	0.29	1.48		1.02		
<i>p</i> -value	0.25	0.00	0.00	0.24		0.01	0.000	
T-2								
Coefficient	-0.80	-15.49	-0.83	-1.59		2.97	229.5	94.13%
Jacknife S.E	0.67	5.08	0.26	1.37		1.00		
<i>p</i> -value	0.23	0.00	0.00	0.25		0.00	0.000	

T-3									
Coefficient		-17.79	5.89	-0.85	-0.04	4.51		211.5	94.37%
Jacknife S.E		-0.51	0.26	1.40	0.02	1.23			
<i>p</i> -value		0.00	0.05	0.54	0.13	0.00		0.000	
T-4									
Coefficient		-19.46	-0.55	-0.83		3.72		182.0	94.50%
Jacknife S.E		6.62	0.28	1.12		1.24			
<i>p</i> -value		0.00	0.05	0.46		0.00		0.000	
T-5									
Coefficient		-18.93	-0.53	-0.80		4.14		169.5	94.39%
Jacknife S.E		6.52	0.22	0.95		1.14			
<i>p</i> -value		0.00	0.02	0.40		0.00		0.000	

Appendix G

Regression Results Equation 6

Rolling Logit (equation 6)	cas	nws	cashs	ebits	invs	qas	cashita	sita	pbp	Chi-square value	Prediction Ability
T-1											
Coefficient	-0.49	-0.36	-1.54	-0.11					2.94	257.5	94.24%
Std. Err.	0.21	0.07	0.39	0.03					0.80		
<i>p</i> -value	0.02	0.00	0.00	0.00					0.00	0.000	
T-2											
Coefficient	-0.45	-0.33	-1.46	-0.10					3.05	231.9	94.13%
Std. Err.	0.21	0.07	0.38	0.03					0.83		
<i>p</i> -value	0.03	0.00	0.00	0.00					0.00	0.000	
T-3											
Coefficient	-0.47	-0.31	-1.43	-0.09					3.12	211.2	94.23%
Std. Err.	0.24	0.06	0.39	0.03					0.88		
<i>p</i> -value	0.05	0.00	0.00	0.00					0.00	0.000	
T-4											
Coefficient	-4.15	-0.32	-2.61		1.41	1.67	0.88	-0.87	3.13	196.9	94.18%
Std. Err.	1.41	0.07	0.71		0.52	0.78	0.41	0.36	0.97		
<i>p</i> -value	0.00	0.00	0.00		0.01	0.03	0.03	0.02	0.00	0.000	
T-4											
Coefficient		-0.20	-1.76						4.29	170.8	94.30%
Std. Err.		0.05	0.40						0.86		
<i>p</i> -value		0.00	0.00						0.00	0.000	

(continued-jackknife validation)

Rolling Logit (equation 6)	cas	nws	cashs	ebits	invs	qas	cashta	sta	pbp	Chi-square value	Prediction Ability
T-1											
Coefficient	-0.49	-0.36	-1.54	-0.11					2.94	257.5	94.24%
Jackknife S.E	0.44	0.12	0.50	0.10					1.02		
<i>p</i> -value	0.26	0.00	0.00	0.27					0.00	0.000	
T-2											
Coefficient	-0.45	-0.33	-1.46	-0.10					3.05	231.9	94.13%
Jackknife S.E	0.38	0.10	0.48	0.09					1.00		
<i>p</i> -value	0.24	0.00	0.00	0.27					0.00	0.000	
T-3											
Coefficient	-0.47	-0.31	-1.43	-0.09					3.12	211.2	94.23%
Jackknife S.E	0.28	0.09	0.49	0.08					1.02		
<i>p</i> -value	0.10	0.00	0.00	0.26					0.00	0.000	
T-4											
Coefficient	-4.15	-0.32	-2.61		1.41	1.67	0.88	-0.87	3.13	196.9	94.18%
Jackknife S.E	1.16	0.12	0.91		0.42	0.64	0.51	0.43	1.32		
<i>p</i> -value	0.00	0.01	0.00		0.00	0.01	0.08	0.04	0.02	0.000	
T-5											
Coefficient		-0.20	-1.76						4.29	170.8	94.30%
Jackknife S.E		0.07	0.58						1.07		
<i>p</i> -value		0.01	0.00						0.00	0.000	

