Charles University

Faculty of Social Sciences
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MASTER'S THESIS

Estimation of company credit rating by means of ordered probit model applied to Czech bond market environment

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Study program: **Economics and Finance**

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, May 4, 2021 Bc. David Pergl

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Abstract

There is a widespread belief among the academics that the bond investors are sufficiently rewarded for taking higher credit risk in their investments. Recent studies confirmed that the well-behaved global markets exhibit adverse relationship of bond credit quality and required bond yield. However, there is no evidence about the Czech market. The purpose of this study is to examine the relationship between credit rating and bond yield or alternatively credit spread on the Czech bond market. As majority of Czech bond issuers are not rated we first had to develop appropriate tool how to measure their credit rating or to build suitable model for credit rating measurement. An ordered probit model is applied, using financial and company-specific data in the pool of US and EU companies structured in the panel of observations in 2008-2019. The study demonstrates that financial and company specific data are sufficient to estimate the credit rating. This model was applied to the Czech market to determine credit scores of Czech bond issuers. These credit scores were employed to examine the relationship between credit risk exposure (credit rating), bond yield and credit spread. The research did not confirm strong linear relationship between credit risk and return and suggests that there are other factors included in the risk feeling of the Czech investors or that the bonds are mispriced.

JEL Classification	C52, C58, G11 , G12, G15, G23, G33
Keywords	credit raiting, ordered probit model, Czech bond market, yield to maturity, credit spread, risk-return relationship
Title	Estimation of company credit rating by means of ordered probit model applied to Czech bond market environment

Abstrakt

Mezi akademiky panuje přesvědčení, že dluhopisoví investoři jsou řádně odměněni za podstupování vyššího rizika při jejich investicích. Nedávné studie potvrdily, že vyspělé světové trhy vykazují inverzní vztah mezi úvěrovou kvalitou dluhopisu a požadovaným dluhopisovým výnosem. Nicméně, o tomto vztahu neexistuje žádná zmínka na českém trhu. Cíl této práce je prozkoumat vztah mezi úvěrovým ratingem a dluhopisovým výnosem nebo eventuálně kreditním spreadem v rámci českého dluhopisového trhu. Bohužel, většina českých emitentů dluhopisů není úvěrově ohodnocena, proto jsme nejprve museli najít vhodný nástroj/model, jak tento úvěrový rating změřit. Pro jeho odhadnutí jsme použili ordered probit model a finanční a podnikové proměnné uspořádané do panelu pozorování v období 2008-2019. Tato studie demonstruje, že finanční a podnikové proměnné jsou dostatečné pro odhad kreditního ratingu. Tento model byl dále aplikován na český trh, tak aby stanovil ohodnocení vybraných českých emitentů dluhopisů. Úvěrové ratingy byly následně použity pro přezkoumání vztahu mezi kreditním rizikem a výnosem dluhopisu a kreditním spreadem. Výzkum nepotvrdil očekávaný silný lineární vztah mezi kreditním rizikem a výnosem. Výsledky dále naznačují existenci jiných rizikových faktorů, které jsou dluhopisovými investory zohledňovány a také, že české dluhopisy vykazují nesprávné ocenění.

Klasifikace	C52, C58, G11 , G12, G15, G23, G33
Klíčová slova	kreditní raiting, ordered probit model, český dluhopisový trh, výnos do splatnosti, kreditní spread, vztah mezi výnosem a rizikem
Název práce	Odhad úvěrového ratingu společnosti pomocí ordered probit modelu aplikovaném na český dluhopisový trh

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Acronyms

CRA Credit Rating Agengy

NRSRO Nationally Recognized Statistical Ratings Organization

PD Probability of Default

EL Expected Loss

AIC Akaike Information Criterion

FE Fixed Effect

YTM Yield to Maturity

CS Credit Spread

PSE Prague Stock Exchange

6M PRIBOR 6 Month Prague InterBank Offered Rate

CNB Czech National Bank

Master's Thesis Proposal

Institute of Economic Studies
Faculty of Social Sciences
Charles University

Author:	**Bc. David Pergl**	Supervisor:	Mgr. Magda Pečená, Ph.D.
Specialization	FFM&B		

