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Corporate Default Prediction with Financial Ratios and Macroeconomic Variables

Economics

Master's thesis

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Abstract

In this master thesis paper I study corporate default prediction with firm specific financial ratios and macroeconomic variables. I show how regressions default prediction ability increases when macroeconomic variables are added into the model of financial ratios. In analysis I have financial ratio data from period 1999 to 2011 from industries of construction and retail including 35000 firms and over 200000 observations. The data is from Suomen Asiakastieto, Tilastokeskus and Suomen Pankki. In measuring the goodness of the models I use different analysis of the predicted values like five levels risk classification. This risk classification can also be thought as credit rating.

Keywords: default prediction, credit rating, risk classification

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Sisällysluettelo

1. Introduction

The default prediction of firms is a widely studied issue. When banks and other financial institutions are giving loans to firms they have to value the risk of those firms. This is where the Credit Rating industry is giving their contribution. Credit Rating institutions are measuring the firms' characteristics from the different data that is available. From these characteristics the firms are rated by their risk and are given a *credit rating* which tells how probable is it that the firm is having payment difficulties or even go to bankruptcy in the near future. Different Credit Rating industries are using slightly different kind of methods how they value the firms and how the rating is written. For example in United States a Credit Rating institution Standard and Poor's is using 21 level ratings from the lowest speculative grade D to the highest investment grade AAA (Cantor & Packer 2006).

In predicting the default of firms, the most used and most important information is coming from the firms' historical data, which contains ratios from the financial statements, information of the firms' previous payment difficulties and information of the management's possible payment difficulties from other firms they are related. Size and age of firm as well as Personal marks of failure in payment behavior also give some information. An example, of default prediction based only on financial statement ratios, is widely referred Edward I. Altman's Z-score. In Z-score model there are five financial statement explanatory variables with different weights, which are giving the Z-score value. The Z-score value is explaining the probability of the firm's default in the near future (Altman 1968).

Even that the issue is widely studied, the models and research is mostly based on firm specific financial statement data. The reason for this might be that firm specific models are already giving very good predictions of the future risks. And if the model is already good enough it might be better to keep it also simple as possible. The simplicity makes it more transparent and easier to use and sell to customers. What I find the problem here is that the firm specific financial information is, firstly historical and secondly does not tell anything about the macroeconomic conditions at certain time. An economic shock can bring huge risks in businesses, but we can't see these risks, if just look to the historical firm specific information.

My contribution is that I'm trying to find new variables from *macroeconomic data* to improve the ability to predict the probability of default. These "new" macroeconomic variables are *industry volumes, gross national income, interest rate, consumption and consumer confidence* *on the economy.* One reasons why I think the macroeconomic variables could give new value to the firm specific models, is that the financial statement information on small firms is historical information and is approximately 18 months old (Asiakastieto), when the macroeconomic data of quarterly macroeconomic accountancy is instead 6 to 9 months old (Tilastokeskus). So if there is an economic shock like sudden financial crisis, the 18 month old firm specific historical data could give a view that everything is fine, but when we are looking the industry index or other macroeconomic conditions, we might see that this is probably not the case.

For analysis I'm using firm specific financial ratio data from Suomen Asiakastieto and macroeconomic data from Tilastokeskus and Suomen Pankki. I'm studying two different industries which are construction and retail.

The firm specific variables are gearing ratio, quick ratio, return on investment and logarithm of net sales.

The macroeconomic variables are industry index or volume, interest rate, consumption, gross national income and consumer confidence on economy,

The null hypothesis H0 is that the new macroeconomic variables are not giving any new value to the existing firm specific models. My ambition is to attack against the null hypothesis and try to reject it. My other hypothesis H1, H2 and H3 are:

H1: The macro level variables are significant in the regression model with financial ratios and macroeconomic variables when the dependent variable is default of a firm.

H2: The macro level variables improve the model's ability to predict future defaults.

H3: The newer the macroeconomic data used in model, the more significant the macro variables are and better it predicts the future defaults.

1.1. Progress of the study in this paper

In section 2 I start with explaining few words about credit rating industry. In section 3 I go through the history of the default prediction and the most important authors and papers written. In early twentieth century the risks were measured with only one variable like current ratio. As decades went by, multiple variable models were used more and more. Finally there are nowadays complex models using many variables. Some literature of research of firm specific- and macroeconomic covariates are also introduced. In section 4 I go through my hypothesis. In section 5 I start to work with the data. I introduce the data and both the firm specific- and macroeconomic variables. Also some graphs of variable means over time are introduced. After description of the data I continue with the regressions. I introduce the linear and logit model and show the outputs of different linear regressions. After regressions I compare the goodness of the model and measure their prediction abilities. My ambiguity is to find the most valuable and credible model and also find evidence for my hypothesis. In section 6 I explain the use of the prediction model to the test data. Unfortunately my time series data is too short to get even a satisfactory test data. There should be at least one economic shock in the macroeconomic data to get some results. Now my only shock is the 2008 financial crisis, but it is already included in sample data. In section 7 I go through the results of my hypothesis and in section 8 the conclusions of this study. In conclusions I also discuss a little bit of the further research possibilities could be done in the future.

2. Credit Rating Industry

When banks and other financial institutions are making loan decisions to the firms and individuals they have to measure the customer's ability to pay. Here is where the credit agencies are giving their contribution. Credit agencies are privately owned firms that analyze the firms and individuals with large set of historical data. Rating firms the credit rating agencies are mostly using the data of firms' financial history and their past payment behavior. The customer of credit rating agency can be the firm itself or the bank between the firm and credit rating agency. The bill of the sold credit rating usually goes to the firm either straight away or it is included in loan expenses. The credit rating gives a probability of the risk the firm will default in its liabilities or how well the firm is expected to success its liabilities.

Richard Cantor and Frank Packer (1994) are bringing out the history and of the credit rating industry and are listing the credit rating agencies in United States. They discuss how financial regulations and markets have reliance into credit rating industries. They also give some criticism to the credit rating industry because there are differences of meanings of ratings over time and also between credit agencies. There is also discussion about the fact that selling credit ratings is business and when there are many private owned credit rating agencies there is a change that customers buy their rating from the agent that gives them a best rating.

Different credit rating agencies have long had their own symbols. Some use letters, other use numbers. Many are using both in ranking the risk of default from extremely safe to highly speculative. For example Standard and Poor's is using 21 level ratings from the lowest speculative grade D to the highest investment grade AAA. They also use one to three letters and plus and minus signs in grading. The other top rated agency named Moody’s is using letters and numbers in their 19 level ratings from the lowest grade D to highest quality grade Aaa (Cantor & Packer 1994).

In Finland the credit rating agency Suomen Asiakastieto Oy is also using same kind of seven levels grading from the lowest level of D to the highest level of AAA which get only few percent of firms. The Suomen Asiakastieto’s rating called Rating Alfa introduces four qualities from the firms’ financial history. These are liquidity, solvency, profitability and volume.

3. Science and models

Erkki K. Laitinen (2005 p.7) state, that science can be defined in many different ways. In most cases the mission of science is defined as producing generic information. For this reason he defines science as systematic observing of the real world events and producing generic information from those events. When we are join the systematic observing and producing generic information, we can talk scientific use of financial information so that the credit decisions can be made generally more efficiently than before.

Efficiency in credit decisions mean two things. First is that less and less credit are granted to firms which fail in their business and can’t take care of their liabilities. Second, efficiency is that less and less happens that the credit is rejected from the successful firms which can take care of their liabilities. When credit is granted to a firm which fails it’s liabilities in the near future the error is called by *Type I error.* When credit is rejected from a successful firm, the error is called by *Type II error.* The objective of scientific invocation of financial information is to reduce the probability of both types of errors with scientific methods. Generally it is considered that Type I errors causes more costs and the interest is more in reducing them. It is although important that the successful company gets the credit it needs. (Laitinen 2005 p.7)

3.1. The use of financial information before 1960

The credit ratings of firms have been under general interest at least from late nineteenth century. The creditors started to interest in measuring the solvency of firms. In other words, measuring the probability that the firm can keep up its’ liabilities. In 1870 in the United States financial statement information was started to use in credit decisions, but in larger scale it became general in 1890. At that time the analysis of financial statement information was more just observing and comparing of different balance sheet items. About the same time the segregation of current from non-current items was begun (Horrigan 1968). Roy A. Foulke (1945, s. 70) state that this was the most important classification, because the firm's solvency base much on short term assets. In the late 1890 they started to compare the current assets and current liabilities. Other ratios were developed too but the most significant was the *current ratio*. (Horrigan 1968).

Before and during the First World War there were many significant steps in financial ratio analysis. First, a fairly large variety of ratios was conceived. For example James Cannon, a pioneer of financial statement analysis, used ten different ratios as early as 1905 in a study of business borrowers. Second, absolute value criteria began to appear, the most famous being the absolute criteria 2 of current ratio. It meant that if current ratio dropped below 2, it meant poor solvency. Third some analysts began to recognize the need for relative ratio criteria. Despite these developments, many analysts tended to use only one, the current ratio. (Horrigan 1968).

In 1912 Alexander Wall reacted to the apparent needs of more types of ratios and for relative ratio criteria by beginning a compilation of a large sample of financial statements from the files of commercial brokers. This analysis was culminated in his classic report of 1919, "Study of Credit Barometrics." In this study, Wall compiled seven different ratios of 981 firms, for an unspecified time period. He stratified these firms by industry and by geographical location, with nine sub-divisions in each of those strata. Although he did not subject this data to any further analysis, he believed he found great ratio variation between types of businesses. His study was historically significant because it was widely read and it made popular the ideas of using many ratios and using empirically determined relative ratio criteria in credit rating. (Horrigan 1968).

During the next decade, the 1920's, interest in ratios increased remarkably. A virtual explosion of publications on the subject of ratio analysis occurred. At the same time, many compilations of industry ratio data were begun by trade associations, universities, credit agencies, and individual analysts. This process of collecting industry ratio data and computing averages therefrom was called "scientific ratio analysis," but the label "scientific" appears to have been a misnomer because there is no evidence that hypothesis formulation and testing were carried out. (Horrigan 1968). The science based on that there was found useful limits for the ratios from the empirical evidence of real world regularities (Laitinen 2005 s.9).

After the classic study of Alexander Wall the simultaneous usage of many ratios increased. Wall himself, attempted mitigate the effects of ratio proliferation by developing a ratio index. This index was essentially a weighted average of different ratios with the weights being the relative value assigned to each ratio by the analyst. This effort was much derided, but he appears to have been engaged in a praiseworthy attempt to develop a naïve linear discriminate function. (Horrigan 1968)

In the next decade, the 1930's the literary discussion of ratios and compilation of industry average ratios continued unabated. The attention to the empirical based ratio analysis increased. There were two significant developments in this decade relating to ratio analysis. The first was that the discussion in the literature of the most efficacious group of ratios. In this respect the most successful promoter of his own particular group of ratios was Roy A. Foulke. He was successful largely because he could supply annual industry data for his group of ratios. Foulke developed a group of fourteen ratios. The publication of his ratios was begun in 1933, and this collection of ratios quickly became the most influential and well-known industry average series. (Horrigan 1968).

In 1930 Raymond F. Smith and Arthur H. Winakor analyzed a sample of 29 firms which had experienced financial difficulties during the period 1923-1931. They analyzed the prior ten years' trends of the means of twenty ratios. They concluded that the ratio of net working capital to total assets was the most accurate and steady indicator of failure, with its decline beginning ten years before the occurrence of financial difficulty. However their study suffered the shortcoming of lacking a contrasting control group of successful firms. (Horrigan 1968).

The predictive power of ratios was also carried out in the early 1930's, and control group were used. Paul J. FitzPatrick, using a case-by-case method of analysis, studied the prior three to five years' trends of thirteen types of ratios for twenty firms which had failed during the period 1920-1929. Following this up with a comparative analysis of a matched sample of nineteen successful firms, he concluded that all his ratios predicted failure to some degree but the net profit to net worth, net worth to debt and net worth to fixed assets ratios were generally best indicators. The shortcomings of this study were that the sample was too small and too selective. In general, the shortcomings of the studies at that time were outweighed by the essential importance of their contribution. They represented an extremely significant event in the development of ratio analysis because they were the first carefully developed attempts to utilize the scientific method for determining the utility of ratios. (Horrigan 1968)

In the early 1940's, Charles L. Merwin published a study, where he analyzed the prior six years' trends of large, unspecified number of ratios of "continuing" and "discontinuing" firms. Comparing industry mean ratios of "discontinuing" firms against "estimated normal" ratios, he concluded that three ratios were very sensitive predictors of discontinuance, up to as early as four to five years in some instances. These ratios were net working capital to total assets, net worth to debt, and the current ratio (Horrigan 1968). FitzPatrick's and Merwin's studies generalized the use of control groups as scientific method. Merwin's study is the first high graded research of ratios as predictors. It attracted many successors in the next decades. (Laitinen 2005)

3.2. Single financial ratios as predictors

An important milestone in the scientific use in research of financial ratios was achieved in 1966 by William H. Beaver, when he published his research "Financial Ratios as Predictors of failure". This research is generally valued as pioneer of single ratio analysis in credit rating. (Laitinen 2005 s.10) His empirical data considered 79 failed firms and 79 non-failed firms. Beaver defines "failure" as the inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the following events have occurred: bankruptcy, bond default, an overdrawn bank account, or nonpayment of preferred stock dividend. (Beaver 1966)

The data was collected from Moody's Industrial Manual, which was the only source available. Moody's Industrial Manual contains the financial statement data for industrial, publicly owned corporations. The population excluded firms of non-corporate form, privately held corporations, and nonindustrial firms (e.g., public utilities, transportation companies, and financial institutions). The firms in Moody's tend to be larger in terms of total assets than are non-corporate firms and privately held corporations, so this study apply only to firms that are members of the population. The choice of this population is admittedly a reluctant one. The probability of failure among this group of firms is not as high as it is among smaller firms. In this sense, it is not the most relevant population upon which to test the predictive ability of ratios. However the chosen population represents over 90 per cent of the invested capital of all industrial firms. (Beaver1966)

The time period being studied was ten years from year 1954 to year 1964. In Moody's there appeared a list of firms that had stopped reporting its financial information. There are many reasons for a firm not reporting any more: the name change, merger, liquidation, lack of public interest, and most importantly, failure. From a list of bankrupted firms, the right firms were chosen. Final list of failed firms contained 79 firms on which financial statement data could be obtained for the first year before failure (Beaver 1966).

