FORECASTING BANKRUPTCY PROBABILITY OF UKRAINIAN FIRMS

by

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Abstract

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Firm`s bankruptcy stands for the inability of an enterprise to satisfy creditors' claims. The primary reasons of bankruptcy are monetary problems, weak management, and large debt burden. Consequently, firm`s failure affects creditors, suppliers, and employees. There is a topical discussion among researchers as to which factors have impact on the firms` failure. The results of previous studies differ substantially between more and less developed economies. Hence, the relationship between financial problems and firms' failure requires additional studies, especially for Ukraine.

We investigated which factors influence bankruptcy risk in Ukraine and analyzed which industry was the most vulnerable in 2011-2016. We estimated different specifications of logit regressions using panel microdata from that period. The main variables of interest were the lagged value of investments and investment opportunities. The latter showed a significant negative marginal effect. Thus, increase in investment opportunities reduces the likelihood of bankruptcy. We conclude that with acquiring new capital a firm has more opportunities for growth which diminishes risk of failure.

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LIST OF ABBREVIATIONS

AIES. Artificially intelligent expert system

ROA. Return on Assets

ROE. Return on Equity

NPM. Net profit margin

DE. Debt to equity ratio

WCD. Working capital to debt ratio

EBITDA. Earnings before interests, tax, depreciation, and amortization

CR. Cash ratio

QR. Quick ratio

CurR. Current ratio

PPE. Property, plant and equipment

CAPEX. Capital expenditures

PSM. Propensity score matching

ASECU. Announcer of Supreme Economic Court of Ukraine

IO. Investment opportunities

ER. Equity ratio

KVED. Classification of economic activities.

UKRSTAT. State Statistic Service of Ukraine

Chapter 1

INTRODUCTION

Nowadays the financial distress in Ukraine is perceived ambiguously in the society. On the one hand, the bankruptcy serves as a method of liquidation of unprofitable enterprises resulting in a healthier economy. On the other hand, it becomes a problem for the state, which loses taxpayers and thus having a negative impact on its financial situation.

According to the Ukrainian legislation the term “bankruptcy” is defined as the permanent inability of a business to satisfy creditors' claims or fulfill its obligations to the budget due to the insufficiency of liquid assets. Therefore, the one of the reasons for going bankrupt is economic conditions. Thus, in financial recessions it is observed that more companies experience financial stress that sometimes results in bankruptcy (Bhattacharjee et. al., 2009).

Another factor of bankruptcy is a type of industry where company operates. The company is always trying to equilibrate between investing in new capital and saving liquid funds in order to be ready to satisfy creditors`s claims. Thus, it is always a question for the enterprise how to realize free funds in order to use them efficiently.

Particularly, (Chava et. al. 2004) concluded that putting industry effects at hazard rate estimation was highly important. In addition, capital-effective industries require more available liquid money than labor-effective industries. The next things that may lead to financial distress are different internal reasons such as bad management and improper location.

There are a plenty of parties affected by bankruptcy except government. First of all, the creditors may fail because of not repaying the debt by the bankrupted firm. Second, suppliers can lose strategic partners which consequently would reduce their revenue. Third, financial distress influences employees. The bankruptcy compels firm to reduce its costs and in the most cases company firstly decrease wage expenditures, which means firing workers.

Since financial distress is a huge issue to those who are engaged in this process and can generate high expenditures, its forecasting is expedient. In case if bankruptcy is forecasted beforehand, companies will obtain more possibilities to secure themselves and take measures to reduce failure risk and therefore chances of losing an enterprise without getting involved into litigation

The first objective of this master thesis is to investigate what factors influence bankruptcy risk in Ukraine. Obviously, there are some relationships between business cycle and the number of bankruptcies. Thus, the number of firms with financial distress was increasing during 2014-2016, which can be explained by the fact that due to the political situation and bad economic conditions Ukraine entered the financial crisis in 2014. Furthermore, according to the Global Bankruptcy Report 2017[1] the frequency of bankruptcies in Ukraine is higher than in most European countries.

The next aim of my research is to analyze which industry is the most vulnerable to bankruptcy. Among econometric approaches I am going to use the binary dependent variable model such as logit. Since various factors influence the bankruptcy risk, we are interested in investigating some new insight into the Ukrainian data. We are going to use panel, microdata, which consist of observations from 2011-2016 years and contain two parts. The first one is the enterprises, which are bankrupted, while the second is the number of

[1] https://dnb.ru/media/entry/56/217433_Global_Bankruptcy_Report_2017_9-20-17.pdf

enterprises, which continue its activity. The dataset includes financial data on firms of a different size and different industries.

Taking mentioned above into account, firstly, in Chapter 2 we consider the previous empirical researches and analyze different methods used to estimate the probability of bankruptcy and what factors have relationship with the likelihood of failure. Next, we introduce specification of our models, expected signs and the intuition behind them. After that, we are going to estimate models with different determinants and proxies and make conclusions.

Chapter 2

LITERATURE REVIEW

The methodology of forecasting bankruptcy has been described by a plenty of researchers. The interest in studies aimed at predicting bankruptcy began to form in the 1930s (Bellovary, et al., 2007). These investigations were based on analyzing financial ratios of bankrupt and non-bankrupt firms obtained from firms` accounting data. Thereby, one of the most famous works on this topic is Altman`s (1968) paper, where the author described what financial indicators were the best predictors of bankruptcy (Z-score). In this study it was shown that the probability of going bankrupt was significantly influenced by such indicators as a share of working capital in total assets, the productivity of assets (ROA*), retained earning scaled by total assets and Market Value of Equity divided by Book Value of Total liabilities. The last one represents how firm`s asset value can decline before the business goes bankrupt. The author used the data from 66 firms, which were bisected by bankrupts and non-bankrupts.

Almost at the same time the Beaver's (1966) study stands out the most prominently, where the number of financial ratios was developed, the author singled out the control values of these coefficients for the company in three states. They are financial sustainability, bankruptcy within five years and bankruptcy within one year. The paper notes that the coefficients developed by the author are able to predict the risk of bankruptcy on the horizon of one year with a probability of 90 to 92%. It should be noted that today the Beaver coefficient system is one of the most popular methods as a part of financial analysis. However, the most significant drawback of Beaver`s (1966) model were that fact that he used univariate models for each financial ratio rather than estimate them jointly in one model.