Proposed Topic:

Estimation of company credit rating by means of ordered probit model applied to Czech bond market environment

Motivation:

External financing is the fundamental issue that has to be addressed in every company regardless of the stage of its life-cycle it finds itself. According to the data provided by Reuters, average debt-to-assets ratio for top 100 non-financial companies of the market index S&P 500 ordered by market capitalization is about 0.67. We can observe that external sources play an important role in corporate finance. Nor it only allows the firms to scale its operations and optimize its return on equity, it is also beneficial in terms of valuation. Despite Miller and Modigliani (1961) irrelevance proposition theorem stating that firm's financial leverage does not affect it, in real world with taxes, transaction costs and agency costs there is rather a symmetric relationship between cost of capital and capital structure.

Access to debt financing might be significant for a firm to be able to finance its operations and expansions. In terms of debt financing, there are two ways for a firm how to raise additional capital - bank financing and bond issuance. Due to highly sophisticated risk management, banks can efficiently evaluate creditworthiness of a company and possible occurrence of default before the transaction is executed. In terms of bond issuance, there is pool of retail investors that do not have access to sophisticated methods used by banks and financial institutions. Thus, assuming higher information asymmetry and that less sophisticated potential investor pool, the market provides a tool for measuring credit risk or in other words probability of default called credit rating. Altman and Rijken (2004) defined credit rating as a quantified assessment of the creditworthiness of a prospective borrower (an individual, a corporation, state or sovereign government) in general terms or with respect to a particular debt or financial obligation. The process of assigning credit rating might be for the issuing entity very beneficial to attract more investors. Generally, there are three rating agencies having vast majority of the credit rating assessment market - Standard & Poor's (S&P), Moody's, and Fitch Group. Moreover, in terms of firms it helps to evaluate the risk premium that the investors will require. In other words, better credit rating allows for cheaper financing.

The firms can find the source of financing in the bond environment. The standard process observable on the market very often is the issuance of a particular bond with the set target amount of money that the company would like to raise. The reward satisfying pool of investors in exchange is called the bond yield. Zvingelis (2019) defined bond´s yield as the composition of two parts. The expected average nominal short-term yield and a bond risk premium. The bond risk premium should reflect the creditworthiness of the company in terms of its characteristic features, i.e. the probability of default and the ability to meet its obligations. Generally speaking, investors who put the money into the firm with assigned high credit rating should be rewarded much lower in terms of risk premium than the investors who are able to bear higher risk of default. That is the basic theoretical concept described in many textbooks on economics. Unfortunately, this concept does not have to hold everywhere because of not so developed bond market environment or relatively short market history.

In this master thesis, we would like to outline the way how to estimate the credit score of a company making use of key accounting-based metrics that significantly influence the assessment of its creditworthiness. Moreover, the author would like to use the determined credit scoring model for examination of the Czech

bond market environment. We would like to explore whether the reward of risk premium reflects correctly the assigned credit rating (probability of default)

Hypotheses:

Hypotheses on the validity of the Model:

Hypothesis #1: Our credit rating model based on simple financial ratios can be adjusted to measure credit rating on the scale comparable with the scales of credit rating agencies.

Hypothesis #2: The credit rating model works satisfactory both in periods of boom and in periods of recession.

Hypothesis #3: The same explanatory variables of the credit rating model can be used for different market sectors

Hypotheses on the applicability of the Model:

Hypothesis #4: Bond yields of Czech companies with higher estimated credit ratings tend to be lower, i.e. yields and ratings are negatively correlated.

Hypothesis #5: Probability of default (i.e. risk premium) is reflected sufficiently in the yield spreads of the Czech bonds.