The failed firms were classified according to industry and asset size. The total asset size of each firm was obtained from the most recent balance sheet prior to the date of failure. The industry and asset size composition were heterogeneous. The 79 failed firms operated in 38 different industries. The classification of the failed firms according to industry and asset size was an essential prerequisite to the selection of the non-failed firms. The selection process was based upon a paired-sample design. That means that for each failed firm in the sample, a non-failed firm of the same industry and asset size was selected as a pair. (Beaver 1966)

Beaver analyzed group of firms' economic performance with 30 different ratios 5 years before failures. He observed in his profile analysis that ratio distributions of non-failed firms were quite stable throughout the five years before failure. The ratio distributions of the failed firms exhibit a marked deterioration as failure approaches. The result is a widening gap between the failed and non-failed firms. The gap produces persistent differences in the mean ratios of failed and non-failed firms, and the difference increases as the failure approaches. Beaver's empirical research was important scientific step in credit rating with financial ratios, and indicated, that single ratios are quite reliable predictors of financial difficulties even 5 years before failure. (Beaver 1966)

After Beaver's research, the selection of financial ratios was given more scientific weight. For example J. Wilcox (1971, 1973, and 1976), A. Santomero and J. Vinso (1977) J. Vinso (1979) and James Scott (1981) developed different kind of theories to justify failure predictive ratios basing on the risk. The basic thought of these theories is to illustrate the firm's value, liabilities and return to equity, when after one or several periods the firm fails because liabilities exceeds the firm's value. (Laitinen 2005 s.11)

With this kind of scientific method, it can be shown that the most vital ratios illustrate the firm's solidity, profitability and its volatility risk. James Scott (1981, s.337-338) add an assumption that when firm is selling its assets in the risk of bankruptcy, it face up some fixed costs. These fixed costs are not size related. Because of this the large companies face smaller fixed costs, which inflect the bankruptcy risk. For this, the size of firm is also an essential predictor. The theory explains the firm's development to bankruptcy with its solvency. Scott presumed that the firm's assets face some liquidity problems and is not easy to sell because of imperfect markets. The liquidity is though also an interpretative factor to the risk of bankruptcy. He states that the prediction of bankruptcy is empirically possible and theoretically explainable.

Aatto Prihti (1975) was pioneer in Finland in research of corporate bankruptcy with balance sheet information. His doctoral thesis was aiming to develop a theoretical model that could notice a risk of upcoming bankruptcy. In his model a firm is seen as series of consecutive investments. The investments are financed with cash flows and with equity and debt. From different cash flows the minimum demand of yield can be measured and the investments should make profits at least that amount. If the firm fail in this, it end up into a situation where it loses credibility in the eyes of interest group and is no longer able to get finance. In the study Prihti tested with three different ratios and their trends in several years. These ratios were:

$$\text{ratio 1} = \frac{quickflow\ after\ taxes}{total\ assets}$$

$$\text{ratio 2} = \frac{(current\ assets\ and\ inventories) - current\ liabilities}{total\ assets}$$

$$\text{ratio 3} = \frac{liabilities}{total\ assets}$$

3.3. Multiple variable models

A single ratio can illustrate the firm's performance quite well, but as predictor of failure it lacks in essential information. For example the *return on equity* doesn't necessary give reliable information of the possible failure in the future, because it doesn't say anything about the firm's debts. Even so, it might still give some good information of the firm's condition. When a single ratio lacks information, it might feel reasonable to use many different types of ratios together.

Edvard I. Altman (1968) was a pioneer in studying multiple variable models. Altman reason his study, because academicians seemed moving toward the elimination of ratio analysis as an analytical technique. He sees the multiple variable analysis as an opportunity to improve the scientific attitude and appreciation in academicians. Altman used *multiple discriminant analysis (MDA)* as the appropriate statistical technique. (Altman 1986)

MDA attempts to derive a linear combination of characteristics which "best" discriminates between groups. If a particular object, for instance a corporation, has characteristics (financial ratios) which can be quantified for all the companies in the analysis, the MDA determines a set of discriminant coefficients. (Altman 1986)

Altman concerned two groups, bankrupt firms on one hand, and non-bankrupt firms on the other. The analysis is transformed into its simplest form: one dimension. The discriminant function of the form $Z = v_1 x_1 + v_2 x_2 + \ldots + v_n x_n$ transforms individual variable values to a single discriminant score or Z-value, which is then used to classify the object,

where $v_1, v_2, \ldots v_n$ = Discriminant coefficients

$x_1, x_2, \ldots x_n$ = Independent variables

The MDA computes the discriminant coefficients, v_j, while the independent variables x_j are the actual values

where $j = 1, 2, \ldots n$.

When utilizing a comprehensive list of financial ratios in assessing a firm's bankruptcy potential, there is reason to believe that some of the measurements will have a high degree of correlation or collinearity with each other. MDA is a statistical technique used to classify an observation into one of several *a priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form. (Altman 1986)

3.4. The use of background information in prediction

When the study of predicting corporate failure is mostly based on financial information, the non-financial background information as predictor is not so studied subject. The first background information based predicting model was developed by John Argenti (1983) in his study "Predicting Corporate Failure". The model is named A-model. The model is based on large amount of bankruptcies and Argenti's own findings, but not into statistical methods. In the model there is subjective pointing system, which is based on an opinion of a risk evaluating company analyst. The analyst makes the justifications by visiting the company and meeting the directors of the company. (Argenti 1983)

In the model there are 17 points answering the defects, mistakes and symptoms of the company. The defects can be can be in management, in accounting system and in attitudes to changes in environment. Mistakes are excessive incurring of a debt, uncontrollable growth and too large project. After mistakes the symptoms follow. The symptoms are weakening ratios, cover-up of financial standing, non-financial symptoms like weakening product or service, sick leaves of management, changes in management and moral down turn. (Argenti 1983)

Keasey and Watson (1987) tested in their study the significance of non-financial based on A-model. Their data considered independently owned companies in the North East of England from 1970 to 1983. A sample contained 73 failed and 73 non-failed companies. Also the results were tested with 20 out-of-sample companies. There were 18 non-financial variables and 28 financial ratios describing the companies. The dependent variables were failure and non-failure. These non-financial and financial variables were studied in three models as follows:

Model 1: Financial ratios only

Model 2: Non-financial information only

Model 3: Financial ratios and non-financial information

The non-financial variables are listed below in table 3.1.

Table 3.1.

Q 1. Age of company (in years)	Q 10. Has the company received a "Going Concern" qualification?
Q 2. Number of current directors	Q 11. Is there a secured loan on the company's assets?
Q 3. Has there been any new directors over the 3 year period?	Q 12. Is there a secured loan on the company's assets held by a bank?
Q 4. Has a director left the company over the 3 year period?	Q 13. Average audi lag (in months) over the 3 year period
Q 5. Number of non-director shareholders	Q 14. Average submission lag (in months) over the 3 year period
Q 6. Has there been any new share capital introduced?	Q 15. Average lag (in months) between auditor's signature and submission
Q 7. Has there been any change of auditors in 3 years?	Q 16. Final year audit lag (in months)
Q 8. Has the company had a qualified audit report in prior 2 years?	Q 17. Final year submission lag (in months)
Q 9. Has the company received a qualified audit report in curren year?	Q 18. Final year lag (in months) between auditor's signature and submission

Keasey and Watson claim in their conclusions that their non-finacial data predicts marginally better than traditional financial ratios. Their results may indicate this, but I have doubts of trusting just this quite small study of just 73 failed and 73 non-failed companies and the test sample only 10 failed and 10 non-failed companies. It feels somehow obvious that there are large differences in the “means” of quality of failed (bankrupted) and non-failed healthy companies.

3.5. Models and macroeconomic

Kenneth Carling, Tor Jacobson, Jesper Lindé and Kasper Roszbach (2007) estimated a duration model to explain the survival time to default for borrowers in the business loan portfolio of a major Swedish bank over period 1994-2000. Their model takes into account both, the firm specific characteristics, such as accounting ratios, payment behavior and loan related information, and the prevailing macroeconomic conditions such as the output gap, the yield curve and consumers expectation of future economic development. They also compared the model with a frequently used model that uses only firm specific information. They find out that their macroeconomic variables had significant explanatory power and their model was able to account the absolute level of risk.

Sudneer Chava, Catalina Stefanescu and Stuart Turnbull (2011) focus modeling and predicting the loss prediction for credit risky assets such as bonds and loans. They model the probability of default and recovery rate given default based on shared covariates. They develop a new class default models that explicitly accounts for sector specific and regime dependent unobservable heterogeneity in firm characteristics. Based on the analysis of a large default and recovery data set over the horizon 1980 to 2008, they document that the specification of the default model has a major impact on the predicted loss distribution, whereas the specification of the recovery model is less important. In particular, they find evidence that industry factors and regime dynamics affect the performance of default model. Implying that the appropriate choice of default models for loss prediction will depend on the credit cycle and portfolio characteristics. They also show that default probabilities and recovery rates predicted out of sample are negatively correlated and that the magnitude of the correlation varies with seniority class, industry and credit cycle.

Darrel Duffie, Leandro Saita and Ke Wang (2005) published a paper named Multi-period corporate default prediction with stochastic covariates. They provided maximum likelihood estimators of term structures of conditional probabilities of corporate default, incorporating dynamics of firm specific and macroeconomic covariates. Their data considered US Industrial firms based on over 390000 firm months and over 2007 firms for the period 1980 to 2004. They find evidence on significant dependence of the level and shape of the term structure of conditional future default probabilities on a firm’s distance to default and on US interest rates and stock market returns, among other covariates. Variation in a firm’s distance to default has a substantially greater effect on the term structure of future default hazard rates than does a comparatively significant change in any of the other covariates. The shape of the term structure of conditional default probabilities reflects the time-series behavior of the covariates, especially leverage targeting by firms and mean reversion in macroeconomic performance. Their model is based on a Markov state vector of firm-specific and macroeconomic covariates that causes inter temporal variation in a firm's default intensity. They also introduce a comprehensive literature review about the issue.

4. Hypothesis

Here I bring out the hypothesis of my research. In this paper my ambition is to bring new variables and new perspectives to the prediction of firms' payment difficulties and bankruptcy. Since traditionally the predictive variables used in the prediction models have only been firms' financial ratios, I'll try to make the models better by attaching there some new macroeconomic variables. The macro level numbers can be newer than the financial ratios at hand at some point of time. The older the financial statement data is compared to the macro level numbers the more significant I assume it to be that the macro level numbers bring new value to the models.

I study three things. First, I study how significant are the macro level variables when they attached into the model created with financial ratios. Second I Study, if the macro level variables make the predictions of default better. Third I study how the freshness of the ratios and macro level variables affect to the results of predictions.

Here are my three hypotheses:

H1: The macro level variables are significant in the regression model with financial ratios and macroeconomic variables when the dependent variable is default of a firm.

H2: The macro level variables improve the model's ability to predict future defaults.

H3: The newer the macroeconomic data used in model, the more significant the macro data is and better it predicts the future defaults.

5. Econometric Research

For empirical research I use Econometrics and linear and logit regression analysis. The dependent variable is default and explanatory variables are firm specific ratios and maybe their variations and different macroeconomic variables. Also default history is taken into account since it expect to have significant part in the risk of future defaults.

5.1. Data

The firm specific financial statement data is collected from the sources of Suomen Asiakastieto Oy. Suomen Asiakastieto collects and analyses data from the Finnish companies and private citizens. Their sources include marks of the payment behavior of firms and individuals also. The macroeconomic data of national economy is collected from Tilastokeskus except interest rate is from the sources of Suomen Pankki.

The firm specific financial statement data collected to this research, consider 35139 firms. These firms have altogether 201708 observations. The number of observations decreases a bit from this, when I start working with the data in section 5.3. The firms are from two different industries, which are construction and retail. The firm specific ratios from financial statements are from the beginning of 1999 to the end of 2011 and occur yearly. There are only firms whose accounting period is calendar year. This is because it's easier to connect the data to the macroeconomic data and the comparison between different periods of time is possible.

The macroeconomic data consider a time period from the beginning of 1999 to the end of 2011 and occur quarterly. When the regression model is used, the best results are supposed to come from the newest data. It means that the newest numbers are used also from the financial statement data and the macroeconomic data. In the research I'm using different quarterly numbers with the last financial statement ratios. This is because it depends which time of year the model is used. I assume that the macroeconomic variables are more significant the older the financial statement data is comparison to the macroeconomic data.

Multicollinearity between financial ratios and macroeconomic variables might give some challenges. Especially when the macroeconomic data is from the same period of time as the financial statement data the problem of multicollinearity can appear. Multicollinearity is also a problem between different macroeconomic variables since they tend to move to the same direction. The best results to prove the significance of the macroeconomic variables probably come when the financial statement data is old and macroeconomic data is new. For example when the financial ratios are from accounting year 1.1.2011 to 31.12.2011 and the macroeconomic numbers are from 31.6. 2012, the macroeconomic numbers should give some new information of the overall economic situation.

5.2. Variables

The dependent variable is default. The dependent variable is a dummy and is explained by five firm specific, financial ratio explanatory variables and four macroeconomic variables. Also default history is taken into account of choosing variables. The financial ratio variables are control variables that stay in the model all the time. The macroeconomic variables are then put into the model of control variables and the model is tested if it's predictive ability increases.

5.2.1. Dependent variable

Default is the dependent variable and it is a dummy variable. If the default variable gets a value of 1 in some year, it means that it has failed in payments on that given year, or it has gone into bankruptcy on that given year. If the firm has gone to bankruptcy it doesn't have any more information after that year. The default variable is collected from years (t+2) and (t+3), if the financial ratio data is from year (t).

Gearing ratio, return on investment, quick ratio **and** ***logarithmic net sales and growth rate of sales*** are the firm specific financial ratios I chose to this research. To justify of choosing just these four ratios I lean on previous research of Altman, Beaver, Prihti and Laitinen. These ratios represent *solidity* (gearing ratio), *profitability* (return on Investment) *liquidity* (quick ratio) and *volume* (net sales). Suomen Asiakastieto Oy is also using these four characteristics in credit ratings. The same ratios were used also in another lately made master thesis of Vilma Virtanen (2010). Her thesis concerned the significance of adjustments of financial statements.