As the opposite of Atman`s model Shumway (2001) developed a simple hazard model which investigates the probability of bankruptcy using the data for 300 bankruptcies for 1962-1992. The author found that hazard models gave results of the same quality as models provided by Altman. However, it was identified that hazard models yielded substantially different statistical outcomes. It was shown that about the half of financial indicators applied to predict financial distress do not statistically influence bankruptcy. Shumway combines such ratios as net income to total assets and total liabilities to total assets and market conditions variables. Such method showed the more precise estimates than Altman`s Z-score. Another Altman`s critique belongs to Grice and Ingram (2001) who tried to analyze whether his model worked for non-manufacturing firms as with manufacturing ones. They founded that the z-score analysis was not effective as it was before. Hall (2002) said that the z-score worked only in the case when financial statements were formed properly and accurately.

With the progress of art of forecasting bankruptcy some other econometric approaches came into application. Particularly, Ohlson (1980), Skosvik (1990) and Berngardsen (2001) estimated models of bankruptcy predictions with such econometric approaches as logit and probit models using the data from Norwegian firms. Notably, Ohlson (1980) found that the size of a company, the measure of the financial structure, performance and liquidity substantially affect the bankruptcy, while Skosvik (1990) and Bernhardsen (2001) used in their studies the following additional factors: costs, capital structure, the age of a company and industry characteristics. Both models showed significant results with high accuracy (about 80%).

As the following step, researches started examining the influence of other determinants, for example while modeling the probability of bankruptcy of firms in Japan after selecting among 61 financial variables Shirata (1998) concluded that the most significant were accounts payable turnover, profitability and growth of liabilities. All variables except payable turnover had negative relationships with the dependent variable the data on which consisted of firms between 1986 -1996. The purpose of this study was to investigate Japanese enterprises` corporate failure after the burst of the bubble economy in 1990.

The study by Lukason (2016) of Estonian and Finnish enterprises answers the question whether financial distress differs across firms` size, age and whether the firm is exporting or not. The author found that there were significant relationships between factors mentioned above and the probability of going bankruptcy. Also the study showed that the process of corporate failure varied across different countries. Thornhill and Amit (2012) formulated the hypothesis that firms' failure was affected not only by the size and age, but also by market conditions such as the level of competitiveness. Furthermore, the authors concluded that financial distress on older enterprises was mostly influenced by business climate, whilst the risk of bankruptcy of younger firms was influenced by internal factors such as low quality of management. The data sample used for empirical analysis consisted of only bankrupted firms, which were liquidated. Bryan et.al (2013) estimated the influence of productivity on the bankruptcy risk. In their research it was found that such a factor as cost leadership and differentiation substantially impacted on the risk of failure. In addition, the risk went down with raising the productivity and level of differentiation, which is quite an obvious result, and increased with the level of cost leadership. The last two variables were generated by using the method of confirmatory factor analysis. Researchers used the yearly data from 1993 to 2006 and ruled out firms of the regulated industry from the sample. Kim (2017) tried to evaluate the risk of bankruptcy of the enterprise from the USA and Korea and to compare the results using the Altman Z-score. The estimation of

Z-score bankruptcy threshold was made, which led to the conclusion that it was to be greater for countries with the greater level of minority investor support. Therefore, the threshold needed to be lower for Korean businesses in comparison with the US where the “quality of institutions” was higher. Under such quality the author means the combination of corporate governance, ownership structure and legal base of bankruptcy procedures.

After investigating main factors of influence of the likelihood of financial distress researchers commence using other techniques different from logit and probit models. Aziz and Dar (2006) discussed different methods of the bankruptcy prediction. There were analyzed 43 articles and 89 empirical studies of the issue, where different methods and data samples were used. It was stated that the most powerful methods in terms of prediction rate were Gambler’s ruin theory, credit risk theory and rough sets. Generally, the author concluded that there is a notable inconsistency between statistical methods, artificially intelligent expert system (AIES) and theoretical models. In addition, other different techniques were used in the literature. Mselmi et. al. (2017) in their investigation based on the data of small French enterprises conducted the research with such methods as Support Vector Machine and Artificial Neural Networks. The prediction rate was about 92%. Also, for estimating the probability of bankruptcy Chou et. al. (2017) used such methods as hybrid genetic algorithm and fuzzy clustering, which showed a significant performance of prediction.

Furthermore, a set of scientific papers provided the analysis of financial distress in the transition economies. For example, Lizal (2002) emphasized three main causes of the firms` bankruptcy in Czech Republic. The first factor is the conditions when business cannot allocate its assets. The second one is its solvency, which is represented by financial ratios. Finally, the third reason is the resource structure and the type of enterprise`s corporate governance. The authors found out that Herfindahl indicators of ownership concentration were significantly negative, as well the indicator of state ownership, which always had negative sign. Furthermore, other scientists (Wilson et. al., 2014) came to the conclusion that foreign ownership decreased the probability of going bankrupt using the evidence from the data of small and medium enterprises of Slovakia.

To sum up, we can conclude that despite the huge number of researches in forecasting bankruptcy there is still an active discussion about which factors have impact on the firms` failure and what technique to use. Moreover, results of previous empirical studies differ substantially across economies with different types. Hence, the problem of predicting financial distress requires additional studies, especially for Ukraine.

Chapter 3

METHODOLOGY

Since the firms` financial distress is impacted by various factors, among which are those that are hard to evaluate (e.g. bad management quality), there are plenty of approaches by which failure can be forecasted. Thereupon, we should compare different methods and find out which is the best predictor taking into account the data availability and specifics of financial reporting of Ukrainian enterprises`.

One of the most common approaches is binary dependent variable models which are probit and logit models. These methods use the standard maximum likelihood procedure the dependent variable of which can take only two values: 0 or 1. Thus, the dependent variable will take value 1 if a firm is under the bankruptcy procedure and 0 if it is not. The dependent variable for the dataset is formed by using the Register of Enterprises, for which the Bankruptcy Proceedings Have Been Instituted (Register)[2]. Thus,

$$B = \begin{cases} 1,\ if\ firm\ is\ present\ in\ the\ Register \\ 0, if\ firm\ is\ not\ present\ in\ the\ Register \end{cases},$$

where B is the probability of going bankrupt.