Methodology:

Hypothesis on the model validity (#1- #3):

Inspired by several authors e.g. Blume (1998), Livingston et al. (2018) and Poon (2003), we are going to measure the credit rating of a company with ordered probit model included 4 key performance indicators defined in S&P Global – Corporate methodology published in 2013 i.e. Profitability, Liquidity, Capital structure and Coverage ratios. The structure of credit rating model is proposed as follows:

$$Rating_i = \alpha_0 + \sum \beta_k Company\ characteristics_{k,i} + Sovereign\ credit\ rating_i + \varepsilon_i$$

Where the dependent variable *Rating* is a quantified credit rating of a company with values from 1-9, while 1 means minimal credit risk and 9 represents the highest risk of bankruptcy; the explanatory variables cover mainly indicators of the company performance, i.e. the set of variables explaining the Profitability, Liquidity, Capital structure and Coverage ratios. More specifically, the list of considered accounting-based ratios is provided below:

- **Profitability**: Operating Profit margin, EBITDA margin, Return on Equity, Return of Assets, Return on Invested Capital, EBIT/Total Sales
- **Liquidity**: Current ratio, Quick ratio, Cash ratio, Working capital/Total Revenues
- **Capital structure**: Net Debt to EBITDA, Total Debt ratio, Total Debt to Equity ratio, Total Debt to Asset ratio
- **Coverage ratios**: Interest Coverage ratio, Debt Service Coverage ratio, Asset Coverage ratio
- **Additional characteristics**: log (Total Revenues), Industry specification (categorical variable derived from the Global Industry Classification Standard (GICS)), Headquarter

We will estimate the parameters of our proposed model for several data sets of different companies with the assigned credit rating and test the hypothesis that the estimates of parameters are statistically significant. We will perform the same tests for various market sectors and different periods of economic cycle. Our goal is to select the set of explanatory variables that fits credit rating estimates the best.

To be more specific, we are going to use an ordered probit model applied to pooled panel data in order to increase the size of the dataset and subsequently the robustness of the model. In case of different credit grades assigned by S&P, Moody's, and Fitch Group we are going to transfer them to the common scale. Generally speaking, the highest grade will be transferred to the value 1 and the lowest grade will be transferred to the value 9. We will provide a table with detailed description of that transformation.

Kaplan and Urwitz, (1979) showed that accounting-based ratios can explain up to 80% of the variation in company's credit rating. However, we intend to take into account not only the firm-specific indicators, but geographical factors as well. Since sovereign credit ratings are reported and updated on regular basis, we propose to use it as the best indicator of creditworthiness of a particular region and period.

The probit model does not belong to the family of linear models. Thus, to estimate its parameters Maximum Likelihood estimation will be used. To test the statistical significance, t-tests, F-test and Brant's test will be carried out.

Hypothesis on the model applicability (#4 - #5):

Ordered probit model will be further used to determine the credit rating scores of selected Czech companies with the purpose to use these estimates for the analysis of Czech bond market environment.

Firstly, the dependence of yield spreads on credit rating score will be tested using simple regression (Livingston et al. (2018)):

$$Yield\ Spread_i = \alpha_0 + \sum_{j=1}^{8} \beta_j Rating_{j,i} + \sum \gamma_k control\ variables_{k,i} + \epsilon_i$$

,where *Yield Spread* is the difference-between the bond yields to maturity and Czech Government bond yields of similar maturity. The explanatory variables *Rating* are defined as a series of dummy variables with AAA rated companies as the base case. The *Control variables* represent the factors that are expected to affect the bond yields, i.e. bond type, maturity, volume issued etc. We believe that they help us to cover the effect of time alongside the yield curve and interest rate fluctuations.

Secondly, the resulting yield spreads will be compared with empirical probabilities of default. The probabilities will be subtracted from 2019 Annual Global Corporate Default And Rating Transition Study (Kraemer, 2020). The relationship of the probability of default and the width of modeled spread will be checked

From the investor's perspective, if the model will be able to reflect the inverse relationship between estimated credit rating and bond yields, i.e. the fall of the bond price in case of credit worsening it could be used as a tool of a fund manager to adjust his/her portfolio on time if the estimated credit rating changes.

Data sources:

The financial data will be retrieved from Thompson Reuters Eikon platform, one of the key providers of financial data of listed companies all over the world. It is a great source of extensive financial information (e.g. balance sheets, income statements, credit ratings, bonds etc.). We suggest to include in our sample only the companies domiciled in Europe and USA to ensure stable political and economic environment.
We intend to cover 12 year observation period that includes both financial crisis (2008 and current COVID-19). The values will be moving-averaged on the 3 year basis.