Solidity is one of the most important characteristics of describing the firm's current situation concerning the probability of getting into payment difficulties. Erkki Laitinen (2005) find that **gearing ratio** is itself the best single ratio predicting the payment difficulty. In test material, as single ratio it classified wrong 30.8 % of poor credit firms (type I error) and 22.0 % of successful firms (type II error), what makes an overall result 26.4 % wrongly classified. This is, as single ratio predictor, almost as good as other models with many variables. The critical value of gearing ratio was 26.64, what means that lower than that are classified as poor credit firms.

Return on investment (ROI) is representing the profitability. This ratio gets its attention also in Laitinen's (2005) research, but as predictor of payment difficulties, it is more like a nice addition to the model and isn't itself success so well. As single ratio it made type I errors 34.0 %, type II errors 44.0 % and overall result 39.0 % wrongly classified.

Quick ratio as single ratio, in Laitinen's (2005) research, made Type II errors surprising 66.4 %, but type I errors only 6.8 %. Its overall result was 36.6 % wrongly classified. But since the type I errors are considered as much more expensive to the creditor, quick ratio seems a very good addition to the model.

Laitinen (2005) have also made a five ratio logistic multivariable model, in which he chose growth of sales %, quick ratio, gearing ratio, income before extraordinary items / current liabilities % and logarithmic net sales. From this model he find that after gearing ratio the **logarithmic net sales** also gave important value to the model. Laitinen mention that after gearing ratio it is not easy to significantly improve the divination of the model with additional variables. It's good to remember that even slightly improvements can have huge economic relevance.

Growth rate of sales variable is telling if the firm's orders are growing too fast and does this have something to do with payment difficulties. When the firm's volumes are growing too fast the cash flows may not keep up and the firm gets into trouble when it tries to handle all the orders.

5.2.2. Macroeconomic explanatory variables

Gross National Income, industry volume, interest rate, consumption, and consumer confidence on economy are the macroeconomic variables. I also considered export and investment in construction, but left them out at this point. Gross national income, industry volume and consumption are 6 to 9 months old information depending on the time it is used. Quarterly Interest rate is approximately 1.5 months old information and consumer confidence on economy is 1 to 2 month old information. The lag, why the information is not totally "fresh," comes from the time they are collected and the time they are published. When these variables are used in predictions, the newest information should be used.

Industry volume is a percentage number and occurs quarterly. It is a percentage change from the corresponding quarter from last year. The value is season equalized and working day fixed (Tilastokeskus 2013). This variable might be close correlated to the firm specific values, like net sales, but I expect it to give some new information to the older data from firms' financial statements. When the financial statement data is approximately 18 months old (Asiakastieto 2012), this is only 6 to 9 months old. A lot can happen in the economy in over that period.

Interest rate is a 12 month euribor and it occurs quarterly. It is measured as mean from last three month's euribor (Suomen Pankki 2013). It is also available monthly, but I decided to use quarterly mean, because it is not that volatile.

Consumption is the percentage change in the sum of public- and private spending from last quarter. The reason why this is change to last quarter and not to last year like other variables is that it's volatility is very low. (Tilastokeskus 2013).

Consumer confidence on economy is a combination of four different components. The components are *consumer's confidence on her own economic situation after 12 months, consumer confidence on national economy (Finland) after 12 months, unemployment after 12 months and household's changes to save money after 12 months.* This information is collected by telephone interviews and is done monthly. The results are published before the end of next month (Tilastokeskus 2013). In my research I use quarterly numbers. The consumer confidence is a so called latent variable.

5.3. Working with data

In analyzing the data I used Excel and Stata. The data collected from Asiakastieto was first in Excel form. In Asiakastieto they made a specific data the way I wanted it. It was important to think every detail, what kind of data I wanted and in what form. It was nice that they were able to make me a *complete cross sectional time series data* or *panel data*. The reason why I needed the data in a panel form, was my intention to merge the macroeconomic variables like industry volumes into the data. Without the macroeconomic variables, a cross sectional data from firms' financial ratios from only one year might have been enough. But for getting some variation in the macroeconomic variables, I also needed many years of time series data also. Finally the data is converted into panel form in Stata. It is an *unbalanced* panel data, since in many cases the firm specific data does not consider the whole time period. Some firms' first information is after the year 1999 and some firms' last information is before 2011. Some firms have holes in their time series. The reason for these might be foundation of firm, bankruptcy, fusion or the firm just doesn't have given information from some particular year. Some observations might also have some error or exceptional cases, and for that, are removed from the data. This panel data I call *the main panel data*.

5.3.1. Cleaning financial ratio data

After cleaning some error and exceptional cases, I focused my attention to the extraordinary low- and high ratio values. Because extraordinary low- and high ratio values can cause unfavorable movement in mean values, I decided to clean some of them also. Here I have to be careful not to clean too much, because the research's object is to predict payment failures, which can be considered a rare phenomenon and quite extreme case also. There might however be some ratio values that are exceptionally abnormal, for example, because the denominator in the ratio formula is close to zero or just because of an error in data. There were also quite many observations that didn't have a value in all of the ratios so I deleted them also.

There are also some quick ratio values below zero. This might be because the firm's bookkeeper has written some assets or debts into wrong side of the balance sheet, making the ratio negative. This can cause quite significant distortion in the ratio mean. The gearing ratio values also have some very large negative values. This is probably because the denominator (total assets - received in advance) is close to zero and the numerator (equity) is negative. In case of gearing ratio I should be cautious, since the weak gearing ratio is considered heavily correlated with the possible defaults (Laitinen 2005).

In cleaning the extremes, I dropped observations when their ratios (sales, quick ratio, ROI, gearing ratio) included below 1st and above 99th percentiles or if the value was negative. With sales and quick ratio I dropped values below zero and above 99th percentile. With gearing ratio I dropped observations below 1st percentile and left the upper tail untouched since the highest value 100 is normal and as it should be. This cleaning decreased the number of observations by 36231 and left 171477 observations in the data. After cleaning, the ratio value extremes look much more realistic. The number of firms decreased by 3259 and left 31880 firms with five different company types with following frequencies in table 5.1:

Table 5.1

Company type	Frequency	Defaults
Ay	58	6
Ky	271	28
OK	304	12
Oy	31044	4012
YEH	203	35
Total:	31880	4093

Where *Ay* is *avoin yhtiö*, *Ky* is *kommandiittiyhtiö*, *OK* is *osuuskunta*, *Oy* is *osakeyhtiö* and *YEH* is *yksityinen elinkeinonharjoittaja*. In generally the YEH is the smallest company type, usually run by one person and Oy is the largest with more owners and workers. This is though only a generalization. 4093 firms had some sort of default mark. That is 12.84 % of all firms. A default can be any kind of mark in credit history from light to serious. Also if a firm has multiple defaults, in Table 6.1, it is considered as one default. There are many firms in the data that have multiple defaults even in one particular year. Maximum number was 129 credit defaults in a firm in one particular year. The reason why the defaults are better to deal as dummy variable, is that the large numbers could twist the deviation giving too much weight to some firms if they are dealt with absolute quantity.

5.3.2. Defaulted firms by industry

From different industry there are 13803 firms from construction and 18374 firms from retail. In construction, 2262 firms have some sort of defaults mark, what is 16.39 % of all construction firms. In retail, 1837 firms have some sort of default mark, what is 10.00 % of all retail firms. So, for credit industries, construction seems slightly more risky business than retail. The yearly percentage defaults and bankruptcies can be seen in appendix 2.

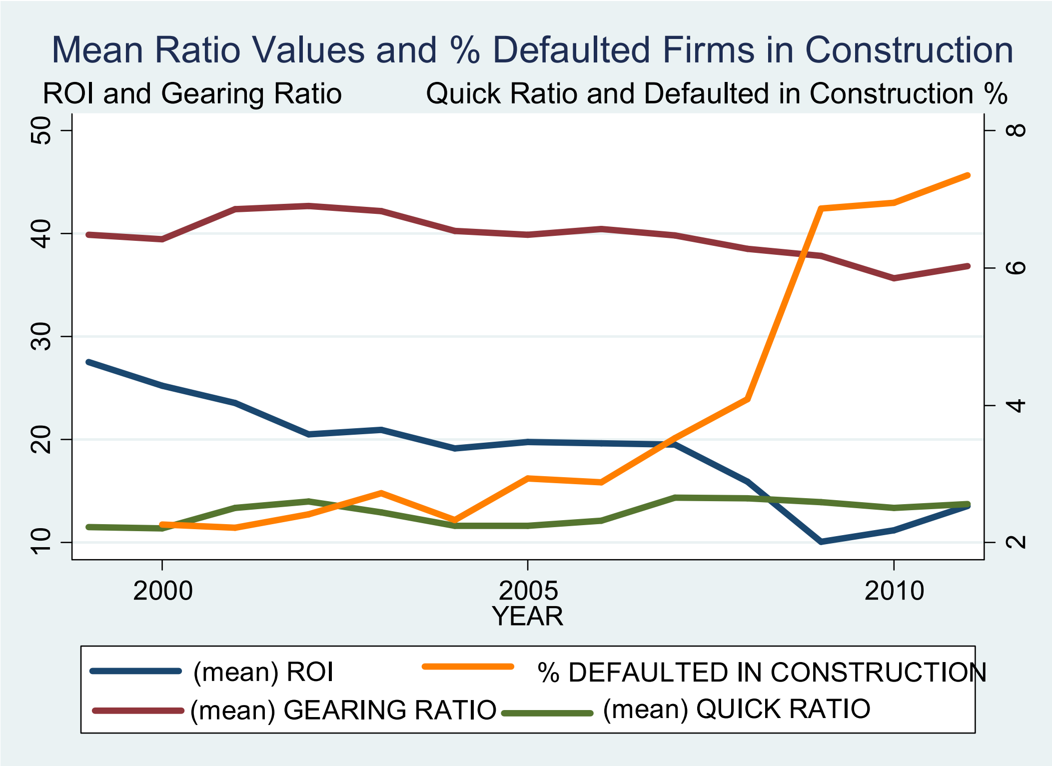
In the thirteen years of data, all firms together have 6408 accounting periods that have followed a default next year. That is 3.74 % of all accounting periods. In construction there are 3611 (5.00 %) and in retail 2797 (2.82 %) accounting periods, that is followed a default next year.

5.3.3. Descriptive statistics of ratios

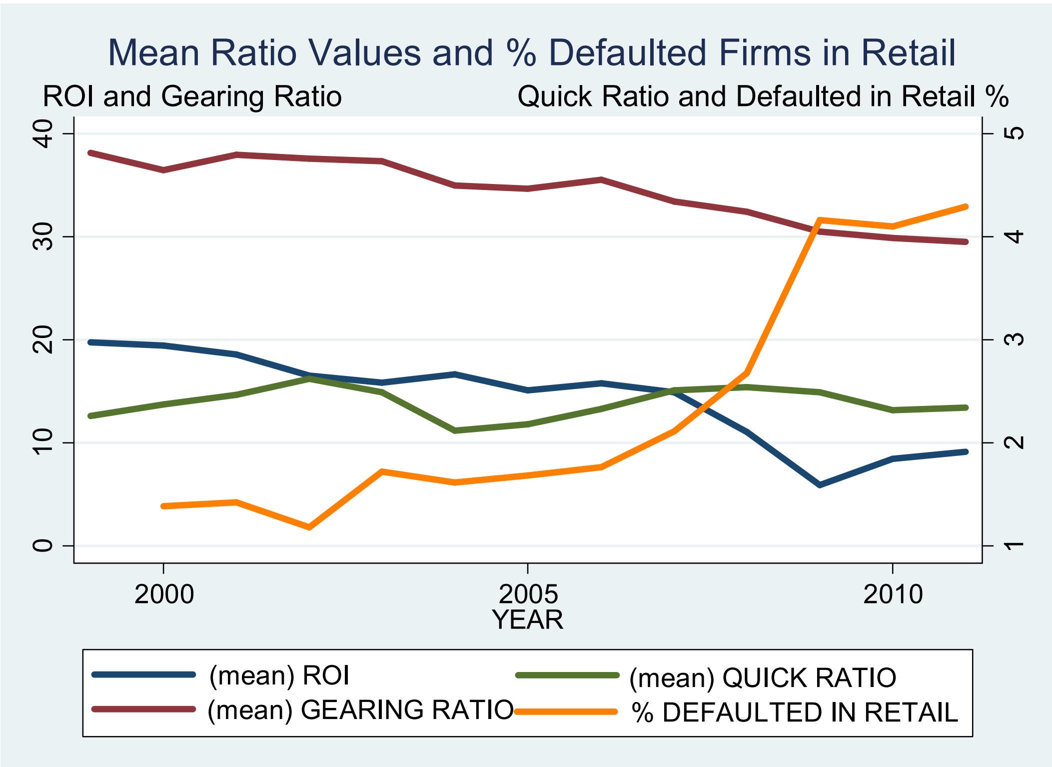
In Table 5.1 we saw the total number of firms and the total number of firms with default after the cleaning of extreme values. Next I measure the median, 25- and 75 percentiles, mean and standard deviation to the ratios of different industry. For getting these statistics from the panel data, the panel must be *collapsed* to a new form, where there are only the main statistic values from all firms of given industry per year. For getting new data to both industries I have to drop the other industry observations before collapse. After this collapse, the both new data consider 13 observations, whose represent the years we have from 1999 to 2011. I call these new data *the main statistics data from construction* and *the main statistics data from retail*. The most important descriptive information of the main statistics data is represented in Appendix 2 and next in the Graphs 5.1 and 5.2.

In Appendix 2 the ratio mean, median, 25- and 75 percentiles are represented with the percentage of firms defaulted and percentage of firms bankrupted next year. In the Graphs 1 and 2 we can see the visual illustration of mean ratio values and percentage of firms defaulted.