The difference between logit and probit models is in its link functions, which are the functions that bound actual Y (dependent variable) with the evaluated one. Hence, the link function for the logit model is the following:

$$\mathrm{F(Y)} = \Phi^{-}(\mathrm{Y}), \tag{1}$$

[2] https://nais.gov.ua/m/ediniy-reestr-pidpriemstv-schodo-yakih-porusheno-vprovadjennya-u-spravi-pro-bankrutstvo

While the link function for logit takes the following expression (Wooldridge, 2013):

$$F(Y) = \ln(\frac{P}{1-P}), \tag{2}$$

where the P in our case is a probability of going bankrupt. In my thesis, I will use logit model as it is common in the literature. After making a decision on the main methods of estimation we are ready to move further and provide model specification for our work. As the independent variables we consider different profitability and solvency ratios in order to control for them. These are variables commonly used in the scientific literature for such kind of topic. The additional variables we are going to include in our model are investment, size of the firm, size of export, type of industry and others:

$$B = P + S + Ind + Size + Turnover + Invest_{t-1} + \varepsilon, \tag{3}$$

Where B – probability of going bankrupt,

P – profitability ,

S – solvency ,

Ind – industry type,

Size – employment,

Turnover – receivables and payables turnover ratios.

Inv – investments in the previous period or investment opportunities.

C h a p t e r 4

DESCRIPTION OF THE VARIABLES

Now we are going deeper into the variables meanings.

Profitablity and Solvency. The group of profitability ratios includes a lot of indicators such as return on assets(ROA), return on equity(ROE) and net profit margin (NPM) as well as solvency ratios, which contain such indicators as Debt to Equity ratio (DE), working capital to debt ratio (WCD) and debt to EBITDA. The formulas for profitability indicators are provided below.

$$OA = \frac{Net\ Income}{Total\ Assets} \tag{4}$$

$$ROE = \frac{Net\ Income}{Total\ Shareholders`\ Equity} \tag{5}$$

$$NPM = \frac{Net\ Income}{Net\ Sales} \tag{6}$$

Obviously, we expect the inverse relationship of profitability with the likelihood of going failure. Certainly, return on assets is the main indicator included in Altman`s Z-Score, which represents firm`s profitability with its earning power (Tian and Yu, 2017). Therefore, we anticipate, despite the industry type, the higher is the profit of the company, the less is the probability that firm enters into the failure state.

Since the concept of firm`s bankruptcy lies in its liquidity (ability to meet short-term debts immediately) we include the measure of the liquidity level into the model. The more liquid is the enterprise, the less are chances the firm is bankrupted, that is the sign of this variable is expected to be negative. From the theory of financial analysis of financial statements (Bernstein and Wild, 2004) there are three indicators that explain the term "liquidity", which are cash, quick, and current ratios (CR, QR, CurR, respectively):

$$CR = \frac{Cash\ and\ Equivalents}{Short - term\ liabilities} \tag{7}$$

$$QR = \frac{Cash\ and\ Equivalents + Accounts\ Receivable}{Short - term\ liabilities} \tag{8}$$

$$CurR = \frac{Current\ Assets}{Short - term\ liabilities} \tag{9}$$

These indicators show which part of the short-term debt a firm could cover if it spent all cash (for cash ratio), or all cash and collect all receivables (for quick ratio) or spent (realize in cash) all current assets (for current ratio) including short-term investments, inventories, and prepaid expenses. Since it is practically impossible to realize in cash all items comprised in the current assets only current and quick ratios are to be used in the logistic regression.

While the idea behind liquidity is centred mainly on short-term liabilities, the concept of solvency is focused more on the firm`s ability to cover all, including long-term, its obligations and conduct its operating activity successfully. That is why these two indicators are different from each other and do not have a direct and strong correlation. In our case solvency of the enterprise is represented by the equity ratio, which is calculated by dividing total share-holders equity by total assets and also known as the investment leverage. As was confirmed in Tian`s and Yu`s (2017) research this ratio is a better predictor of bankruptcy for European markets, that is why, we prefer ER to other measures of solvency. Equity ratio reveals how much of assets of the company are actually owned by shareholders. The higher is this ratio, the better is the status of the firm, that is, the less risky it is for investors and the less costs a firm will bear associated with servicing debts. Definitely, the sign of this variable should be negative in the model.

The next indicators we are going to test as the predictors of bankruptcy are account receivables and payables turnover ratios. These are also known as activity ratios. Particularly, account receivables turnover gauges the speed of collecting the money that is owed to the company by its clients while payables turnover represents how often the firm pay off the debt to its suppliers. We expect inverse relationships between company`s failure and turnover ratios with the intuition behind this that the more often the company receives payments from its customers or pays obligations to its suppliers the higher is the working capital of the company (current assets less current liabilities), which, in fact, represents the firm`s solvency. In addition, Zheng, Q. and J. Yanhui (2007) showed that such turnover ratios were the strong determinants of bankruptcy in their decision tree model.

Industry type. This is going to be the categorical variable, which represents the type of industry according to the classification of economic sectors (KVED, (APPENDIX A). We are going to analyze our model for different sectors and include categorical variable based on the letter of the code (e.g. "C" – manufacturing sector). The effect of industry is ambiguous and differs across the literature, that is why, we are uncertain about the sign of this variable.

There are a lot of different approaches how to measure the **size of the firm**. In this master thesis we use the proxy, which is the average number of employees per year. The most interesting in this variable is its dynamics, since it is believed that before going bankrupt the firm is cutting down its operating costs, particularly wage costs, which can be observed from reducing the number of workers. Hence, apart from using number of employees we are to try proxying size of the enterprise by total assets and compare which proxy fits better for Ukrainian data.

When identifying the investment variable, first of all, we assume that all investments are made in property, plant and equipment (PPE). Secondly, we assume the following motion of capital in the firm.

$$k_{t+1} = (1-\delta)k_t + i_t + r \qquad (10)$$

Where $\mathbf{k}$ means capital in the next period, $\boldsymbol{\delta}$ means depreciation, $\mathbf{i}$ is an investment and **r** is an income from revaluation of PPE. Forthwith, we can calculate the investments in the following way.

$$i_t = k_{t+1} - (1-\delta)k_t - r, \qquad (11)$$

This item could obtain either positive or negative value, which is related to whether the company is buying or selling fixed assets. According to M. Peat (2007) the way managing the enterprise strictly influence the company`s financial position and business success. Specifically, when an enterprise attracts additional funds through borrowing activity for the purpose to conduct investment activity the debt reported in financial statements will enlarge with further raising of the interest paid. Moreover, investments in property, plant and equipment may be funded not only by borrowing resources but also from retained earnings, or even by the blend of these. Therefore, it is expected that with increasing investments the probability of the firm failure also increases. However, this statement is a controversial, since investments could be financed from internal resources of the enterprise, to wit, from retained earnings. In such a case the company indeed loses some liquidity (e.g. in the form of spending cash and equivalents on the PPE), but with obtaining more innovative (and possibly more productive) capital it may have an opportunity to conduct its activity more efficiently and, as a result, obtain higher revenue. Moreover, since the decision on making investment for the company influences its activity results only in the next period, we include this variable with one lag.