Based on our ordered probit model, we intend to structure our data for selected companies as follows: (1) basic information about the company (industry, country of domicile); (2) accounting-based financial metrics and (3) macroeconomics indicator, i.e. sovereign credit ratings assigned by Standard & Poor's (S&P), Moody's, and Fitch Group companies.

Financial data for selected Czech companies will be subtracted from the public source justice.cz or private platform MagnusWeb, which is an extensive database of business information, including facts and figures on Czech enterprises, capital markets, industries and other economic categories.

Data about Czech bond yields will be retrieved from the set of different sources like Thompson Reuters Eikon platform, Central Securities Depository Prague and Prague Stock Exchange webpages.

Expected Contribution:

We plan to test how the proposed models of credit rating work with real data sets and to provide discussion on the results. We are also going to use the estimated model for examination of Czech bond market environment. Mainly, how such market is able to reflect creditworthiness of a particular company in the bond yield, more specifically in its risk premium. **In other words, we would like to investigate how the Czech bonds market has developed in the course of past years and how it has followed other world markets in terms of cultivation, globalization and ability to satisfy the relationship between probability of default and bond yields.**

Furthermore, the model may also serve well for:

- The retail investors who are going to invest in stocks or bonds of companies without official credit rating. They might be looking for a sophisticated and easily accessible tool that could help them to analyze quickly financial health of companies they invested in and to make right decisions in the right time.

Corporate managers and directors who would like to control the creditworthiness of their company. They could use the proposed model for comparison of financial health of their company with other key players on the market. The model might be also helpful during the Merge & Acquisition processes as one of the first metrics assessing the quality of a company.

Outline:

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Author **Supervisor**

1 Introduction

External financing is the fundamental issue that has to be addressed in every company regardless of the stage of its life-cycle. Average debt-to-assets ratio for top 100 non-financial companies of the market index S&P 500 is about 0.67 suggesting that external sources play an important role in corporate finance.

In terms of debt financing, there are two ways for a firm how to raise external capital - bank financing and bond issuance. Due to highly sophisticated risk management process, banks can efficiently evaluate creditworthiness of a company and assess probability of default before the loan is provided. In terms of bond issuance, there is a pool of non-professional retail investors that do not have access to sophisticated methods used by banks and financial institutions. They are not able to evaluate the risk that the bond issuer will not be able to fulfill its obligation to pay the promised return and repay the bond principal at maturity.

Thus, assuming higher information asymmetry and less sophisticated investors, the market provides a tool for measuring credit risk called credit rating. The rating means that the company as a bond issuer is rated on the alphabetic-oriented standardized scale by its relative creditworthiness or equivalently the probability of default. Credit rating is provided by established rating agencies. However, there is a lot of bond issuers who are not rated. This study explores models that allow for estimation of credit rating and applies them for Czech bond issuers.

The basic economic risk-return relationship with regard investments assumes that the statement *„the higher the risk, the greater the return*" defined by Sharpe (1964) holds. There is a widespread belief among the academics that the bond investors are sufficiently rewarded for taking higher credit risk in their investments. We shared this opinion and used it as a benchmark for our study.

As confirmed by Livingston, et al. (2018) and He, et al. (2000) and others, the well-behaved global markets exhibit adverse relationship of bond credit quality and required bond yield. It means that the lower the credit rating the higher the bond yield. Thus one can expect that such basic relationship holds for all bond markets.

The main objective of this study is to examine the relationship between credit rating and bond yield or alternatively credit spread on the Czech bond market and confirm that bond yields correspond the credit ratings of bond issuers.

As majority of Czech bond issuers and issues are not rated we first had to develop appropriate tool how to measure their credit rating or to build suitable model for credit rating measurement. Following previously published literature e.g. Blume, et al. (1998), Poon (2003) we decided for the ordered probit model technique. These models estimate credit rating on the base of simple company-specific and financial ratios. Due to the lack of rating data on the Czech bond market we estimated their parameters using financial and company-specific data in the pool of U.S. and EU companies structured in the panel of observations in 2008-2019. We proved that our model is able to provide estimates comparable with the scales of credit rating agencies.