Graph 5.1 Mean ratio values and percentage of defaulted firms in construction



Graph 5.2 Mean ratio values and percentage of defaulted firms in retail



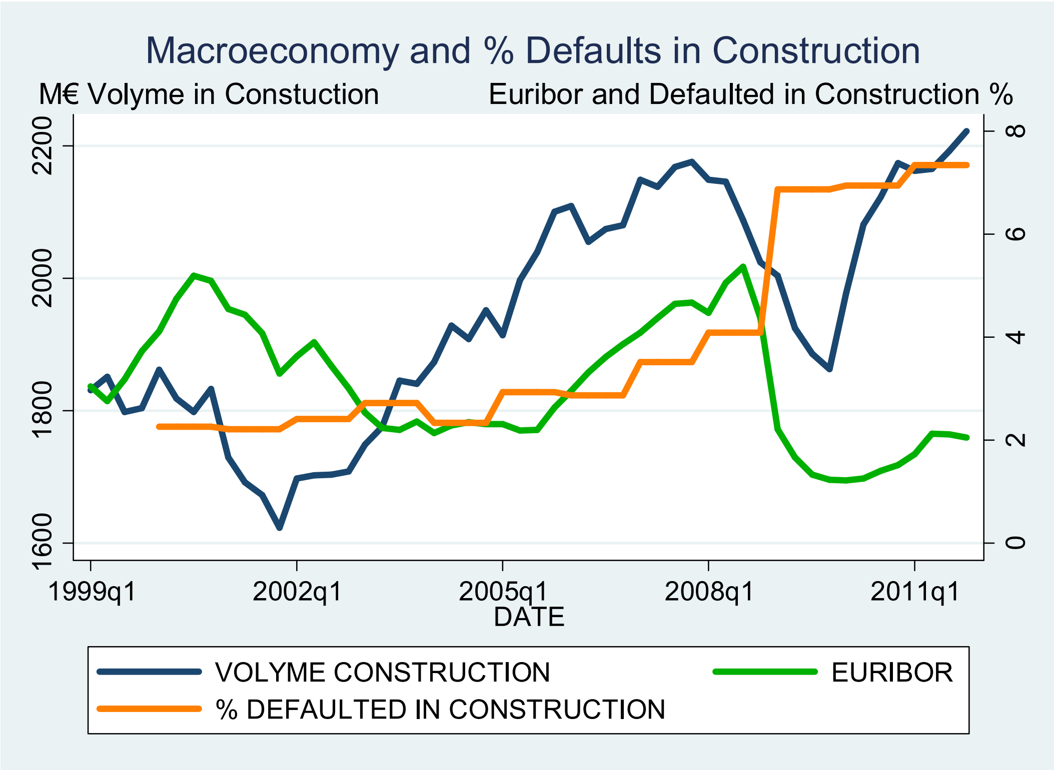
After the collapse, I merged the quarterly macroeconomic variables into the main statistics data. The merged data has now 52 quarters of information. The ratio statistics are still yearly, and the same values are just represented four times in the four quarters of a given year. With the main ratio statistics and macro values, they can be represented in graphs together.

5.3.4. Descriptive statistics of macroeconomic variables

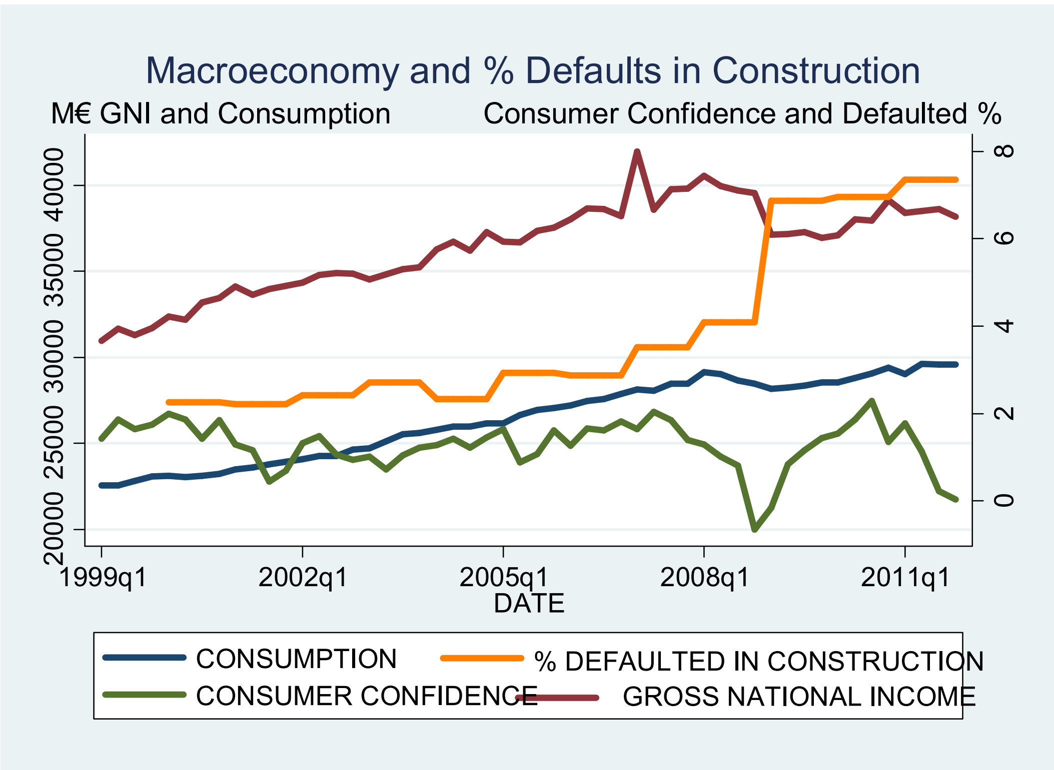
The quarterly macroeconomic variables, volume in industry (construction and retail), interest rate (12 month euribor), consumption, consumer confidence on economy and gross national income are represented in Graphs 5.3 to 5.6.

In these graphs we can see the shock in the year 2008, when financial crisis took place all over the world. This kind of shock is a good example of random variable that is very hard to be prepared in individual firms. Even solid firms with good performance and liquidity can end up into payment difficulties and bankruptcy. We can see the quite obvious (negative) correlation between the macroeconomic curves and defaulted firms in around 2008, but before the financial crisis the correlation is not so obvious. It even looks that they have some sort of positive correlation. When the gross national income, consumption and volumes in industries are increasing, the percentages of defaulted firms are slowly increasing also. The curve of consumer confidence on economy seems to go best along with the curve of defaulted firms. The consumer confidence also seems to be the first that react to the upcoming crisis around 2007 and 2008. Sadly this data has only 13 years of observations starting from 1999. It would be nice to see the curves from the recession of early nineties.

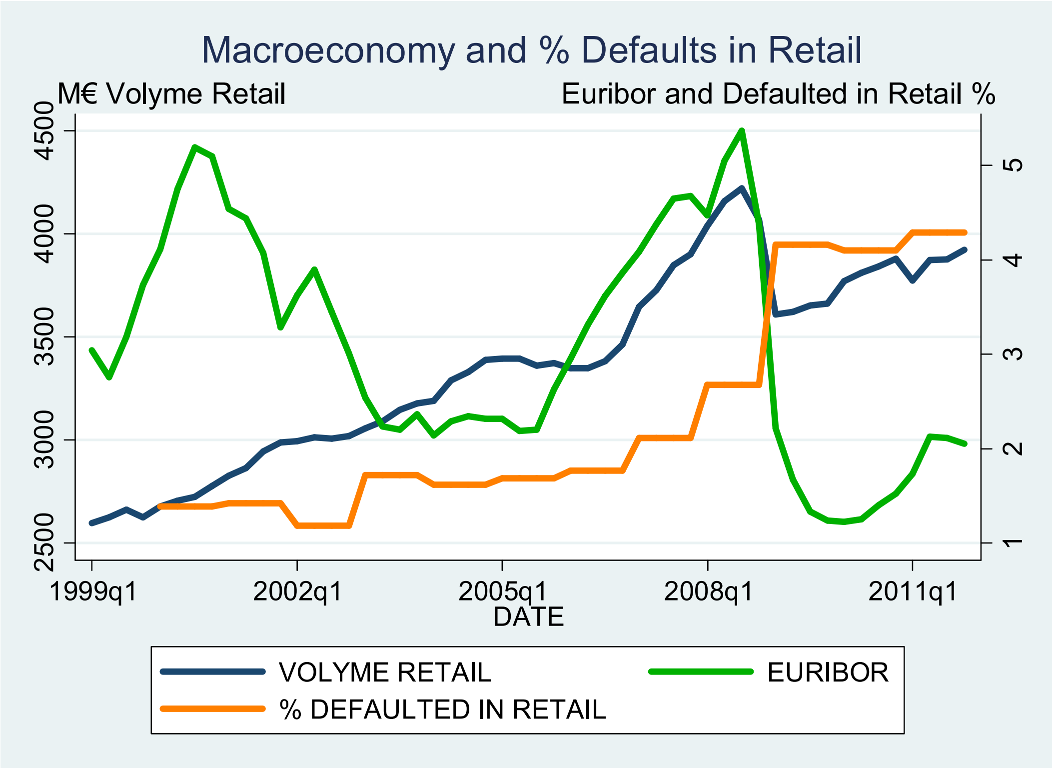
Graph 5.3 Macroeconomic and percentage of defaulted firms in construction



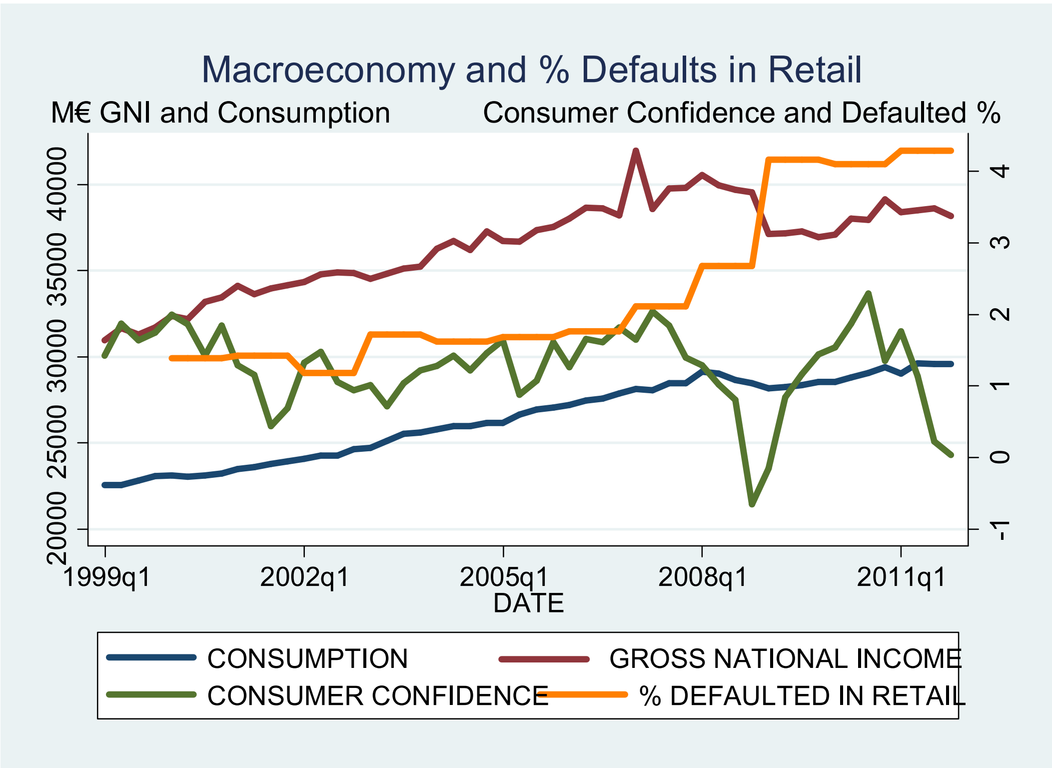
Graph 5.4 Macroeconomic and percentage of defaulted firms in construction



Graph 5.5 Macroeconomic and percentage of defaulted firms in retail



Graph 5.6 Macro economy and percentage of defaulted firms in retail



5.4. Regression models

When we have a situation where we want to consider if some event occurs or not it mathematically convenient to define a dichotomous random variable y, which takes a value of 1 if the event occurs and value of 0 if it does not. We assume that the probability of an event depends on a vector of independent variables x^* and a vector of unknown parameters θ. Using the subscript i to denote the i-th individual we can write the univariate dichotomous model generally as

(1.1) $p_i \equiv p(y_i = 1) = G(x_i^*, \theta),$
$i = 1, 2, \dots , n.$

Equation (1.1) merely states, for example, that the probability that the i-th firm defaults on the vector x_i^* representing the condition of the firm and the economic situation. We will consider the problem of choosing the appropriate function G for a given set of data. (Amemiya 1981)

5.4.1. The linear probability model

In this case I start choosing the appropriate function for G in (1.1) and begin with a simple one explanatory variable linear function

(1.2) $p_i \equiv p(y_i = 1) = \beta_1 + \beta_2 X_i$

Here in (1.2), we have the simplest binary choice model, *the linear probability model* where, as the name implies, the probability of the event occurring, p, is assumed to be a linear function of a set of explanatory variables. (Dougherty 2007)

The dependent variable Y_i of observation i is the expected value of Y_i, given X_i,

(1.3) $E\ (Y_i \mid X_i),$

because Y can take only two values. It is 1 with probability p_i and 0 with probability $(1 – p_i)$.

Putting this together we get:

(1.4) $E\ (Y_i \mid X_i) = 1 \times p_i + 0 \times (1 - p_i) = p_i = \beta_1 + \beta_2 X_{i.}$

The expected value in observation I is therefore $\beta_1 + \beta_2 X_i$. This means that we can rewrite the model as

(1.5) $Y_i = \beta_1 + \beta_2 X_i + u_{i,}$

where u_i is the disturbance term.

One problem in this simple linear probability model is that is that the predicted probability may get values greater than 1 or less than 0 for extreme values of X (Dougherty 2007). Even some weaknesses of the model, it is easy to use and gives very understandable results.

5.4.2. The logit model

(1.6) $$Z_i = \beta_1 + \beta_2 X_i$$

Next in (1.6) I suppose that p is a sigmoid (S-shaped) function of Z. Below a certain value of Z there is good chance that a firm does not default in near future, and above a certain value, the firm is a probable failure. In between, the probability is sensitive to the value of Z. (Dougherty 2007)

Next there is a question what form of mathematical function this p should be. There is no definite answer to this. Amemiya (1981) states that the two most popular forms are the logistic function, which is used in *logit estimation*, and the cumulative normal distribution, which is used in *probit estimation*. Both give satisfactory results most of the time and neither has any particular advantage. I choose the logistic regression model or the logit model leaning on Erkki Laitinen's researches.

In the logit model one hypothesizes that the probability of the occurrence of the event is determined by the function

(1.7) $$p_i = F(Z_i) = \frac{1}{1 + e^{-Z_i}}.$$

This is a s-shaped function, where p gets values from 0 to 1. As Z tends to infinity, e^{-Z} tends to 0 and p has limiting upper bound of 1. As Z tends to minus infinity, e^{-Z} tends to infinity and p has limiting lower bound of 0. Hence there is no possibility of getting predictions of the probability being greater than 1 or less than 0.