Instead of investments some researchers (Lyandres and Zhdanov, 2013) used investment (or growth) opportunities of the firm as the predictor of bankruptcy. According to the literature this variable had negative relationship with the likelihood of firm failure, which had ordinary explanation. The higher is the level of a company`s growth opportunity the longer creditors are ready to wait for introducing their debt claims. Furthermore, the higher is the value of the firm's investment opportunities, the more facilely it is to receive external financial resources. That is, despite the fact that whether the bankruptcy is driven by reluctance of the shareholders to keep respecting their debt obligations or by impossibility to obtain external financing for paying the debt, the failure is negatively associated with investment opportunities, which is anticipated to confirm in this master thesis.

However, the growth opportunity is typically impossible to measure and the only remedy for this fact is using the appropriate proxy for which a lot of options exist. The one to be chosen in this research is the Capital-Expenditures-to-Net-Plant-Property-and-Equipment Ratio, which is calculated by dividing capital expenditures (CAPEX) by the net value of property, plant and equipment (PPE) at the beginning of the year. Since CAPEX is actually represents the investment we simply divide investments obtained with the formula mentioned above and then divide them by PPE. According to Adam and Goyal (2007) this is one of the best proxies for describing investment opportunities. The intuition behind this is that CAPEX are "largely discretionary and lead to the acquisition of new investment opportunities". Firms that invest more acquire more growth opportunities than those which invest less.

It is assumed that having a panel data involves using relevant techniques such as using logit with fixed or random effect models. However, financial distress happens only once in a period, that is why, we choose applying simple logit model but controlling for time effects.

Chapter 5

DATA DESCRIPTION

Our dataset was combined from the two main sources. The first one was the data from annual financial statements from 2011 to 2016 years which contained all items needed for calculating the indicators serving as the explanatory variables. The second one is the Unique Register of Enterprises for which the Bankruptcy Proceedings Have Been Instituted (Register), from which the dependent variable is constructed. It was obtained from the open source called state-owned enterprise "National Information Systems"[3]. The Register was comprised of the names of the enterprise, the code of the case in the court, the date of going bankrupt and the current status of the enterprise. Unfortunately, the information about the unique identification number of legal entities, which was crucial for combining two datasets, was absent. To deal with this problem the Announcer[4] of Supreme Economic Court of Ukraine (ASECU) was used[5]. The ASECU published the information about business entities under the bankruptcy procedure based on the Register, which, in fact gave us an opportunity to obtain identification codes of the financially distressed enterprises. Following this, the next step of constructing our desirable dataset was aggregating all bankrupted enterprise available in the ASECU including only private firms. We expelled such types of entities as state-owned enterprises and individual entrepreneurs and then integrated the datasets.

After merging the datasets and removing outliers we came to the 100 thousand observations including only 560 bankrupted firms, whose share is less than 1%.

[3] https://nais.gov.ua/m/ediniy-reestr-pidpriemstv-schodo-yakih-porusheno-vprovadjennya-u-spravi-pro-bankrutstvo
[4] http://infoboro.com.ua/index1.html
[5] http://vgsu.arbitr.gov.ua/pages/157

Such a situation with the data may severely bias our estimations, thus we apply the propensity score matching (PSM) procedure in order to obtain a balanced dataset. For obtaining adequate results for our model we need to construct our sample of enterprises that have more or less similar characteristics. On the strength of this, we employed such parameters as year, total asset, and sales. We used the method of the nearest neighbor and end up with 6129 number of observations with about 10% of bankrupted firms. After exploitation of PSM the t-test on difference between samples was conducted. We compared four variables of matched and unmatched datasets and found out that for all of them the difference is insignificant. The results of t- test is given in the Table1.

Table 1. T-test on difference between some variables between matched and unmatched sample

Variable (Mean)	Unmatched Data	Matched Data	T- test p-value
Investments	55163	85684	0.65
Employment	237	238	0.97
Return on Assets	-0.03	-0.15	0.16
Liquidity, Quick Ratio	2.5	2	0.53

At the end of constructing the sample we got the following distribution of bankrupted and non-bankrupted enterprises between years, which is provided in Table 2 and Figure 1.

Table 2. Number of observations per year

Year	2011	2012	2013	2014	2015	2016
# non-bankrupted firms	759	1028	921	1121	773	969
# of failed firms	43	139	52	207	25	92

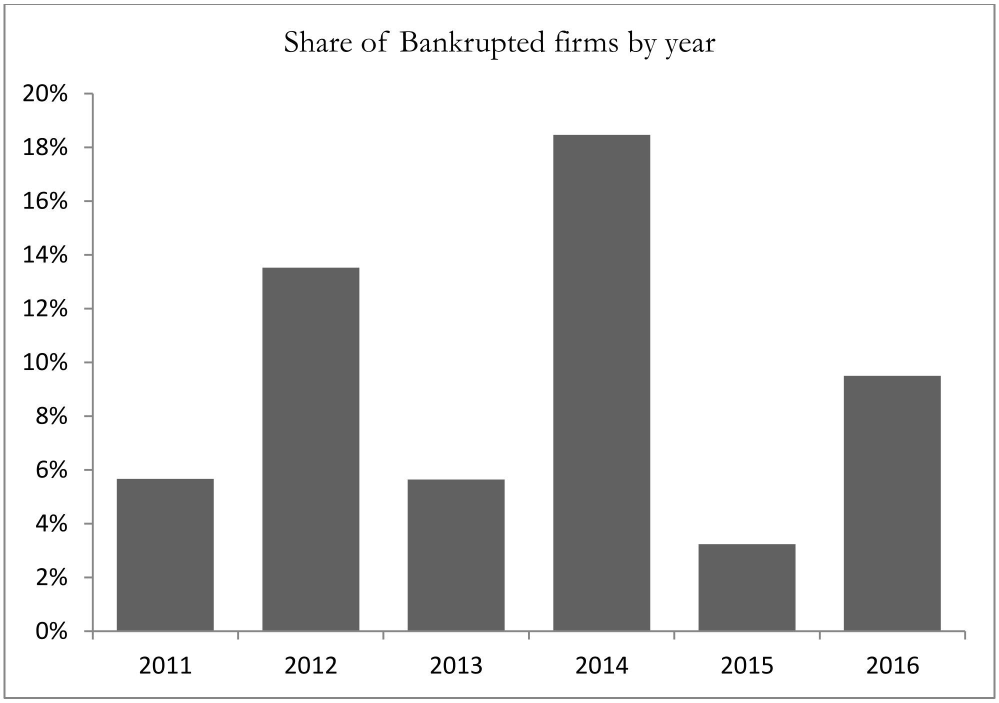

Figure 1. The share of bankrupted firms in the sample by year

From the Figure 1 we can observe an extreme hike in 2014. Such dynamics can be explained by the fact that Ukraine entered the financial crisis in 2014-2015 due to the several political and, as a result, economic reasons. Consequently, as the result of economic instability and a sharp decline in production, a lot of businesses did not withstand such pressure and fail due to the inadaptability to the stringent economic conditions. Moreover, it is important to mention that firms with quite different characteristics (such as size and industry) underwent the crisis.