Nevertheless, we were not sure how strong the regional bias between U.S. and EU regions might be. We explanined in the study why we selected EU model structure for a use in the Czech bond market. We proved among other things that with the variables Sector and Time as the proxy of business cycle has been improved considerably the statistical significance of estimates.

Equipped with our model we were able to examine Czech bond issuers and the relationship between their credit ratings and yield of their bonds. We used both yields to maturity and credit spreads. To evaluate this relation we were inspired by Livingston, at al. (2018) and his approach applied onto the Chinese market. It means that we used simple linear regression of control and dummy variables to explain the corresponding yield of Czech bonds. What seems to be clear in theory was not so easy in practice. The Czech market for corporate bonds exhibits very low liquidity. Missing market prices limits the interpretation of bond yields. Bonds with variable coupons are not traded at all. Therefore, we were forced to find a proxy for their yields and to explore the relationship separately from the bonds with fixed coupons.

Our empirical results confirmed that for our sample of selected Czech bonds, it is not the credit rating that is the main factor influencing their yields. There are other

unobserved factors that disturb the expected adverse relationship between their yields and estimated credit ratings.

Even if our conclusions might have been biased as a result of lack of data and overall business heterogeneity of issuers of selected bonds there is clear evidence of incorrect pricing and that the mispriced Czech bonds do not reflect correctly the riskiness of the investment. This finding also means that Czech investors are not fairly rewarded for taking higher credit risk.

Our study is the first that analyzes the relationship of credit risk and bond yield on the Czech corporate bond market. The study also answers the question whether publicly traded bonds on Prague Stock Exchange are fairly priced with regard to credit rating of the issuer. Our study and the models used may also assist to non-professional retail investors in examination of financial health of a particular company without official credit rating and help them to manage their bond investments accordingly.

The thesis is structured as follows: Chapter 2 provides a brief overview of previously published applications of ordered probit models. It also defines the credit rating metrics. Chapter 3 describes our methodology and introduces our explored datasets. The last chapters are reserved for the presentation of our results and conclusions.

2 Literature review

In this chapter, we are going to briefly describe credit rating metric and provide an overview of some previously published literature focused on its estimation. In the first subsection, we discuss credit rating definition and its main features. We mainly focus on its use in the real life situation. The following subsections are reserved for brief history, introduction of methodology of credit rating agencies and its shortcomings observed on the market. The second part of this chapter is primarily focused on the credit rating estimation. We outline the basics of its estimation in 1960s and investigate econometrical approaches used. Finally, we relate previously published studies to our research.

Credit rating

Definition and its main feature

A common question in every potential or actual lending/borrowing relationship is whether the borrower will be able to meet his commitments and pay a borrowed amount of money back to the lender. In terms of such relationship, we refer to situation in which the lender is exposed to the credit risk. Brown & Moles, (2016) defined the credit risk as the potential that a contractual party will fail to meet its obligations in accordance with the agreed terms. To address such question, a lending party is demanded to collect the set of information primarily focused on the current borrowers´ financial situation, i.e. financial prospects, the ability to pay its past obligations, the structure and stability of income streams etc. Among other things, the lender should be aware of information asymmetry or the problem of adverse selection[1] (White, 2013). Furthermore, lender would like to be sure that the financial situation of borrowers will not be worsening and, if there is a sign of worsening, the lender would like to learn about it as soon as possible to salvage the entire or at least some amount of lent money in case of default.

[1] Lewis (2011) defined the adverse selection as the condition where the information asymmetry occurs i.e. seller has more information than the buyer, or vice versa, about some aspects/conditions of the product.

External financing plays very important role in these days. Averaged debt-to-assets ratio for top 100 non-financial companies of the market index S&P 500 ordered by market capitalization is about 0.67. There are basically two ways for a firm how to raise an additional capital – bank financing and bond issuance.