5.5. Regressions

In this section I focus on the regressions and issues that relates to them. The regressions are run with the firm specific financial ratios using default as dependent variable. Before running any regressions I study if there are some differences between industries and the behavior of ratios. If the ratios in different industries behave differently, then I have to regress the industries separately. After that I define how I'm going to measure the goodness of the models ability to predict defaults. Then I'm starting to run regressions for both industries.

First I show the regression with ratios only. Then I start to add more independent variables into the model. First I add a dummy variable that tells if there are defaults occurred before. This variable should be very significant in predicting future defaults. Then I add two dummy variables that react on the "too" fast growth or decrease of the sales. Finally I start to study the effects of macroeconomic variables. The macroeconomic variables are used as such and also as dummy variables defining some economic turning point. After regressions I measure the prediction abilities of the regression models and compare the goodness between different models.

In regression, we are most interest of the situation where the default variable is set at time (t+2) or later and the financial ratio variables are set at time (t). This is because the case in real life is close to this situation. When we are in situation to decide ratings or loans to a firm, we are in time (t+1), we have financial ratio data from (t) and we want to know the risks of default in future (t+2), (t+3) or even later. I just use years (t+2) and (t+3), because of the quite short 13 year period of data. The other reason for not including the default (t+1) into the model is the time set of macroeconomic variables. The macroeconomic variables can be used for example from a year (t+1) second quarter, when some of the year has already passed. It wouldn't be reasonable to predict the possible already occurred default at early year (t+1). I'll call the year (t+1) as information time lag. This information time lag forms on the lag of release of financial statement, lag of analyzing the financial statement information, lag of default processed and marked into the systems and lag of the release macroeconomic numbers.

5.5.1. Testing industry variables

Before I run regressions with ratios, I study if there are differences between ratios in different industries. In studying ratios I look at their distributions and behavior in predicting defaults. When looking at the mean values of ratios and defaults next year we can see that there are differences. The yearly by industry mean, 25- and 75 percentiles of ratios with defaults next year can be seen in appendix 2. Here are the by industry mean values of ratios of whole data in table 5.2:

Table 5.2 Mean values of ratios and defaults

Mean estimation				
Construction			**Retail**	
variable	Mean	Std. Err.	Mean	Std. Err.
gearing ratio	38.30714	.1777944	33.09243	.1806616
roi	18.98686	.128437	15.60471	.1028041
quick ratio	2.475509	.0147148	2.38586	.0140301
sales	1117925	3890309	2209688	6304274
default	.0499993	.000811	.0281797	.0005253

The mean values of ratios in construction are significantly higher than in retail, but so are the mean of defaults. The higher ratio values should denote lower probability of default, but in comparing the industries this is not the case. The difference can also be seen with the Kolmogorov-Smirnov test where the equality of distributions of ratios is tested. The K-S test is used because all the ratios are not normally distributed. The K-S test shows that the null hypothesis of equal distributions is rejected with 0.1 percent level.

Because of the difference of ratio behavior between industries, I have to make the regressions of different industries separately.

5.5.2. Defining the goodness of a regression model

For getting a prediction model for ratios, I run a regression with default as dependent variable and ratios as independent variables. After regression I go through the significance levels of the independent variables with t-values. Then I create a prediction value for each observation with this model. The prediction value shows how probable it is for a firm getting a default after a certain accounting period.

The prediction number gets values between 0 and 1. In linear regression model, there can incorrectly be values below zero and above one in extreme cases. This is a weakness of a linear model. The occurred default gets a value of 1 and non-occurred default gets a value of 0. The higher the predicted value is the higher probability it is for a firm after a certain accounting period for getting a default. The predicted value actually gives a percentage probability, because of the dummy 0-1 format of the dependent variable.

The goodness of the model can be studied, for example, by measuring the mean value of predicted value if a default is actually occurred. When the default variable gets value of 1 if default occurs, the better the model is in predicting the higher mean value it has among the actually defaulted firms. The extreme cases of the mean of the predicted values, and so the model's predicting ability, are the mean of defaults and 1. When the mean of the predicted values is the same as the mean of defaults, it means that the model has no ability to predict at all and is the same as a firm is picked by random. The other extreme where the mean of predicted values is 1 and defaults are predicted with 100 percent accuracy is not realistically possible. The 100 percent predicting accuracy is not realistically possible because for many reasons, but one is that there is always a change for even a rating AAA firm to default and also for a junk-class C-rated firm to avoid a default. This is good to keep in mind that the target is not, because it is not possible, to divide the defaulted firms and non-defaulted with 100 percent accuracy. The target is to give the firms best possible probabilities in which a default may occur in the future.

One very popular way to study the goodness of the model is to measure the errors it makes. Here ***Type I errors*** are those defaulted that are below a certain limit of predicted probability and ***Type II errors*** are those non-defaulted that are above a certain limit of predicted probability. This certain limit can be any probability we want to be under investigation. One limit could be the mean of predicted value among those actually defaulted. Here I focus more on probabilities but I also use the default frequencies. When using the mean of predicted value among **actually defaulted**, then higher the mean of predicted value lower the sum of Type I errors. When using the mean of predicted value among **actually non-defaulted,** then the lower the mean of predicted value the lower is the sum of Type II errors.

The other way of studying the goodness is make different classifications for different default probabilities and compare this to actually defaulted firms. These classifications give a wider picture of the default probability distribution. The classification method is actually same as giving ratings to the firms. For example if a predicted value is 0.005 (very small risk) then there should be close to 0.5 percent of actually defaulted firms below and 99.5 percent of actually non-defaulted firms above that predicted value 0.005. If the predicted value is between 0.005 and 0.02, then the percent of actually defaulted firms should be somewhere in the middle of 0.5 and 2 percents of firms. For help to make my own classifications I use the rating and default statistics from the Standard & Poor's document "*2011 Annual Global Corporate Default Study and Rating Transitions*." We can see that firms rated with A or better have defaulted quite rarely even in seven year from the original rating. When we are moving to the left to speculative rated firm BBB to CCC/C the risks of get a default rises strongly. In rating CCC/C the percentages are surprisingly getting lower, especially when more years have gone by. This might be because these C category firms are near bankruptcy so after that they don't have defaulted because they don't exist anymore. The S&P's document is seen in table 5.3.

Table 5.3

Cumulative Defaulters By Time Horizon Among Global Corporates From Rating (1981-2011)

	AAA	AA	A	BBB	BB	B	CCC/C	NR	Total
Number of issuers defaulting within:									
One year			10	66	173	885	1716	113	2,963
Three years		7	43	162	515	1950	2080	264	5,021
Five years		11	67	253	794	2549	2164	340	6,178
Seven years	2	19	93	336	978	2834	2192	391	6,845
Total	9	71	266	592	1365	3213	2227	497	8,240
Percent of total defaults per time frame:									
One year	0.0	0.0	0.3	2.2	5.8	29.9	57.9	3.8	
Three years	0.0	0.1	0.9	3.2	10.3	38.8	41.4	5.3	
Five years	0.0	0.2	1.1	4.1	12.9	41.3	35.0	5.5	
Seven years	0.0	0.3	1.4	4.9	14.3	41.4	32.0	5.7	
Total	0.1	0.9	3.2	7.2	16.6	39.0	27.0	6.0	

Sources: Standard & Poor's Global Fixed Income Research and Standard & Poor's CreditPro®.

I use this S&P's table and also information from Suomen Asiakastieto to make my own risk classifications. Instead naming the ratings with letters I show the percentages of risks in my 5 level classifications so it is easy to see how the default predictions work. Predicting the year (t+2) and (t+3) defaults with accounting period (t) financial ratios, I use the following table 5.4 for the predicted value distributions:

Table 5.4

Risk	Predicted probability of default in years (t+2) and (t+3)
Very small risk	$p \leq 0.5$
Small risk	$0.5 < p \leq 2$
Moderate risk	$2 < p \leq 7$
High risk	$7 < p \leq 27$
Very high risk	$27 < p$

Reading the previous studies of Altman, Beaver, Laitinen, Prihti and others, they have created a data of two groups with same number of firms in both of them. In first group there are the healthy firms and in the second the defaulted firms. Then they have compared how the models improve their prediction ability from just random 50-50 probability. This seems to be quite used method in the area. It makes very readable and understandable answers, but at the same time it loses some credibility in statistics because the data is manipulated. I'm not using this kind of pair-sample method.

Before the regressions are introduced there has to be left out some observations. Because the macroeconomic variables for some of the quarters are from the year (t+1), when ratios are from year (t), the regressions with macroeconomic variables have less observations. There are exactly 40087 observations that must to be left for regression of ratios. These observations are those that don't have an observation for next year. This is of course removes those firms that have bankrupted on the first year they have given data. This is good to keep in mind but not necessary make the results worse, because now the regressions considers more on the firms that have been existed more than one year. Here in table 5.5 are default frequencies and percentages at (t+1) and at (t+2) or (t+3).

Table 5.5 Default frequencies and percentages at (t+1) and at (t+2) or (t+3)

		Period (t+1)		Period (t+2) or (t+3)	
Industry	Default	Freq.	Percent	Freq.	Percent
Total	0	128,200	97.57	124,994	95.13
	1	3,190	2.43	6,396	4.87
Construct.	0	53,623	96.79	51,859	93.61
	1	1,776	3.21	3,540	6.39
Retail	0	74,577	98.14	73,135	96.24
	1	1,414	1.86	2,856	3.76

In evaluating the goodness of the models I first look out regression outputs and check the t – values of variables. Then I check that the values and signs of coefficients are reasonable. The number of observations is large enough so I shouldn't have to worry about that. If everything looks fine I can focus on the goodness of the model, which is its ability to predict defaults.

Finding out which model is the best to predict I look the mean of predicted value among actually defaulted and non-defaulted. After that I look at the risk distribution of the predicted value. The results of regressions A, B and C are seen in tables 5.25 to 5.28.

5.5.3. Linear regression with financial ratios only

Table 5.6 Regression A. default with ratios in construction

Regression A Construction				F(4, 55394) = 592.02 R-squared = 0.0410	
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:	
gearing ratio	-.0010765	.0000276	-38.95		
roi	-.0002475	.0000328	-7.56	defaulted	.1022773
quick ratio	-.0009924	.0003176	-3.12	non-defaulted	.0675164
logsales	-.0007408	.0005455	-1.36		
_cons	.1241098	.0068593	18.09		

Table 5.7 Regression A. default with ratios in retail

Regression A Retail				F(4, 75986) = 539.94 R-squared = 0.0276
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:
gearing ratio	-.0005329	.0000153	-34.81	
roi	-.0002599	.0000234	-11.13	defaulted .0641821
quick ratio	-.0007284	.000191	-3.81	non-defaulted .0335313
logsales	-.0017328	.0003074	-5.64	
_cons	.0851499	.0040042	21.27	

Here we can see the regression model A, where only financial ratios are represented. We can see that the ratios in both industries have same sort of significance levels (values). The most significant ratio is the gearing ratio, which have t-values -38.95 and 34.81 in construction and retail respectively. Second significant is the return on investment and third the quick ratio. The logarithm of sales is quite significant on retail but in construction the t-value is only -1.36. In regressions B and C I have dropped the logarithm of sales and used only the first three ratios.

In right hand side we can see the mean of predicted value among actually defaulted and non-defaulted. We can use these numbers when we are measuring the goodness of regression B and see if the prediction ability is improved after adding the variables of history of defaults and sales growth over 70 % per year.

5.5.4. Regression with already occurred default and growth variable added

Table 5.8 Regression B. default with ratios, sales growth >70 % and history of defaults

Regression B Construction				F(5, 55393) = 1399.64 R-squared = 0.1122
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:
default history (t),(t-1)	.4324929	.0064986	66.55	
gearing ratio	-.0008216	.0000269	-30.58	defaulted .168899
roi	-.0002765	.0000311	-8.90	non-defaulted .0567326
quick ratio	-.0010109	.0003026	-3.34	
sales growth >70%	.0219682	.003578	6.14	
_cons	.0930437	.0015137	61.47	

Table 5.9 Regression B. default with ratios, sales growth >70 % and history of defaults

Regression B Retail				F(5, 75985) = 1231.61 R-squared = 0.0750
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:
default history (t),(t-1)	.3551466	.0056715	62.62	
gearing ratio	-.0004494	.0000149	-30.10	defaulted .1097334
roi	-.0002696	.0000225	-11.97	non-defaulted .0347659
quick ratio	-.0005263	.0001836	-2.87	
sales growth >70%	.0050641	.0023517	2.15	
_cons	.0540943	.0009228	58.62	

Here above we can see the regression B where sales growth over 70 % and history of defaults variables are added. We can see that the significance levels of the ratios have stayed quite stable. The default history variable which takes into account defaults from year (t) and (t-1) seems to have very significant role in the model. After adding the default history into the model it is quite hard to improve the prediction ability. This makes a good sense why payment failure registers are so much used. Also sales growth >70% seem to have some role in both industries. When a firm is

In the right hand side we can again see the mean of predicted values among actually defaulted and non-defaulted. We can see that the regression B work much better when we are looking the predicted mean value among defaulted, but among non-defaulted only in construction it has lower value, when in retail it actually has higher value than regression A. In result tables 5.25 to 5.28 we can though see also the risk classifications and we can see that regression B works much better than regression A.

5.5.5. Regression with macroeconomic variables

There are numerous methods to use macroeconomic variables in prediction models. The macroeconomic variables can be used alone, all together, integrated together as categorical- or dichotomous variable, it can be used as integration variable with ratios or there can be used a method of primary component analysis. I'm going to make regressions with multiple ways and try to find the most valuable method.

Before I do any regressions I have to clarify how I'm going to use different quarterly macroeconomic values with ratios and defaults. So as described before the default is used at time (t+2) and (t+3) when ratios are used at time (t). But when we are adding the macroeconomic variables, we have to think when we have the macroeconomic data available in real life compared to the financial ratio data. Here is next in table 5.10 a list of the periods used at different quarters.