In obedience to the Ukrainian legislation enterprises are divided by size into four groups by such features as the number of employees and size of the net income. If to take into account only the first characteristic, an enterprise is considered as a micro firm having from 0 to 10 employees, as a small firm hiring from 11 to 50 workers, as a medium enterprise with 51-250 peoples employed and as a big firm, which conducts its activity with more than 250 workers. Thereby, we have the following distribution of bankrupted enterprises by size in our sample (Figure 2).

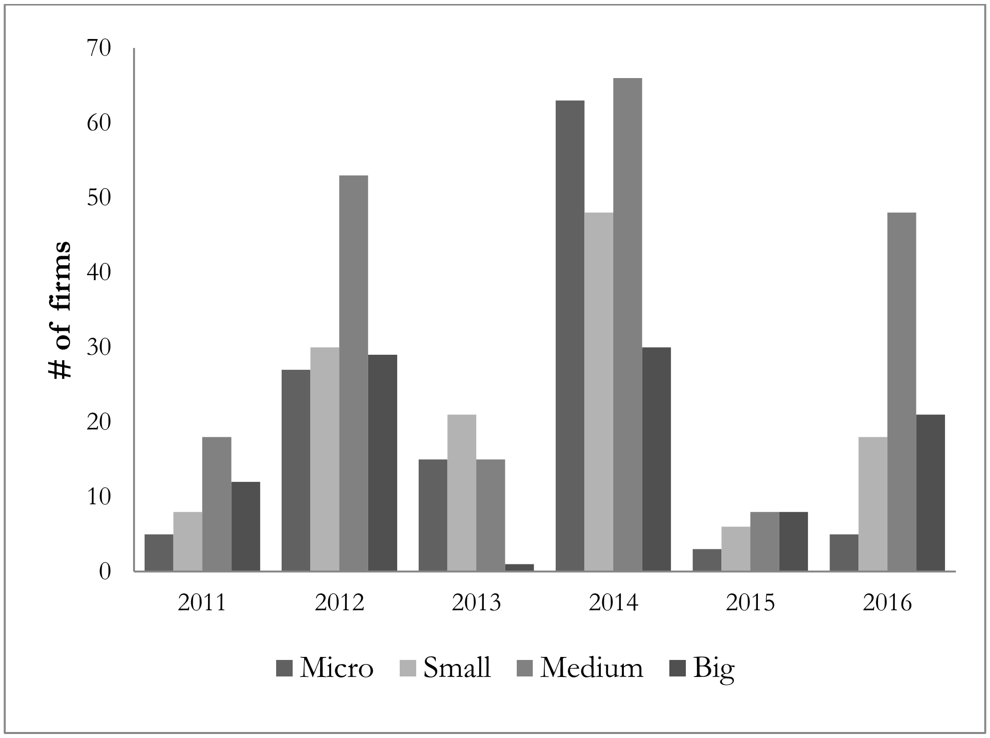

Figure 2. The frequency of bankrupted firms by size from 2011-2016 years

As demonstrated by the Figure 2 the largest share of bankrupted firms is attributed to medium enterprises. However, according to the various empirical researches small companies are more vulnerable to bankruptcy failure. A precise influence of the firm`s size, particularly employment, is investigated in Chapter 5.

Since it is believed that the type of industry has some impact on the probability of failure we should examine which industry has a large share of firm failures. This is represented on Figure 3.

The largest proportion of bankrupted firms is attributed to the sector D – which is the manufacturing sector. This can be explained that the manufacturing sector requires a lot of capital resources, which usually are old and inefficient on the enterprises. Herewith, the firm are less productive and, as a result, less able to cover financial claims of creditors and suppliers.

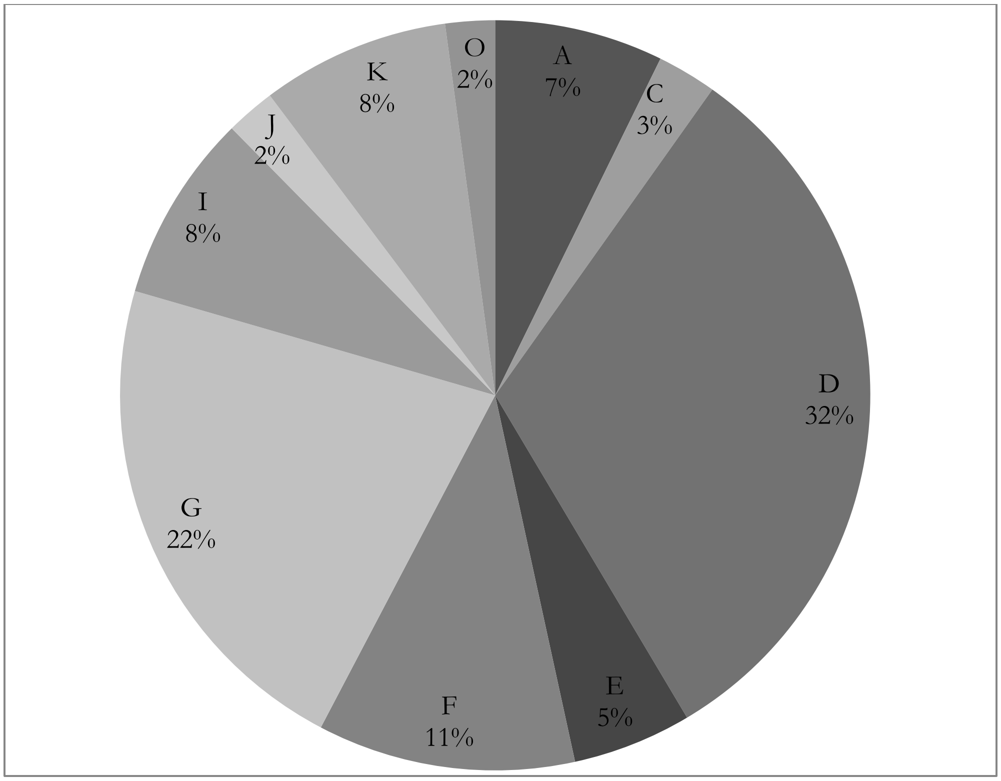

Figure 3. Share of sectors among bankrupted firms

In order to compute necessary ratios we need to have the data without outliers and zeros. The descriptive statistics of the main variables is provided in the tables below. Moreover, we find negative values of such items as current liabilities, which cannot be possible and means mistakes in the financial statements. Henceforth, we leave only positive values of this item in the data. In addition, since possess 5 year data we adjusted variables in absolute values (investment, liabilities etc.) for inflation, and now we have everything in constant of 2011 year.