In terms of bank financing, the lender is represented by banks, finance, or investment companies that are usually able to gather and analyze the required information themselves due to highly sophisticated processes of risk management. Credit risk management serves as a tool for monitoring and evaluation of risk and, in some cases, for initiation of actions aimed at management of the undertaken risk. The riskiness of the entire transaction is reflected in the interest rate levels as some kind of a reward for financial institutions for bearing the risk of lending and may be losing money.

On the contrary, in terms of bond issuance, there is often a pool of non-professional investors that do not have access to such sophisticated methods used by banks or financial institutions. Thus, assuming higher information asymmetry and less sophisticated investors, the market created and offers third-party service of risk evaluation. Specialized institutions are sufficiently equipped to analyze credit risk exposure (probability of default) and provide very easy and understandable outcomes by means of credit ratings. They are issued by credit rating agencies (CRAs).

S&P Global Ratings (S&P), Moody's, and Fitch Group are considered as three CRAs with broad history that have developed into the most important providers of creditworthiness advisory services in the world. They currently cover almost 90% share on the market. For almost 15 years, these “Big three rating agencies” were the only ones approved by U.S. Securities and Exchange Commission as nationally recognized statistical rating organizations (NRSRO)[2]. In these days, the list of NRSRO agencies increased to 9 entities.

[2] To be considered as a nationally recognized statistical ratings organization (NRSRO), the SEC must deem the agency to be "nationally recognized" in the U.S., and it must provide reliable and credible credit ratings. Other features taken into consideration by the SEC are the size of the credit rating agency, operational capability, and the agency's financial resources. (U.S. Securities and Exchange Commision, 2003)

The main purpose of the CRAs as defined by Kuvíková (2015) is to mitigate an information asymmetry on the market by transferring their credit risk measurement of issuers into an alphabetic-oriented rating scale reflecting the relative creditworthiness of various issuers or, equivalently the probability of default. Altman & Rijken, (2004) defined credit rating as a quantified assessment of the creditworthiness of a prospective borrower, i.e. an individual, a corporation, state or sovereign government in general terms or with respect to a particular debt or financial obligation.

Each CRA has own system of grades e.g. S&P/Fitch and Moody´s use grades from AAA to D and Aaa to C, respectively. AAA/(Aaa) indicates extremely strong capacity to meet issuers´ financial commitments on the obligation and D/(C) reflects the failure of payment of financial commitments. Generally, credit ratings can be assessed based on the duration as long-term or short-term or by the extent of riskiness of potential default as investment grade[3] or speculative, or non-investment grade. The overview of different rating scales is provided in the Table A.1.

The history of credit risk measurement started in mid of 19th century when the US railroad companies started raising large amount of capital from the private investors with the aim to finance their projects and operations. Currently, each rating agency considers a corporate credit rating as an overall assessment of the creditworthiness of a company reflecting both qualitative and quantitative aspects of an issuer. (Poon, 2003). The assessment, itself, is divided into two phases. The first phase encompasses the evaluation of the overall business risk which represents qualitative aspects. The second phase is focused on the overall financial risk representing quantitative aspects. Representatives of S&P Global Ratings (2020) claimed that the business risk profile consists of the return potential on the market in which a certain company operates, the level of competitiveness (called industry risk), the country where the operation is running (called country risk), and the competitive advantages or disadvantages (called competitive position). One the other hand, analysts identify financial policy and flexibility, profitability, capital

[3] Investment grade represents the category of securities that are more stable with limited risk. While the term speculative grade relates to companies with higher probability to default (De Servigny & Renault, 2004)

structure, and cash-flow protections as five key aspects to correctly assess the overall financial risk. As proposed by Blume, et al. (1998) to quantify business and financial risk CRAs employ both publicly available information, such as accounting statements, market reports and nonpublic information, such as confidential interviews with management.

Nevertheless, it is very important to understand that CRAs do not offer exactly the same information via their credit ratings, as mentioned by De Servigny & Renault (2004). The slight difference, as it was pointed out by Boehm, (2013), relates to the process of final interpretation of assigned ratings which could be presented as the probability of default (PD)[4] or one step further as the expected loss (EL)[5]. Caouette, et al. (1998) proposed that such difference may lead to producing a big split in ratings of riskier entities so called a non-investment grades or sometimes referred as junk bonds.