Table 5.10

Quarter	Ratios at year	Default history from year	Macroeconomic variables at year
1	t	t and t-1	t+1
2	t	t and t-1	t+1
3	t	t and t-1	t+1
4	t	t and t-1	t

Let's consider that we are living at year (t+1) and the third quarter has just started. At this point we have the financial data from year (t) and we macroeconomic data from 1st quarter of year (t+1). We want to use the newest information so this data is what we are using. The quarterly macroeconomic data is available about 3 months after the quarter has ended (Tilastokeskus). The financial ratio data should also be available after about 3 months from the end of last accounting period (year). The 4th quarter's macroeconomic data is from the same year (t) as the financial ratio data. This is because when the macroeconomic data from the 4th quarter from year (t) is available after 3 months, the newest financial ratio data from year (t) should also be available.

The most valuable and credible regression method founded was the one that included all the macroeconomic variables in one dummy variable. This dummy variable gets a value 1, if at least three out of four macroeconomic dummy variables get a value of 1, and 0 otherwise. These four macroeconomic variables and the combined macroeconomic dummy variable are represented in table 5.11 below. Sorensen & Whitta-Jacobsen (2010) describes in their text book (p.358), that business cycles are characterized by a co-movement of a large number of economic activities and not just by movements in a single variable like real GDP.

When studying the regressions with financial ratios and macroeconomic variables when financial ratios where dealt all together but separately as own variables, the results are not so clear. The significance level of macroeconomic variables vary between

Table 5.11. Macroeconomic variables

Macroeconomic variable	Value description	Dummy gets values:
a. Gross national income	% change to same quarter last year	$\begin{cases} 1, if\ x < 0 \\ 0\ otherwise \end{cases}$
b. Industry volume	% change to same quarter last year	$\begin{cases} 1, if\ x < 0 \\ 0\ otherwise \end{cases}$
c. Consumption	% change to last quarter	$\begin{cases} 1, if\ x < 0 \\ 0\ otherwise \end{cases}$
d. Consumer confidence on economy	Descriptive number	$\begin{cases} 1, if\ x < 12 \\ 0\ otherwise \end{cases}$
Combined macro-economic dummy variable	Combined from variables above	$\begin{cases} 1, if\ a+b+c+d > 2 \\ 0\ otherwise \end{cases}$

Table 5.12. Regression with economic downturn dummy variable

Regression C.
Construction
Ratiodata available from (t)
Macrodata available from (t+1) 1st quarter

F(6, 55392) = 1206.37
R-squared = 0.1156

Mean of predicted value among:
defaulted .1720859
non-defaulted .0565151

default (t+1),(t+2)	Coefficient	Std. Err.	t
default history (t),(t-1)	.4297769	.0064889	66.23
gearing ratio	-.0008193	.0000268	-30.55
roi	-.0002471	.0000311	-7.96
quick ratio	-.0011912	.0003022	-3.94
sales growth >70%	.0231638	.0035721	6.48
economic downturn	.0332713	.0022785	14.60
_cons	.0845546	.0016188	52.23

Table 5.13. Regression with economic downturn dummy variable

Regression C.
Construction
Ratiodata available from (t)
Macrodata available from (t+1) 2nd quarter

F(6, 55392) = 1184.88
R-squared = 0.1137

Mean of predicted value among:
defaulted .1703778
non-defaulted .0566317

default (t+1),(t+2)	Coefficient	Std. Err.	t
default history (t),(t-1)	.4318726	.0064932	66.51
gearing ratio	-.0008183	.0000269	-30.47
roi	-.0002757	.000031	-8.88
quick ratio	-.0010786	.0003024	-3.57
sales growth >70%	.0222684	.003575	6.23
economic downturn	.0302121	.0030405	9.94
_cons	.0894924	.001554	57.59

Table 5.14. Regression with economic downturn dummy variable

Regression C. Construction Ratiodata available from (t) Macrodata available from (t+1) 3rd quarter				F(6, 55392) = 1203.45 R-squared = 0.1153
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:
				defaulted .1718543
default history (t),(t-1)	.4319351	.0064872	66.58	non-defaulted .0565309
gearing ratio	-.0008147	.0000268	-30.37	
roi	-.0002809	.000031	-9.06	
quick ratio	-.0011101	.0003021	-3.67	
sales growth >70%	.0224221	.0035719	6.28	
economic downturn	.0330701	.0023521	14.06	
_cons	.0857129	.0015984	53.62	

Table 5.15. Regression with economic downturn dummy variable

Regression C. Construction Ratiodata available from (t) Macrodata available from (t) 4th quarter				F(6, 55392) = 1184.88 R-squared = 0.1137
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:
				defaulted .1703778
default history (t),(t-1)	.4318726	.0064932	66.51	non-defaulted .0566317
gearing ratio	-.0008183	.0000269	-30.47	
roi	-.0002757	.000031	-8.88	
quick ratio	-.0010786	.0003024	-3.57	
sales growth >70%	.0222684	.003575	6.23	
economic downturn	.0302121	.0030405	9.94	
_cons	.0894924	.001554	57.59	

Table 5.16. Regression with economic downturn dummy variable

Regression C. Retail Ratiodata available from (t) Macrodata available from (t+1) 1st quarter				F(6, 75984) = 1043.90 R-squared = 0.0762
default (t+1),(t+2)	Coefficient	Std. Err.	t	Mean of predicted value among:
				defaulted .1108745
default history (t),(t-1)	.3544619	.0056683	62.53	non-defaulted .0347213
gearing ratio	-.000448	.0000149	-30.03	
roi	-.0002655	.0000225	-11.79	
quick ratio	-.0005566	.0001835	-3.03	
sales growth >70%	.0058018	.0023513	2.47	
economic downturn	.0215534	.0021826	9.87	
_cons	.0517618	.000952	54.37	

Table 5.17. Regression with economic downturn dummy variable

Regression C.				F(6, 75984) = 1043.90
Retail				R-squared = 0.0762
Ratiodata available from (t)				
Macrodata available from (t+1) 2nd quarter				Mean of predicted value among:
default (t+1),(t+2)	Coefficient	Std. Err.	t	
				defaulted .1108745
default history (t),(t-1)	.3544619	.0056683	62.53	non-defaulted .0347213
gearing ratio	-.000448	.0000149	-30.03	
roi	-.0002655	.0000225	-11.79	
quick ratio	-.0005566	.0001835	-3.03	
sales growth >70%	.0058018	.0023513	2.47	
economic downturn	.0215534	.0021826	9.87	
_cons	.0517618	.000952	54.37	

Table 5.18. Regression with economic downturn dummy variable

Regression C.				F(6, 75984) = 1062.21
Retail				R-squared = 0.0774
Ratiodata available from (t)				
Macrodata available from (t+1) 3rd quarter				Mean of predicted value among:
default (t+1),(t+2)	Coefficient	Std. Err.	t	
				defaulted .1120608
default history (t),(t-1)	.3545851	.0056642	62.60	non-defaulted .034675
gearing ratio	-.000445	.0000149	-29.84	
roi	-.0002676	.0000225	-11.89	
quick ratio	-.0005874	.0001834	-3.20	
sales growth >70%	.0063671	.0023504	2.71	
economic downturn	.0232666	.0016487	14.11	
_cons	.0491978	.0009847	49.96	

Table 5.19. Regression with economic downturn dummy variable

Regression C.				F(6, 75984) = 1043.90
Retail				R-squared = 0.0774
Ratiodata available from (t)				
Macrodata available from (t) 4th quarter				Mean of predicted value among:
default (t+1),(t+2)	Coefficient	Std. Err.	t	
				defaulted .1108745
default history (t),(t-1)	.3544619	.0056683	62.53	non-defaulted .0347213
gearing ratio	-.000448	.0000149	-30.03	
roi	-.0002655	.0000225	-11.79	
quick ratio	-.0005566	.0001835	-3.03	
sales growth >70%	.0058018	.0023513	2.47	
economic downturn	.0215534	.0021826	9.87	
_cons	.0517618	.000952	54.37	

From the regression C outputs we can see that the control variables (regression B) still has same kind of role in the model. The macroeconomic variable called *economic downturn* has also significant role in both industries and in all quarters. The results of mean of predicted values among actually defaulted and non-defaulted are represented in tables 5.25 to 5.28.

5.5.6. Results of regression B with macroeconomic variables added one by one

First I introduce the macroeconomic variables individually with control group of financial ratio variables, occurred defaults and too fast growth of sales. The mean of predicted values among actually defaulted are compared to the corresponding values of regression B. This tells if the added variable give new prediction value. The mean of predicted value among actually non-defaulted is left aside at this point, because the changes in the value are so small.

Table 5.20

Gross national income percentage change to last year corresponding quarter

Variable	time serie	coefficient	std. error	t –value	Mean of predicted value among actually defaulted	
Construction						Reg. B .168899
gni4	(t) Q4	-.0026241	.0002558	-10.26	.1704746	
gni1	(t+1) Q1	-.0025111	.0002007	-12.51	.1712411	
gni2	(t+2) Q2	-.0023131	.0002791	-8.29	.1699285	
gni3	(t+3) Q3	-.0044185	.000328	-13.47	.1716129	
Retail						Reg. B .1097334
gni4	(t) Q4	-.0017007	.0001848	-9.20	.110725	
gni1	(t+1) Q1	-.0016578	.00014	-11.84	.1113736	
gni2	(t+2) Q2	-.0016127	.0001948	-8.28	.1105357	
gni3	(t+3) Q3	-.0030555	.0002286	-13.37	.1118227	

In table 5.20 we can see the macroeconomic variable of *gross national income.* From t-values we can see that the variable is significant and it negatively correlates with the future defaults. From the predicted mean values among actually defaulted we can see that GNI alone gives some new value to the regression B. No clear difference between industries.

Table 5.21

Consumer confidence on economy (dummy variable)
1 if $x < 12$, 0 if $x \geq 12$

Variable	time serie	coefficient	std. error	t –value	Mean of predicted value among actually defaulted	
Construction						Reg. B .168899
confidum4	(t) Q4	.0043965	.0023095	1.90	.1689533	
confidum1	(t+1) Q1	.0120169	.0025539	4.71	.169231	
confidum2	(t+2) Q2	.0049767	.0019672	2.53	.168995	
confidum3	(t+3) Q3	.0010727	.0019991	0.54	.1689033	
Retail						Reg. B .1097334
confidum4	(t) Q4	.0034131	.0015464	2.21	.1097905	
confidum1	(t+1) Q1	.0084826	.0017478	4.85	.1100093	
confidum2	(t+2) Q2	.0037336	.0013344	2.80	.1098251	
confidum3	(t+3) Q3	.0013819	.0013593	1.02	.1097455	

In table 5.21 we can see the macroeconomic variable of *consumer confidence on economy*, which is represented in dummy form. The dummy form is used because the consumer confidence is a descriptive number. From t –values we can see that it is merely significant and the actual consumer confidence variable (not the dummy) correlates negatively with future defaults. The t –values are quite low in this kind of large data, so using this variable alone might not be recommended. With other variables as integration variable this might give some information to the current macroeconomic state. From predicted values among actually defaulted we can see that there might be some value in this variable for making the regression model B better. No clear difference between industries.

Table 5.22

Consumption percentage change to last quarter						
Variable	time serie	coefficient	std. error	t –value	Mean of predicted value among actually defaulted	
Construction						Reg. B .168899
consuq4	(t) Q4	-.0189688	.0016828	-11.27	.1708009	
consuq1	(t+1) Q1	-.0005356	.0009406	-0.57	.1689038	
consuq2	(t+2) Q2	-.0097701	.0011915	-8.20	.1699065	
consuq3	(t+3) Q3	-.0078001	.0012845	-6.07	.1694519	
Retail						Reg. B .1097334
consuq4	(t) Q4	-.0128375	.0011742	-10.93	.1111316	
consuq1	(t+1) Q1	-.000042	.0006653	-0.06	.1097335	
consuq2	(t+2) Q2	-.0062477	.0008215	-7.61	.1104106	
consuq3	(t+3) Q3	-.0049692	.0008713	-5.70	.1101144	

In table 5.22 we can see the macroeconomic variable of *consumption*. From t- values we can see that it is significant except in (t+1) Q1. This might be because the growth of consumption has been quite stable in the whole period. The only small decline in consumption is in 2008 financial crisis. This low volatility is also the reason why this variable is measured as percentage change to last quarter and not to last year corresponding quarter as the other variables are. In any case I call this variable significant and it negatively correlates with future defaults. From predicted mean values among actually defaulted we can see that this variable gives some new value to the regression B. No clear difference between industries.

Table 5.23

Industry volume percentage change to last year corresponding quarter						
Variable	time serie	coefficient	std. error	t –value	Mean of predicted value among actually defaulted	
Construction						Reg. B .168899
conq4y	(t) Q4	-.0009582	.000117	-8.19	.1699043	
conq1y	(t+1) Q1	-.001756	.0001799	-9.76	.1703262	
conq2y	(t+2) Q2	-.0008691	.0001733	-5.01	.1692761	
conq3y	(t+3) Q3	-.0006356	.0001495	-4.25	.16917	
Retail						Reg. B .1097334
retq4y	(t) Q4	-.0002381	.0001157	-2.06	.1097831	
retq1y	(t+1) Q1	-.0004094	.0001161	-3.52	.109879	
retq2y	(t+2) Q2	-.0003372	.0001015	-3.32	.1098627	
retq3y	(t+3) Q3	-.0003634	.0000978	-3.72	.1098952	

In table 5.23 we can see the macroeconomic variable of *industry volume*. This variable is different number in industries. From t –values we can see that the variable is significant and negatively correlates with the future defaults. There is some quite remarkable difference between industries. The construction firms correlate much stronger to the changes in industry volumes. From the predicted mean values among actually defaulted we can see that there is some improvement to the regression B.

Table 5.24

Interest rate (euribor)						
Variable	time serie	coefficient	std. error	t –value	Mean of predicted value among actually defaulted	
Construction						Reg. B .168899
eurq4	(t) Q4	.0024973	.0007825	3.19	.1690518	
eurq1	(t+1) Q1	-.0025312	.0008813	-2.87	.1690227	
eurq2	(t+2) Q2	-.0025546	.0007567	-3.38	.1690699	
eurq3	(t+3) Q3	-.0020697	.0006992	-2.96	.1690304	
Retail						Reg. B .1097334
eurq4	(t) Q4	.0018677	.0005446	3.43	.1098712	
eurq1	(t+1) Q1	-.0013278	.0006019	-2.21	.1097904	
eurq2	(t+2) Q2	-.0013848	.0005163	-2.68	.1098177	
eurq3	(t+3) Q3	-.0010852	.0004787	-2.27	.1097936	

In table 5.24 we can see the macroeconomic variable of *interest rate.* From t –values we can see that it is not very significant, especially when take into account that (t) Q4 has positive coefficient when others are negative. Maybe this variable could give some information, but it might require more study of how it affects to the economy and to the default rates. Also different time lags could be considered. Although it seems to give some value to the regression B, I leave it out from my final model. No clear difference between industries.