The indices of inflation were taken from the site of State Statistic Service of Ukraine (UKRSTAT).[6]

Basic descriptive statistics of the main items is provided in Table 3.

Table 3. Basic Descriptive statistics of the main variables

	Total Assets	Invest	Liailities	ROA	Quick Ratio	IO	PT	Emp
min	10.96	-5109705	1.50	-513	0	-68	0	1
max	125mln	389 mln	22 mln	3.6	1914	118200	198	61773
median	17693	414.63	10303	0.001	0.3	0.1	5	76
mean	136609	86 mln	139323	-0.15	1.2	30	16	238
std.dev	1706944	5104912	838370	6.7	38	1567	29	1532

Note: IO – investment opportunities, PT – payables turnover, Emp – employment

In order to cope with skewness, and therefore biased estimations, we transform all variables in absolute terms in logarithmic form, except investments, because by construction they can obtain negative values.

Inasmuch as, we suspect that such features as profitability, liquidity, and investment opportunities differ between bankrupted and non-bankrupted firms. Therefore, it is expedient to look at means of these indicators for both groups of firms, which is introduced in Table 4.

As observed from the table, the means of all presented indicators are lower for failed firms. Now we are to explore at the influence of them and other variables on the probability of going bankrupt by estimating logit models in the next section

[6] *http://www.ukrstat.gov.ua/*

Table 4. Comparison of the main indicators between bankrupted and non-bankrupted firms

	2011	2012	2013	2014	2015	2016
			ROA			
Non-Bankrupted	-0.003	-0.02	-0.03	-0.17	-0.01	-0.01
Bankrupted	-0.30	-0.12	-0.10	-2.90	-0.34	-0.36
			Quick Ratio			
Non-Bankrupted	1.06	1.683	1.04	2.890	1.11	4.265
Bankrupted	0.35	0.34	0.22	0.26	0.28	0.61
			Investment Opportunities			
Non-Bankrupted	1.22	1.33	3.04	20.30	19.72	143.27
Bankrupted	-0.54	-0.325	-0.65	-0.890	-0.81	-0.930

C h a p t e r   6

ESTIMATION RESULTS

In this section we provide estimation results for different model specifications and interpret the obtained results. Since we are going to estimate our model applying logit regression, the coefficients from its results are out of our interest. More valuable for the analysis of determinants of bankruptcy are marginal effects. In addition, to be convinced of the quality of our model we estimate pseudo R-squared and predictive power. Then we compare our results with empirical researches in order to find out whether the probability of financial distress on the enterprises in Ukraine has the same patterns as in the literature.

For the initial specification of the model (*Model 1*) we included such features as return on assets and liquidity (quick ratio). For the second model (*Model 2*) we added the factor variable, which was industry type of the enterprise and control for a year. Then we run other logistic regression (*Model 3)* with the same variables but also included the size variable proxying it with total assets in logarithmic form and lagged investment. Then we compared the results from the previous model with the next one (*Model 5*), but now with the investment made in the period of bankruptcy. Estimation results (marginal effects) are provided in Table 5. Estimation results of regressions are provided in appendices E and F. Analyzing them we can conclude that the quick ratio is significant in all models except Model 3. The marginal effect of the liquidity indicator varies from – 0.03 to -0.018, which means that with increasing the liquidity by 1 point the probability of going bankrupt decreases by 0.02, which was expected. Return on Assets is also with negative a sign and significant in the Model 2 and Model4. Increasing ROA will result in dropping the likelihood of failure by about 2%. Adding the lagged value of investment made the *Model 3* totally insignificant, meaning that no variables have any significant impact on the probability of failure, however, all variables have the expected sign. This happened because of losing number of observations when introducing lagged value of investments. Since we have an unbalanced panel dataset large number of firms has missing values in investments of the previous period.

Table 5. Estimation results (marginal effects) for the first set of model

	Model 1	*Model 2*	*Model 3*	*Model 4*
ROA	-0.0014 (0.0014)	-0.0155** (0.0057)	-0.0023 (0.0284)	-0.02** (0.005)
Quick Ratio	-0.0234*** (0.0012)	-0.0331*** (0.0027)	-0.0185 (0.2236)	-0.03*** (0.003)
Invest t-1			-8.09E-06 (9.83E-05)	
Invest, mln UAH				-1.70E-05* (9.38E-06)
Log(Assets)				0.0065*** (0.0015)
Sector D		0.0374** (0.0144)	0.0234 (0.2789)	0.028* (0.012)
Sector E		0.1108 * (0.0481)	(0.1008) 1.0987	0.073* (0.037)
Sector F		0.0612* (0.0261)	0.0471 (0.5457)	0.052* (0.023)
Sector G		0.0542** (0.0199)	0.0390 (0.4564)	0.037* (0.016)
Sector I		0.0388* (0.0222)	0.0196 (0.2331)	0.036* (0.020)
Year 2012		0.0319*** (0.0086)		0.027*** (0.008)
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors are in parentheses			

Though including instead of investments in the previous period investments in the current period made the situation better (all variable became statistically significant), the marginal effect of investments has a substantially small value, which basically shows us no impact of this item on our dependent variable.

Including the logarithm of total assets demonstrated a good result and showed that with incrementing total assets by 1% will enlarge the probability of financial distress by 0.7%. A positive marginal effect of the size variable was not anticipated and represented quiet strange results, since according to the previous empirical researches the bigger is the firm, the less it is assailable for being in the financial distress. In the next set of estimations, which is given in the Table 6 we try another proxy for measuring the size of the firm and examine its coefficient. Also all three models show that operating of the firm in manufacturing (more precisely energy or water supplying enterprises) or in the food industry increases the probability of bankruptcy. This can be justified by the fact that these industries are capital intensive and require more time for adjusting to change in the market conditions, which also necessitates supplemental financial resources for conducting the operating activity and updating capital.