Appendix H

Regression Results Equation 7

Rolling Logit (equation 7)	invs	cashs	nws	ebits	cas	qas	qacl	ebitta	ffnw	cashta	cata	β_1/β_3	pbp	Chi-square value	Prediction Ability
T-1															
Coefficient	4.92	-15.40	-0.87	-1.49	-5.44	4.48	-0.23						3.04	264.6	94.30%
Std. Err.	2.03	4.23	0.18	0.46	2.05	2.03	0.11						0.82		
<i>p</i> -value	0.02	0.00	0.00	0.00	0.01	0.03	0.05						0.00	0.000	
T-2															
Coefficient		-17.68	-0.52					-2.50				0.34	3.55	231.5	94.20%
Std. Err.		3.96	0.11					1.05				0.14	0.75		
<i>p</i> -value		0.00	0.00					0.02				0.01	0.00	0.000	
T-3															
Coefficient		-17.79	-0.51	-0.85					-0.04				4.51	211.5	94.37%
Std. Err.		4.02	0.11	0.28					0.02				0.83		
<i>p</i> -value		0.00	0.00	0.00					0.04				0.00	0.000	
T-4															
Coefficient		-19.46	-0.55	-0.83									3.72	182.0	94.50%
Std. Err.		4.21	0.11	0.33									0.84		
<i>p</i> -value		0.00	0.00	0.01									0.00	0.000	
T-5															
Coefficient		-28.03	-0.67	-0.92						10.35	-1.84		3.46	179.0	94.12%
Std. Err.		6.32	0.14	0.45						4.02	0.77		0.91		
<i>p</i> -value		0.00	0.00	0.04						0.01	0.02		0.00	0.000	

(continued-jackknife validation)

Rolling Logit (equation 7)	invs	cashs	nws	ebits	cas	qas	qacl	ebitta	ffnw	cashita	cata	$\beta_i F_3$	pbp	Chi-square value	Prediction Ability
T-1															
Coefficient	4.92	-15.40	-0.87	-1.49	-5.44	4.48	-0.23						3.04	264.6	94.30%
Jackknife S.E	1.68	5.76	0.31	1.37	1.84	1.79	0.19						1.09		
<i>p</i> -value	0.00	0.01	0.01	0.28	0.00	0.01	0.22						0.01	0.000	
T-2															
Coefficient		-17.68	-0.52					-2.50				0.34	3.55	231.5	94.20%
Jackknife S.E		6.23	0.32					1.29				0.11	1.22		
<i>p</i> -value		0.01	0.11					0.05				0.00	0.00	0.000	
T-3															
Coefficient		-17.79	-0.51	-0.85					-0.04				4.51	211.5	94.37%
Jackknife S.E		5.89	0.26	1.40					0.02				1.23		
<i>p</i> -value		0.00	0.05	0.54					0.13				0.00	0.000	
T-4															
Coefficient		-19.46	-0.55	-0.83									3.72	182.0	94.50%
Jackknife S.E		6.62	0.28	1.12									1.24		
<i>p</i> -value		0.00	0.05	0.46									0.00	0.000	
T-5															
Coefficient		-28.03	-0.67	-0.92						10.35	-1.84		3.46	179.0	94.12%
Jackknife S.E		7.69	0.15	0.57						4.70	0.78		0.99		
<i>p</i> -value		0.00	0.00	0.11						0.03	0.02		0.00	0.000	

Appendix I

Regression Results Equation 8

Rolling Logit (equation 8)	cashs	nws	invs	ebits	cas	qas	qacl	cashta	sta	$\beta/F3$	pbp	Chi-square value	Prediction Ability
T-1													
Coefficient	-1.50	-0.36	1.14	-0.09	-3.14	1.59	-0.41				3.13	267.1	94.36%
Std. Err.	0.56	0.12	0.38	0.09	1.07	0.64	0.34				1.08	0.000	
p-value	0.01	0.00	0.00	0.30	0.00	0.01	0.23				0.00	0.000	
T-2													
Coefficient	-1.75	-0.22		-0.05			-0.40			0.39	3.98	238.3	93.99%
Std. Err.	0.63	0.14		0.10			0.27			0.11	1.34	0.000	
p-value	0.01	0.12		0.59			0.14			0.00	0.00	0.000	
T-3													
Coefficient	-1.43	-0.31		-0.09	-0.47						3.12	231.9	94.23%
Std. Err.	0.49	0.09		0.08	0.28						1.02	0.000	
p-value	0.00	0.00		0.26	0.10						0.00	0.000	
T-4													
Coefficient	-2.61	-0.32	1.41		-4.15	1.67		0.88	-0.87		3.13	211.2	94.18%
Std. Err.	0.91	0.12	0.42		1.16	0.64		0.51	0.43		1.32	0.000	
p-value	0.00	0.01	0.00		0.00	0.01		0.08	0.04		0.02	0.000	
T-5													
Coefficient	-1.77	-0.20		-0.04							4.14	172.5	94.30%
Std. Err.	0.60	0.08		0.05							1.10	0.000	
p-value	0.00	0.01		0.36							0.00	0.000	