From the regression models, where the macroeconomic variables are used individually one by one we have seen that they are giving some new value to the model. There is however a small problem when we want to use these variables together. Many of them are strongly correlated with each other causing a problem of collinearity. A solution to this problem is to use them together in one variable. This is exactly what have been done in regression C, where four macroeconomic variables are turned into one dummy variable. There is also a little bit more sophisticated way to do it called *primary component analysis*, where many variables are brought together in one variable using different weights. I'm leaving this out of my research.

5.5.7. Result of regression models A, B and C

Here I introduce the results of the regressions A, B and C in one packet. Regression A with financial ratios. Regression B with financial ratios, dummy of growth of sales and default history from years' (t) and (t-1). Regression C includes same as Regression B, but also a macroeconomic dummy variable that represents possible economic downturn. The results are from the linear regression model and from the logit regression model. We compare the different regressions and see if they get better when we are moving down from regression A to C. We also look if the "freshness" of the macroeconomic variable has some significance. The lowest regression C has the most fresh macroeconomic data available from (t+1) Q_3.

The interpretation of the results in tables 5.25, 5.26, 5.27 and 5.28 has four dimensions. First we take a look at the mean of predicted value among actually defaulted. The value is calculated from the predicted values that are between 0 to 1, if ignore some extreme cases below zero in the linear regression model. In this case there are no values over 1 because of the mean value of defaults is so low. Anyhow this problem is solved in using the logit regression model also. When the firm is defaulted the default (dependent) variable gets a value of 1. So among those that are defaulted, the better the result is, the closer the predicted value is to 1. The larger the value is the smaller is the risk for Type I errors.

Second we take a look at mean of predicted value among actually non-defaulted. The lower value it gets the better the model has worked and smaller is the risk for Type II errors. Third we look at the percentages of risk classifications and how the regression model has distributed the firms by their risk from the actual risk probabilities chart. The value is better the better it fits in between the percentages around p. The most attention gets the low and high p –values since they tell something how the model has distributed the low and high risk firms in the right categories. Finally fourth we look at the number of defaulted in risk categories and see the frequencies how the regression model has distributed the firms in the risk categories.

Table 5.25 Results of regression models' default prediction abilities (linear model)

Linear regression			Construction			
Regression & quarter of macro variable	Mean of predicted value among actually: defaulted	p≤0.5	Actual risk probabilities % 0.5<p≤2	2<p≤7	7<p≤27	27p>0.27
A	.1022773	1.23	1.40	3.23	11.82	20.99
B	.168899	1.12	1.27	3.56	11.19	48.44
C (t) Q_4	.1703778	1.07	1.24	3.61	11.13	48.51
C (t+1) Q_1	$\boxed{.1720859}$	1.04	1.41	3.59	11.21	48.32
C (t+1) Q_2	.1703778	1.07	1.24	3.61	11.13	48.51
C (t+1) Q_3	.1718543	$\boxed{1.02}$	1.38	3.57	11.20	$\boxed{48.68}$
	non-defaulted	p≤0.5	Number of defaulted in risk categories 0.5<p≤2	2<p≤7	7<p≤27	27p>0.27
A	.0675164	36	82	797	2540	85
B	.0567326	35	88	1029	1676	712
C (t) Q_4	.0566317	41	84	1020	1677	718
C (t+1) Q_1	$\boxed{.0565151}$	48	93	991	1690	718
C (t+1) Q_2	.0566317	41	84	1020	1677	718
C (t+1) Q_3	.0565309	47	92	978	1703	720

Table 5.26 Results of regression models' default prediction abilities (logit model)

Logit regression			Construction			
Regression & quarter of macro variable	Mean of predicted value among actually: defaulted	p≤0.5	Actual risk probabilities % 0.5<p≤2	2<p≤7	7<p≤27	27p>0.27
A	.1001041	1.89	1.36	3.47	12.42	22.84
B	.1690754	1.72	1.26	3.81	12.34	47.23
C (t) Q_4	.1712586	1.51	1.19	3.85	12.38	47.38
C (t+1) Q_1	$\boxed{.173694}$	1.45	1.22	3.86	12.22	$\boxed{47.93}$
C (t+1) Q_2	.1712586	1.51	1.19	3.85	12.38	47.38
C (t+1) Q_3	.1733425	$\boxed{1.29}$	1.21	3.84	12.32	47.53
	non-defaulted	p≤0.5	Number of defaulted in risk categories 0.5<p≤2	2<p≤7	7<p≤27	27p>0.27
A	.0614287	21	51	1111	2233	124
B	.0567206	17	55	1446	1305	717
C (t) Q_4	.0565716	15	55	1455	1292	723
C (t+1) Q_1	$\boxed{.0564053}$	15	61	1439	1294	731
C (t+1) Q_2	.0565716	15	55	1455	1292	723
C (t+1) Q_3	.0564293	13	62	1423	1320	722

In tables 5.25 and 5.26 we can see the results of linear and logit regression models' default prediction abilities in construction. The regression models seem to get better when we add new significant variables.

From regression A to B the prediction ability increases seemingly when previous defaults of year (t) and (t-1) and dummy variable of fast sales growth are added. The mean of predicted value among actually defaulted increases significantly in both models. The mean p of non-defaulted is also decreased seemingly and though reduces the risk of Type II errors. Also the risk classifications look much better in regression B. Both the very small risk and very high risk actual probabilities look seemingly closer to the p –class they should be. The frequencies are also seemingly better distributed. Regression A is almost unable to classify the very high risk firms' p>0.27. One unexpected observation is the higher values in p <0.005 than in 0.005<p≤0.02 in the logit model. In linear regression model this doesn't occur. Here is one example where the linear model might fail. The reason why this happens is probably the possibility the linear model to get values below zero. If we look at the frequencies we see that the linear model has accepted much more firms in the very small risk class than the logit model. This speak something about that the linear model treats the p -value 0.005 like it is actually higher. This is because there are values below zero and thus more than 5 % of observations below the p<0.005. **For this reason I trust more in the logit model and base the assumptions of the results on that and leave the linear model on less attention.**

From regression model B to C we also can see some improvement. The change is not large, but there seem to be some. The mean of predicted value among defaulted and non-defaulted is better in all quarters and the best predicted value is in year (t+1) 1st quarter. Also the very small risk class probabilities improved slightly from B to C. In fourth quarter of regression C the actual precentage risk in very small risk category improves to 1.29 from 1.72 from regression B. This is almost 0.5 % and can be seen quite large change, because the category itself is 0.5 % wide. In the very high risk class there is also little improvement. The percentages may not tell much, but the frequencies tell that the macroeconomic variable have found few more very high risk firms comparing to regression B.

Table 5.27. Results of regression models' default prediction abilities (linear model)

Linear regression			Retail			
Regression & quarter of macro variable	Mean of predicted value among actually: defaulted	$p\leq0.5$	Actual risk probabilities % $0.5<p\leq2$	$2<p\leq7$	$7<p\leq27$	$p>27$
A	.0641821	0.79	1.06	3.80	12.40	4.44
B	.1097334	0.89	1.02	3.64	11.69	$\boxed{41.21}$
C (t) Q_4	.1108745	0.75	1.10	3.62	11.46	$\boxed{41.21}$
C (t+1) Q_1	.1108745	0.75	1.10	3.62	11.46	$\boxed{41.21}$
C (t+1) Q_2	.1108745	0.75	1.10	3.62	11.46	$\boxed{41.21}$
C (t+1) Q_3	$\boxed{.1120608}$	$\boxed{0.70}$	1.10	3.59	11.54	$\boxed{41.21}$
	non-defaulted	$p\leq0.5$	Number of defaulted in risk categories $0.5<p\leq2$	$2<p\leq7$	$7<p\leq27$	$p>27$
A	.0335313	54	165	1767	868	2
B	.0347659	65	184	1648	518	441
C (t) Q_4	.0347213	63	192	1605	555	441
C (t+1) Q_1	.0347213	63	192	1605	555	441
C (t+1) Q_2	.0347213	63	192	1605	555	441
C (t+1) Q_3	$\boxed{.034675}$	67	184	1562	602	441

Table 5.27. Results of regression models' default prediction abilities (logit model)

Logit regression			Retail			
Regression & quarter of macro variable	Mean of predicted value among actually: defaulted	$p\leq0.5$	Actual risk probabilities % $0.5<p\leq2$	$2<p\leq7$	$7<p\leq27$	$p>27$
A	.0628406	0.91	1.01	3.73	13.24	12.46
B	.1113446	0.84	1.06	3.54	13.07	38.24
C (t) Q_4	.1130827	0.79	1.06	3.57	12.43	$\boxed{38.52}$
C (t+1) Q_1	.1130827	0.79	1.06	3.57	11.43	$\boxed{38.52}$
C (t+1) Q_2	.1130827	0.79	1.06	3.57	11.43	$\boxed{38.52}$
C (t+1) Q_3	$\boxed{.1146744}$	$\boxed{0.76}$	1.01	3.58	12.68	38.39
	non-defaulted	$p\leq0.5$	Number of defaulted in risk categories $0.5<p\leq2$	$2<p\leq7$	$7<p\leq27$	$p>27$
A	.0365971	28	152	1953	684	39
B	.0347029	24	191	1793	440	408
C (t) Q_4	.0346351	23	203	1754	470	406
C (t+1) Q_1	.0346351	23	203	1754	470	406
C (t+1) Q_2	.0346351	23	203	1754	470	406
C (t+1) Q_3	$\boxed{.0345729}$	23	208	1689	531	405

In retail in tables 5.27 and 5.28 there are similar improvements from regression A to B as in the case of construction. This difference is quite obvious and so I move on studying the regression C. One reason why I chose to take regression A into this paper is to show how the prediction ability improves when new significant variables are added.

Comparing regressions from B to C small improvement in mean of actually defaulted and non-defaulted can be observed. The best results are in regression C (t+1) Q_3, where also the $p<0.005$ has the smallest value 0.0076 comparing to the regression B 0.0084. This gives some support for the hypothesis H3. Even that the differences seems quite small they might have some value. If we look at the table 5.3 we see default percentages and probabilities of Standard & Poor's credit ratings. The default percentages and frequencies are very small in AAA and AA rated firms and even a 0.1 % change in default probability can change the whole credit rating of a firm.

The reason why the quarterly predicted values have similar answers in retail is that the macroeconomic variable is a dummy and react only very rare situations. It has same values in same years of quarters $Q_{4,}$ (t+1) Q_1 and Q_2 so the results are also identical.

5.5.8. Correlation between variables

The coefficient of correlation will get values between -1 and +1. If correlation coefficient is equal to 1, the variables are perfectly positive correlated and move though to the same direction all the time. If correlation coefficient is equal to -1, the variables are perfectly negatively correlated and move though to the opposite direction all the time. If correlation coefficient is equal to 0, the variables have no systematic relationship. Other values between -1 and +1 indicate that they have some negative or positive correlation and they have co-movement to the same or opposite direction. If the variables are highly correlated with each other, there might rise a problem of collinearity. In the situation of collinearity it is hard to find out which one of the variables is causing the changes in the dependent variable. There can be seen some quite strong correlation between the macroeconomic variables. This is why the macroeconomic variables should be treated together in one variable, either with very simple method like I combine them into one dummy variable or in more complex forms like in primary component analysis.

6. Testing regression model to test data

Testing the regression models on out-of-sample test data found to be difficult, because the appropriate data was not available. I have some data from firms' financial ratios and defaults. This data is from year 1991 to year 1998. First problem of the test data was that the equations of ratios are different and are not comparable with the sample data. Second problem is that the early nineties there are only few firms' information available. Also those firms that are available are much larger firms than those in the sample data. The reason for the second problem is that the financial data was not gathered with the same way and quantities as are done nowadays. Third problem concerns the macroeconomic data. The consumer confidence information is available from 1995. This data could be easily manipulated to the dummy form, because the confidence was probably not very high in the early nineties.

All in all, the target of this paper was to evaluate the benefits of adding macroeconomic variables into the regression model of financial ratios and other background information like already occurred defaults. The possibility of having a change to evaluate these benefits needs an appropriate data. This data should of course have comparable variables, but also strong macroeconomic variation of shock(s). These shocks could be the financial crisis started in 2008 or the depression in Finland early nineties.

If I had test data I would have used the regression models B and C. I would have used the coefficients and constant from the regression outputs and multiplied the test data variables with those coefficients. The model would have calculated a predicted value for each observation. Then I would have made the same mean value analysis comparing the regressions B and C and studying if there were any improvement. Also the risk classification analysis could have been made with the same way as in the sample data.

The difference of testing the model is that the regression coefficients and constant is calculated from the different data and the regression line is fitted by the sample data. Using a given model to the test data could give whole different answers than in the sample data where the model is been made.

7. Results to hypothesis

H1: The macro level variables are significant in the regression model with financial ratios and macroeconomic variables when the dependent variable is default of a firm.

Most of the macroeconomic variables are significant. The most significant is the gross national income. The least significant are consumer confidence on economy and interest rate. All the variables alone gave some new value to the model, but when they are used together they raise a problem of collinearity. Many of the macroeconomic variables are highly correlated with each other that using them together is not recommended. The problem to this solution is to use them together in one variable. With this way also the significance level increases. Hypothesis H1 is thus proven right and is not rejected.

H2: The macro level variables improve the model's ability to predict future defaults.

From mean of predicted value analysis and risk classifications we can see that the regression with financial ratios, occurred defaults and fast growth of sales is improved when the macroeconomic variables are added. In this paper the macroeconomic variables are used together in one dummy variable. This variable reacts quite rarely, but when it does, it has some quite reliable information of the macroeconomic state. The prediction abilities do not improve dramatically, but there is some improvement. Even that the improvement is very small, it can be valuable information. For example the Type I errors in lending decisions (loan is granted to a firm that defaults) can be very costly. Avoiding even few of Type I errors can have significant savings. Also avoiding Type II errors is important. That is improvement in finding good firms and lending money at healthy economic situations is important for the lender and for the firms also. Hypothesis H2 is thus proven right and is not rejected.

H3: The newer the macro data used in model, the more significant the macro data is and better it predicts the future defaults.