The full texts of definitions are provided in the Appendix B. However, to highlight the slightly different approaches we summarized key parts of definitions below.

"An S&P Global Ratings issue credit rating is a forward-looking opinion about the creditworthiness of an obligor with respect to a specific financial obligation, or a specific financial program. The opinion reflects S&P Global Ratings view of the obligor's capacity and willingness to meet its financial commitments as they come due, and this opinion may assess terms, such as collateral security and subordination, which could affect ultimate payment in the event of default." (S&P Global Ratings, 2020)

"Fitch's credit ratings relating to issuers are an opinion on the relative ability of an entity to meet financial commitments, such as interest, preferred dividends, and repayment of principal, insurance claims or counterparty obligations… In the default components of ratings assigned to individual obligations or instruments, the agency typically rates to

[4] PD stands for the likelihood of default i.e. the inability to repay entity's debt obligation over a particular period of time.

[5] EL stands for the sum of money reflecting all possible losses a lender/creditor can expect if the borrower defaults.

the likelihood of non-payment or default in accordance with the terms of that instrument's documentation." (FitchRating, 2020)

"Ratings assigned on Moody's global long-term and short-term rating scales are forward-looking opinions of the relative credit risks of financial obligations issued by non-financial corporates, financial institutions, structured finance vehicles, project finance vehicles, and public sector entities… Long-term ratings are assigned to issuers or obligations with an original maturity of one year or more and reflect both on the likelihood of a default on contractually promised payments and the expected financial loss suffered in the event of default." (Moody's Investors Service, 2020)

Despite small differences in interpretation of credit rating results, the principal approach remains the same through each CRAs. (Ederington, (1985) and Hsueh & Kidwell, (1998)) Thus, we can expect that such credit ratings are fully comparable and eligible for transformation into ordinal numbers as proposed by Poon (2003), Livingston, et al. (2018) and Kuvíková (2015).

Shortcomings

Despite increasing popularity of credit assessment business, rating agencies have been criticized several times primarily for misstatements in the periods preceding the biggest financial crises. Brunnermeier (2009) focused on the period after the collapse of Leman Brothers in 2008 (the beginning of Great Recession) and the mass defaults of highly rated structured financial products. To prevent such great impacts of CRAs, the U.S. Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act in 2010 which simultaneously increases the CRA's liability for issuing inaccurate ratings.

It is relevant to point out that rating can be subject to changes no matter the time of the year and the rating level, sometimes without warning. (Pichereau, 2016) Even the securities with the high credit quality can be suddenly downgraded to the lowest level (U.S. Securities and Exchange Commision, 2003).

Estimation of Credit rating

Historical basics

Kaplan & Urwitz (1979) pointed out to the fact that in the first half of 20th century, rating agencies and many institutional writers were skeptical about being able to use a classical statistical model to capture the bond-rating process. Despite such skepticism, we have witnessed significant development of many statistical models in this period that have laid groundings for further studies. Present studies basically proceed from 4 following academic perspectives that were presented between 1966-1970.

Horrigan (1966) performed the first study to estimate and predict bond ratings based on the characteristics of the bonds and the issuing firms. He used accounting data and ratios such as total assets, net worth to total assets, net operating profit to total assets and working capital to total sales as explanatory variables. In addition to that he codded the dependent variable (i.e. credit rating) on a nine-point scale as 9 for AAA/Aaa (the best) to 1 for C (the worst).

Another academic, West (1970) criticized Horigan´s focus on accounting based variables. He proposed instead rather 4 market/company related variables as coefficient of variation of earnings, number of years without loss, market value of stock to debt and market value of traded bonds. However, West followed the Horrigan´s idea of nine-point scale transformation. The results showed that predicted power did not significantly change.

On the other hand, Pogue & Soldofsky (1969) disregarded the ordinal character of credit rating score. They tried to avoid the problem with its transformation to intervals. Hence, they replaced ordinal dependent variable by dummy variable for two selected rating categories. They used long-term debt to total assets, return on assets, coefficient of variation of earnings, and total assets variables. Unfortunately, dummy character of dependent variable quite biased the results and showed significantly lower predicted power.