(continued-jackknife validation)

Rolling Logit (equation 8)	cashs	nws	invs	ebits	cas	qas	qacl	cashta	sta	$\beta/F3$	ppp	Chi-square value	Prediction Ability
T-1													
Coefficient	-1.50	-0.36	1.14	-0.09	-3.14	1.59	-0.41				3.13	267.1	94.36%
Jackknife S.E	0.40	0.07	0.47	0.03	1.20	0.73	0.20				0.82	0.000	
<i>p</i> -value	0.00	0.00	0.02	0.00	0.01	0.03	0.05				0.00	0.000	
T-2													
Coefficient	-1.75	-0.22		-0.05			-0.40			0.39	3.98	238.3	93.99%
Jackknife S.E	0.38	0.05		0.02			0.18			0.14	0.74	0.000	
<i>p</i> -value	-2.50	0.00		0.00			0.02			0.01	0.00	0.000	
T-3													
Coefficient	-1.43	-0.31		-0.09	-0.47						3.12	231.9	94.23%
Jackknife S.E	0.39	0.06		0.03	0.24						0.88	0.000	
<i>p</i> -value	0.00	0.00		0.00	0.05						0.00	0.000	
T-4													
Coefficient	-2.61	-0.32	1.41		-4.15	1.67		0.88	-0.87		3.13	211.2	94.18%
Jackknife S.E	0.71	0.07	0.52		1.41	0.78		0.41	0.36		0.97	0.000	
<i>p</i> -value	0.00	0.00	0.01		0.00	0.03		0.03	0.02		0.00	0.000	
T-5													
Coefficient	-1.77	-0.20		-0.04							4.14	172.5	94.30%
Jackknife S.E	0.40	0.04		0.02							0.86	0.000	
<i>p</i> -value	0.00	0.00		0.03							0.00	0.000	

Appendix J

Summary of Regression Model Predicting Ability

Equation	T-6	T-5	T-4	T-3	T-2	T-1	Average
Equation 1							
Predicting Ability	93.95%	94.10%	94.23%	93.99%	93.98%	94.27%	94.09%
Type 1 Error	5.26%	5.18%	5.04%	5.20%	5.20%	5.03%	5.15%
Type 2 Error	0.79%	0.72%	0.73%	0.81%	0.81%	0.70%	0.76%
Equation 2							
Predicting Ability	93.68%	94.02%	94.23%	93.99%	94.05%	94.27%	94.04%
Type 1 Error	5.35%	5.26%	5.04%	5.20%	5.14%	5.03%	5.17%
Type 2 Error	0.96%	0.72%	0.73%	0.81%	0.81%	0.70%	0.79%
Equation 3							
Predicting Ability	93.86%	94.10%	94.23%	93.99%	94.05%	94.27%	94.08%
Type 1 Error	5.35%	5.18%	5.04%	5.20%	5.20%	4.97%	5.16%
Type 2 Error	0.79%	0.72%	0.73%	0.81%	0.75%	0.76%	0.76%
Equation 4							
Predicting Ability	94.21%	94.02%	94.23%	93.99%	93.98%	94.21%	94.11%
Type 1 Error	5.26%	5.26%	5.04%	5.20%	5.20%	5.09%	5.18%
Type 2 Error	0.53%	0.72%	0.73%	0.81%	0.81%	0.70%	0.72%
Equation 5							
Predicting Ability		94.39%	94.50%	94.37%	94.13%	94.17%	94.31%
Type 1 Error		5.00%	5.02%	4.97%	4.99%	4.95%	4.99%
Type 2 Error		0.61%	0.48%	0.66%	0.88%	0.88%	0.70%
Equation 6							
Predicting Ability		94.30%	94.18%	94.23%	94.13%	94.24%	94.21%
Type 1 Error		5.00%	4.94%	4.97%	4.99%	4.88%	4.96%
Type 2 Error		0.70%	0.88%	0.80%	0.88%	0.88%	0.83%
Equation 7							
Predicting Ability		94.12%	94.50%	94.37%	94.20%	94.30%	94.30%
Type 1 Error		5.00%	5.02%	4.97%	5.06%	4.82%	4.98%
Type 2 Error		0.88%	0.48%	0.66%	0.74%	0.88%	0.73%
Equation 8							
Predicting Ability		94.30%	94.18%	94.23%	93.99%	94.36%	94.21%
Type 1 Error		5.00%	4.94%	4.97%	5.26%	4.76%	4.99%
Type 2 Error		0.70%	0.88%	0.80%	0.74%	0.88%	0.80%