As the following step we estimate the next set of regressions employing some of the explanatory variables used in the previous estimations and add others that in our opinion could serve as the appropriate determinants of firms` failure. Now we add the variable investment opportunities instead of the investment as was done in the previous estimations. Moreover, now we include the logarithm of the number of employees as the proxy of the firm`s size. In the *Model 5* there were additionally included such determinants as the investment opportunities and logarithm of the sum of long-term and current liabilities. In the *Model 6* we involved payables and receivables turnover ratios while in the *Model* 7 such a variable as the equity ratio at the beginning (in fact in the previous) period was appended. There is no high correlation between explanatory variables, therefore we do not face the problem of multicollinearity.

Table 6. Estimation results (marginal effects) for the second set of model

	Model 5	Model 6	Model 7
Quick Ratio	-0.0140***	-0.0103***	-0.0103***
	(0.0028)	(0.0027)	(0.0027)
ROA	-0.0097*	-0.0073*	-0.0075*
	(0.0043)	(0.0035)	(0.0036)
Log(Liabilities)	0.0101***	0.0071***	0.0071***
	(0.0019)	(0.0016)	(0.0016)
Investment Opportunities	-0.0050***	-0.0038***	-0.0038***
	(0.0011)	(0.0009)	(0.0009)
Log(employment)	-0.0083***	-0.0055***	-0.0055***
	(0.0019)	(0.0015)	(0.0015)
Receivables Turnover		-0.0001	-0.0001
		(0.0001)	(0.0001)
Payables Turnover		-0.0007***	-0.0007***
		(0.0002)	(0.0002)
Equity Ratio			-0.0005
			(0.0024)
Sector D	0.0174*	0.0124*	0.0124*
	(0.0094)	(0.0075)	(0.0075)
Sector E	0.0671*	0.0460*	0.0461*
	(0.0344)	(0.0261)	(0.0262)
Sector F	0.0293*	0.0169	0.0168
	(0.0161)	(0.0114)	(0.0114)
Sector 2012	0.0183**	0.0146**	0.0146**
	(0.0061)	(0.0051)	(0.0051)
Sector 2013	-0.0085*	-0.0067*	-0.0067*
	(0.0049)	(0.0040)	(0.0040)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses

From the Table 6 we can observe that all variables except receivables turnover are statistically significant. In particular, increasing the quick ratio by 1 will reduce the probability of going bankrupt by almost 1% in all three models. The marginal effect of the return on assets is also significant and has a negative sign. The main variable of interest in these estimations is investment opportunities. The marginal effect of this determinant is highly significant and has an inverse relationship with the likelihood of financial distress. The marginal effect of investment opportunities in our model varies from -0.005 to -0.004 indicating that the more growth (investment) opportunities a firm has the less likely it goes bankrupt.

Furthermore, it turned out that the logarithm of the number of employees fits better as the proxy for measuring the firm`s size. As anticipated, it had a negative sign and has a statistically significant influence on financial distress of the company. Specifically, if some enterprise has an average number of employees of the firm bigger by 1% bankruptcy is less likely to occur on that enterprise by 0.5-0.8%. Such results support our main hypothesis that smaller firms are more vulnerable and have higher chances for financial failure.

Payables turnover ratio also show significant results and has a statistically significant marginal effect. That is, rising the payable turnover by 1 will cut the likelihood of going bankrupt.

When estimating a predictive power we transformed fitted values from our model into binary variable (0 and 1). Since our sample is not balanced, we used statistical software to compute optimal cutoff of the fitted values, which differs across our models. Generally all model showed high predictive power, which varied from 90 to 92 %. To be sure that our results are robust we estimate probit regression for the same model specifications. Since we obtained almost similar results, it could be a good sign in our robustness check.

Chapter 7

CONCLUSIONS

In this master thesis we analyzed the factors that influence the likelihood of bankruptcy occurrence on the enterprises. Different model specifications were provided with different determinants of bankruptcy. After thorough literature review we formulated the main hypothesis about relationship between the explanatory variable and the probability of firm failure. Such a variable as return on assets and level of liquidity have a significant influence on the probability of going bankrupt and having an inverse relationship with the dependent variable. Particularly, according to the results of the last model the increasing ROA and Quick ratio by 1 will reduce the chances for failure by 0.7 and 1%, respectively. The main variables of interest were the lagged value of investment and investment opportunities which gave us absolutely opposite results. While the lagged value of investment is totally insignificant, investment opportunities presented a significant marginal effect with negative signs. According to the model performance, increasing the ratio of investment opportunities by 1 point reduces the likelihood of bankruptcy, which was expected and confirmed the results of previous researches.

Moreover, it was found that such an indicator as payables turnover, which showed how often an enterprise payed off its current liabilities to suppliers, had a substantial impact on the dependent variable. Specifically, by magnifying the payables turnover by 1 the firm diminishes the probability of going bankrupt.

In addition, it was shown that enterprises of heavy industries such as energy sector have potentially more chances for failure due to its capital intensiveness and possibly obsolete and insufficient capital resources. If considering a year, according to the estimation results enterprises had more threats of going bankrupt in 2013 than in other years, which could be explained by the severe economic and political climate in Ukraine.

In addition all models provided a high accuracy (about 90%), which gives us strong possibility to claim that we can trust our estimations.

Based on the obtained results we affirm that in the stages of bankruptcy and pre-bankruptcy a firm should focus mostly on such indicators as profitability and liquidity and factors that influence them. Since we found that investment opportunities have positive impact on enterprise`s stability in terms of lowering bankruptcy probability, a firm should invest more funds in new capital, especially if it belongs to manufacturing sector. The latter is related to companies in the heavy industry in Ukraine usually having old and insufficient assets, which can significantly reduce their productivity. Moreover, it was proven that the size of the firm negatively influences the likelihood of failure. Thereby, small firms need more support from the government.