The results to hypothesis H3 are quite marginal. We can see some indications that the newer macroeconomic data is more valuable, but the significance is so weak that any serious conclusions can't be made. The mean of predicted value of the actually defaulted, non-defaulted and risk classifications give some indications that the model improves with newer macroeconomic data. There is though a change for this happening on coincidence. The same discussion as above about Type I- and Type II errors hold here too, but hypothesis H3 does not have enough evidence and is this point rejected. Further research with more data is recommended.

8. Conclusions

The ambition of this paper was widen the view of the credit ratings from firm specific view to more macroeconomic view where also the surrounding world is taken into consideration of predicting the default risks. The reason why a firm defaults can be an external shock that has nothing to do with the firm's own actions and qualities. Example of this kind of shock is the 2008 financial crisis that hit the whole world. In this paper the impacts of it can also be seen in quickly risen number of defaults and fallen financial ratios.

Macroeconomic variables are giving new value to the prediction model, but it seems that this value comes exposed mostly in the situations of economic shocks. In normal and smaller business cycles these variables seem to live their own lives and alone their default prediction value is not so credible.

The models used in this paper were quite simple and the macroeconomic variable was represented in very simple form. I though find it good that the model and variables are simple. It is very easy to understand how the macroeconomic variable works in the model. The simplicity reduces the risk of wrong conclusions. Even with the simple models there was seen some results to the hypotheses.

I think this is a very good starting point in building a new model and improve it. There are infinite possibilities to continue from here. For future research I recommend finding new variables. Like *export* and *investment* was not included in my models. Also improving the models itself is one direction. One example is to use *primary component analysis* for the macroeconomic variable. There are also some much more complicated models available in literature. The data could also be expanded. There are a dozen or so industries that could be studied and those industries include thousands of firms. Also longer time periods could be used. In this paper there is only one large economic shock that affected to the results. The study of business cycles could be more represented. The data of economic shocks from history may not be easily available or doesn't even exist, but maybe in the future when new shocks occurs this study could be continued.

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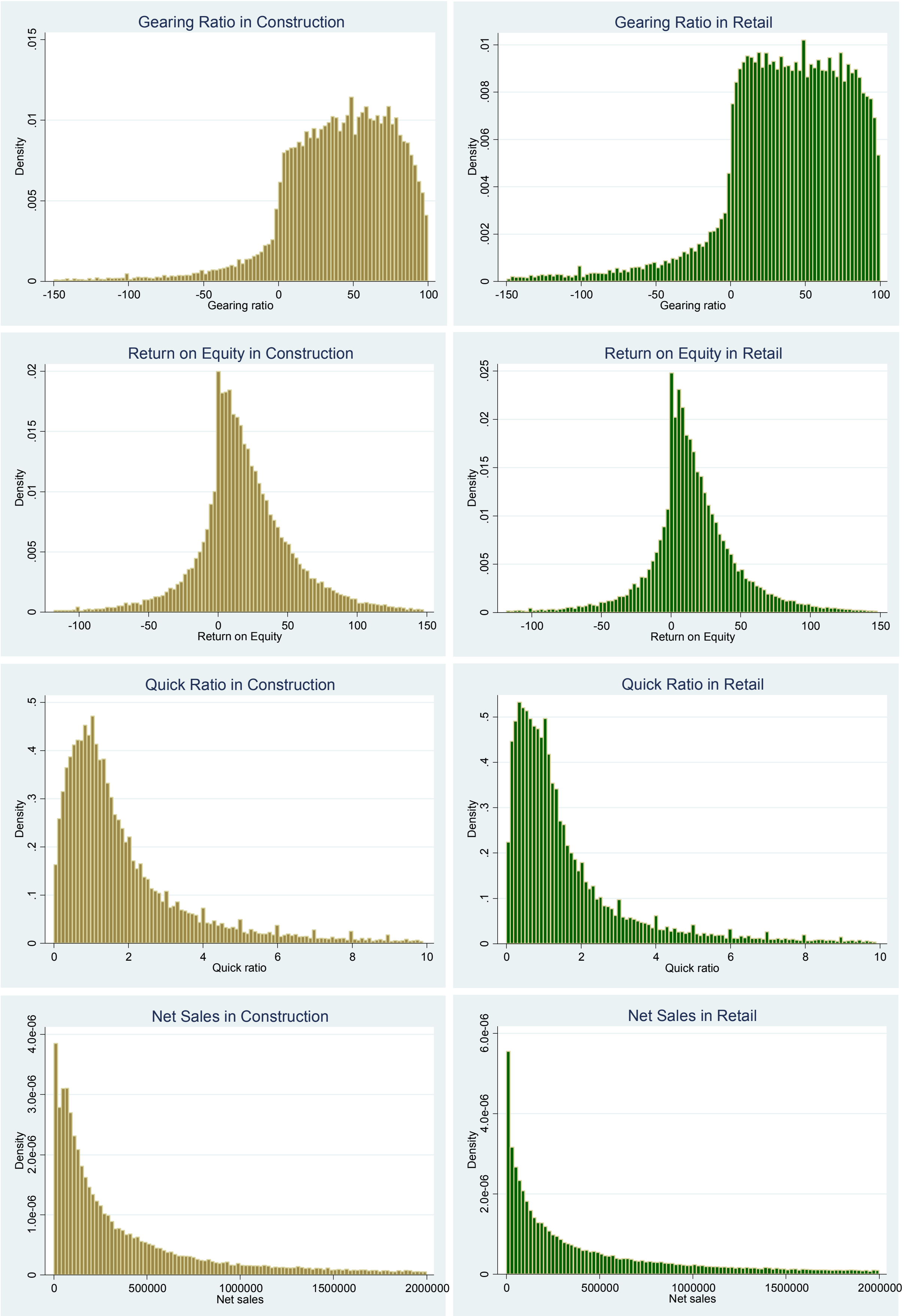
Appendices

Appendix 1. Finanancial ratio distribution over all observations



Appendix 2. Main yearly statistics from construction and retail

Construction mean of ratios at (t) and default percentages at (t+1)

year	roi	gearing	quick	sales	% defaulted	% bankrupted
1999	28.828542	39.604201	2.1376042	1362169.843	2.222222	.3472222
2000	26.705769	39.279304	2.0733822	1254052.546	2.258852	.2136752
2001	25.065766	41.73308	2.3380631	1273275.956	2.533784	.1407658
2002	21.733832	41.996269	2.4902538	1224508.565	2.690355	.1522843
2003	22.215339	41.53177	2.4047785	1106389.413	2.334715	.1090988
2004	20.468346	39.462947	2.2242874	1053844.326	2.990767	.080289
2005	21.137463	39.476536	2.2979776	1130029.069	3.004123	.1767131
2006	21.010924	39.861191	2.2956066	1175322.96	3.56224	.178112
2007	21.209915	39.080891	2.5771729	1165528.496	4.157515	.3294635
2008	18.22688	37.850696	2.6894969	1135338.135	7.06449	.990099
2009	11.729873	36.12863	2.6914595	1024789.849	7.235206	.9199404
2010	12.893372	34.734462	2.5554311	970607.2869	7.70138	.978889
2011	15.706737	35.754681	2.6459781	1054800.858	7.772936	.9186197

Construction 25 percentiles of ratios at (t) and default percentages at (t+1)

year	roi25	gearing25	quick25	sales25	% defaulted	% bankrupted
1999	7.6	20.45	.7	99231	2.222222	.3472222
2000	7.1	20.6	.7	104108	2.258852	.2136752
2001	5.95	22.2	.7	103082.5	2.533784	.1407658
2002	3.6	22	.7	98273.5	2.690355	.1522843
2003	3.3	21.4	.8	90962	2.334715	.1090988
2004	2.2	20	.7	87000	2.990767	.080289
2005	2.7	19.9	.7	93000	3.004123	.1767131
2006	3	20	.8	98000	3.56224	.178112
2007	2.6	18.4	.7	93588	4.157515	.3294635
2008	0	16.7	.7	86000	7.06449	.990099
2009	-3.4	14.6	.7	75000	7.235206	.9199404
2010	-2.4	14.3	.7	75000	7.70138	.978889

2011	0	14.9	.7	79000	7.772936	.9186197

Construction median of ratios at (t) and default percentages at (t+1)

year	roi50	gearing50	quick50	sales50	% defaulted	% bankrupted
1999	24.6	42.8	1.3	280285	2.222222	.3472222
2000	22.9	44.1	1.3	294665.5	2.258852	.2136752
2001	21.8	47.1	1.3	288792.5	2.533784	.1407658
2002	18.9	47.6	1.3	267820.5	2.690355	.1522843
2003	18.2	46.7	1.4	251197	2.334715	.1090988
2004	16.9	44.4	1.3	249000	2.990767	.080289
2005	17.3	44.3	1.3	261501	3.004123	.1767131
2006	17.5	45	1.3	283876	3.56224	.178112
2007	17.5	44.3	1.4	265447	4.157515	.3294635
2008	14.3	44.15	1.4	243026.5	7.06449	.990099
2009	8.8	45.2	1.4	203000	7.235206	.9199404
2010	10.1	43.1	1.3	211000	7.70138	.978889
2011	12	43.8	1.4	227000	7.772936	.9186197

Construction 75 percentiles of ratios at (t) and default percentages at (t+1)

year	roi75	gearing75	quick75	sales75	% defaulted	% bankrupted
1999	48.2	63.2	2.1	813861.5	2.222222	.3472222
2000	45.15	65.45	2.3	849601.5	2.258852	.2136752
2001	42.65	69	2.5	818948.5	2.533784	.1407658
2002	38.6	70.95	2.5	774122	2.690355	.1522843
2003	39.1	69.5	2.6	676351	2.334715	.1090988
2004	38.5	66.7	2.4	673000	2.990767	.080289
2005	37.5	67.9	2.4	727025	3.004123	.1767131
2006	36.9	68.6	2.4	803759	3.56224	.178112
2007	37.8	69.4	2.6	748136	4.157515	.3294635
2008	35.8	71.4	2.8	729463	7.06449	.990099
2009	27.8	71.8	2.9	602340	7.235206	.9199404
2010	28.2	70.5	2.6	614000	7.70138	.978889
2011	32.3	70.3	2.7	688000	7.772936	.9186197

Retail mean of ratios at (t) and default percentages at (t+1)

year	roi	gearing	quick	sales	% defaulted	% bankrupted
1999	21.203833	37.173044	2.102398	2447069.31	1.382811	.1050236
2000	21.244539	36.241772	2.2388243	2443713.935	1.440969	.0818733
2001	20.472496	37.45669	2.3076525	2570744.013	1.213396	.0647144
2002	18.107816	36.759797	2.3850008	2431805.647	1.757361	.138739
2003	17.618129	36.38635	2.3521181	2227026.04	1.740123	.0855798
2004	18.307806	34.489897	2.1474778	2139214.685	1.736159	.1093643
2005	16.841294	34.070958	2.2209989	2306179.035	1.779801	.1241722
2006	17.562592	34.776603	2.3261933	2443720.82	2.04978	.0732064
2007	16.873907	33.009999	2.4914313	2166617.484	2.719494	.2461611
2008	13.324572	31.163442	2.6137628	2055804.568	4.366438	.6956336
2009	7.9052026	29.417887	2.5922928	1895320.403	4.374933	.4299688
2010	10.691651	28.308805	2.4448726	1972045.827	4.681997	.5386369
2011	11.466733	28.252937	2.4979857	2069351.271	4.448174	.3881662

Retail 25 percentiles of ratios at (t) and default percentages at (t+1)

year	roi25	gearing25	quick25	sales25	% defaulted	% bankrupted
1999	4	16.3	.6	129505	1.382811	.1050236
2000	4.5	16	.6	139764	1.440969	.0818733
2001	4	16.7	.6	135559	1.213396	.0647144
2002	2.5	16.6	.6	128570	1.757361	.138739
2003	1.9	15.9	.5	117106	1.740123	.0855798
2004	2	15.2	.5	105000	1.736159	.1093643
2005	.9	14.25	.5	113000	1.779801	.1241722
2006	2	14.8	.6	123000	2.04978	.0732064
2007	1	13.5	.5	95000	2.719494	.2461611
2008	0	11.8	.5	79214.5	4.366438	.6956336
2009	-3.8	10.5	.5	72000	4.374933	.4299688
2010	-1.6	9.9	.5	70000	4.681997	.5386369
2011	-1.7	9.7	.5	70000	4.448174	.3881662

Retail median of ratios at (t) and default percentages at (t+1)						
year	roi50	gearing50	quick50	sales50	% defaulted	% bankrupted
1999	17.8	39.5	1	472440	1.382811	.1050236
2000	18.1	40.8	1.1	484213	1.440969	.0818733
2001	17.2	41.9	1.1	500864	1.213396	.0647144
2002	15.2	42.3	1.1	456722	1.757361	.138739
2003	14.3	42.9	1.1	414000	1.740123	.0855798
2004	14.4	41.1	1.1	379000	1.736159	.1093643
2005	13.1	41	1.1	409000	1.779801	.1241722
2006	14.5	41.7	1.1	453000	2.04978	.0732064
2007	13.4	41.4	1.1	375000	2.719494	.2461611
2008	10.2	41.55	1.1	323000	4.366438	.6956336
2009	6.3	41.1	1.1	297000	4.374933	.4299688
2010	7.9	40	1.1	295648.5	4.681997	.5386369
2011	8.4	39.8	1.1	298500	4.448174	.3881662

Retail 75 percentiles of ratios at (t) and default percentages at (t+1)						
year	roi75	gearing75	quick75	sales75	% defaulted	% bankrupted
1999	38.1	64.2	2	1705426	1.382811	.1050236
2000	36.7	65.8	2	1709462	1.440969	.0818733
2001	34.9	67.6	2.1	1769776	1.213396	.0647144
2002	33.1	68.7	2.2	1677762	1.757361	.138739
2003	32.8	69	2.2	1536269	1.740123	.0855798
2004	33.4	66.7	2.1	1404639	1.736159	.1093643
2005	31.3	67.55	2.1	1513869	1.779801	.1241722
2006	31.6	68.8	2.2	1630000	2.04978	.0732064
2007	31.1	70.2	2.3	1384241	2.719494	.2461611
2008	27.6	71.8	2.4	1233120.5	4.366438	.6956336
2009	21.2	72.2	2.4	1089000	4.374933	.4299688
2010	24	70	2.3	1131300	4.681997	.5386369
2011	24.5	69.7	2.3	1195500	4.448174	.3881662