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APPENDIX A

KVED Classification Codes

Table 7. Description of KVED classification codes

Section	Name
A	Agriculture, hunting, forestry
B	Fishing, fish farming
C	Mining industry
D	Manufacturing industry
E	Production and distribution of electricity, gas and water
F	Construction
G	Retail; repair of cars, household products and personal items
H	Activities of hotels and restaurants
I	Transport and communication activities
J	Financial activities
K	Real estate operations, leasing, engineering and services to entrepreneurs
L	Public administration
M	Education
N	Health care and social assistance
O	Provision of communal and individual services; cultural and sporting activities
P	Households activities
Q	Extraterritorial organizations activity

APPENDIX B

Distribution of Firms by Size

Table 8. Distribution of firms by size

ALL							
	2011	2012	2013	2014	2015	2016	Total
Micro	51	118	133	218	122	65	707
Small	166	261	226	275	164	218	1310
Medium	432	611	471	651	385	580	3130
Big	153	177	143	184	127	198	982

Table 9. Distribution bankrupted and non-bankrupted firms by size

Non-Bankrupted Firms							
	2011	2012	2013	2014	2015	2016	Total
Micro	46	91	118	155	119	60	589
Small	158	231	205	227	158	200	1179
Medium	414	558	456	585	377	532	2922
Big	141	148	142	154	119	177	881
Bankrupted Firms							
Micro	5	27	15	63	3	5	118
Small	8	30	21	48	6	18	131
Medium	18	53	15	66	8	48	208
Big	12	29	1	30	8	21	101

APPENDIX C

Correlation Matrix

Table 10. Correlation matrix of main variables

	ROA	Receivable Turnover	Log(employ)	IO	QR	Payable Turnover	ER	Assets
ROA	1	0.01	0.04	0.00	0.00	0.02	-0.01	0.03
Receivable Turnover	0.01	1	0.10	-0.01	-0.02	0.22	-0.01	-0.16
Log(employ)	0.04	0.10	1	0.02	-0.03	0.09	-0.03	0.36
Investment Opportunities	0.00	-0.01	0.02	1	0.00	-0.01	0.00	0.03
Quick Ratio	0.00	-0.02	-0.03	0.00	1	0.00	0.00	-0.01
Payable Turnover	0.02	0.22	0.09	-0.01	0.00	1	-0.01	-0.11
Equity Ratio	-0.01	-0.01	-0.03	0.00	0.00	-0.01	1	-0.09
Log(Assets)	0.03	-0.16	0.36	0.03	-0.01	-0.11	-0.09	1

APPENDIX D

Distributions of firms by Assets and Employees

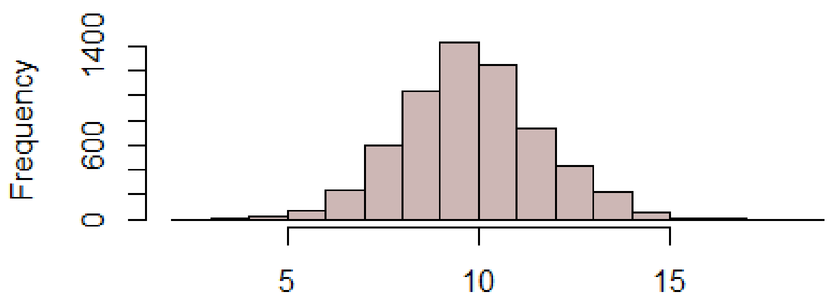

Figure 4. Distribution of firms by log (Assets)

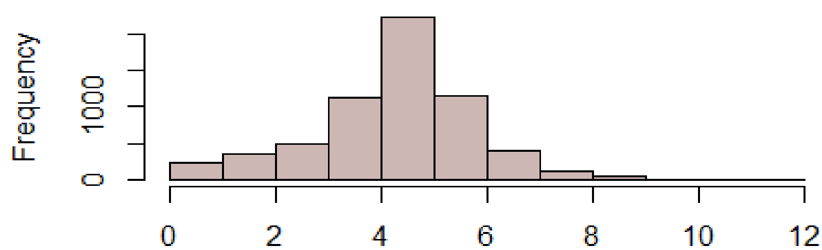

Figure 5. Distribution firm by log(number of employees)

APPENDIX E

Regression Results for the First Set of Model

Table 11. Regressions Results for the first set of models

	Bankruptcy Probability			
	Model 1	*Model 2*	*Model 3*	*Model 4*
ROA	-0.051	-0.498***	-0.243	-0.698***
	(0.047)	(0.156)	(0.228)	(0.167)
Quick Ratio	-0.836***	-1.063***	-1.922***	-1.040***
	(0.102)	(0.189)	(0.314)	(0.190)
Invest t-1			-0.00000	
			(0.00000)	
Invest				-0.001*
				(0.0004)
Log(Assets)				0.247***
				(0.041)
Sector D		0.951***	1.586***	0.846***
		(0.279)	(0.413)	(0.281)
Sector E		1.647***	2.613***	1.404***
		(0.408)	(0.538)	(0.417)
Sector F		1.194***	1.953***	1.177***
		(0.330)	(0.460)	(0.333)
Sector G		1.170***	1.880***	0.989***
		(0.292)	(0.431)	(0.295)
Sector I		0.863**	1.184**	0.909***
		(0.351)	(0.494)	(0.353)
2012		0.914***		0.893***
		(0.185)		(0.187)
Constant	-1.899***	-3.284***	-2.729***	-5.683***
	(0.058)	(0.296)	(0.396)	(0.502)

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses

APPENDIX F

Regression Results for the First Set of Model

Table 12. Regressions Results for the second set of models

	Bankruptcy Probability		
	Model 5	*Model 6*	*Model 7*
Quick Ratio	-0.606***	-0.552***	-0.553***
	(0.179)	(0.189)	(0.189)
ROA	-0.421**	-0.393**	-0.401**
	(0.164)	(0.166)	(0.171)
Log(liabilities)	0.439***	0.380***	0.379***
	(0.044)	(0.047)	(0.047)
Investment Opportunities	-0.217***	-0.206***	-0.206***
	(0.045)	(0.043)	(0.043)
Log(empl)	-0.362***	-0.292***	-0.292***
	(0.051)	(0.055)	(0.055)
Receivables turnover		-0.004	-0.004
		(0.004)	(0.004)
Payables Turnover		-0.036***	-0.037***
		(0.011)	(0.011)
Equity Ratio			-0.028
			(0.130)
Sector D	0.646**	0.577**	0.578**
	(0.287)	(0.289)	(0.289)
Sector E	1.446***	1.302***	1.304***
	(0.428)	(0.434)	(0.434)
Sector I	0.778**	0.768**	0.768**
	(0.361)	(0.365)	(0.365)
2012	0.725***	0.717***	0.715***
	(0.193)	(0.194)	(0.194)
Constant	-5.565***	-4.925***	-4.904***
	(0.491)	(0.517)	(0.525)
Observations	2,931	2,931	2,931
Log Likelihood	-657.038	-642.791	-642.766

Note: * p<0.1; **p<0.05; ***p<0.01
Standard errors are in parentheses

APPENDIX G

Predictive Power of Estimated Models

Table 13. Predictive power and pseudo R-squared of estimated models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Predictive power	0.9	0.92	0.92	0.921	0.92	0.92	0.92
Pseudo R-squared	0.038	0.605	0.746	0.616	0.648	0.656	0.656