Slightly different approach was used by Altman (1968) who presented the first version of famous Z-score model. He basically investigated the set of financial and economic ratios in a bankruptcy prediction context wherein a multiple discriminant statistical methodology was employed. He determined that the most significant variables were Working Capital to Total Assets, Retained Earnings to Total Assets, Eairnings

Before Interest and Taxes to Total Assets, Market Value of Equity to Book Value of Total Debt and Total Sales to Total Assets. Altman Z-score on the first trial showed the accuracy nearly 72% in predicting bankruptcy two yeas before the event.

These studies presented 2 crucial guidelines that need to be followed in credit rating estimation. The dependent variable credit rating has to be ordinal to correctly reflect different risk levels of entity/instrument. In case of independent variable, the authors demonstrated that to estimate sufficiently the credit rating both accounting-based and market-based variables are significant. Kaplan & Urwitz (1979) and Ross (1976) suggested later that the process of assessment of creditworthiness relies mostly on accounting based information rather than on stock or bond market data. More specifically, they found that accounting-based ratios can explain up to 80% of the variation in company's credit rating.

Econometrical approach

To estimate credit rating scores the researchers usually used classical ordinary least square (OLS) approach. The study of McKelvey & Zavoina (1975) discussed ordinal dependent variables in term of OLS from the statistical point of view and found some significant imperfections. They claimed that when the dependent variable in the regression equation is ordinal rather than continuous, the model´s assumptions are easily violated such as the expected value of the error term does not equal to zero, the variance of the error term is not constant, and the error term is not normally distributed. However, the ordinal feature of dependent variable was considered as crucial. Thus, the academics started thinking about the appropriate econometrical tool. The overview of all considered statistical approaches was provided e.g. in Altman, et al. (1981). He presented techniques as multiple regression analysis, multiple discriminant analysis, unordered and ordered logit and probit models. To choose which one is the most suitable is hard to say. Nevertheless, Ederington (1985), Blume, et al. (1998), Poon (2003), Kuvíková (2015), Livingston, et al. (2018) and others used ordered probit model.

Recent studies

One way how to use ordered probit model in terms of credit rating estimation was proposed by Blume, et al. (1998) who analyzed whether the quality of credit rating

standards in the US changed over time. They tried to confirm whether the significant drop in creditworthines of American companies could be explained by decreasing credit quality of their corporate debts. In order to test this hypothesis, they used panel data structure of U.S. companies with investment grades in the observed period 1978-1995 and regressed the model using the mix of market and accounting based independent variables. These variables were market value, market model beta, standard error, pretax interest coverage, operating income to sales, long-term debt to assets, and total debt to assets and time. Their results showed that stricter conditions of credit assessment caused downward bais of actual credit rating levels.

Another study introduced by Poon (2003) utilized ordered probit model to explore the relationship between unsolicited and solicited credit ratings. The author assumed that unsoliced ratings are biased downward with respect to solicited ones. Specifically, he studied whether S&P assigned different degrees of importance to the same factors when deciding on the ratings of firms with solicited and unsolicited ratings. He employeed pooled time-series cross-sectional data of 265 firms from 15 countries and regressed the ordered probit model using 4 financial variables such as EBIT interest coverage, return on assets, total debt to capital and short-term debt to capital ratios and other variables of dummy character. He concluded that unsolicited ratings were biased downward in contrast to solicited. Additionaly, the study showed that S&P used different standards and weights of the same financial variables to assign the solicited and unsolicited rating.

Slightly different way of use of ordered probit model was proposed by Kuvíková (2015) who examined the accuracy and timeliness of credit ratings in explaining the financial health of debt issuers over the recent financial crisis. Employing accounting based data and macroeconomic indicators collected between 2005-2013 for the set of 2500 financial and non-financial companies, she contributed to existed literature by several ways. She founded that CRA Moody's is more conservative in its assessment of default risk for non-financial companies and, on the other hand, that S&P is more conservative in case of financial companies. Additionally, she outlined that increasing market share of Fitch significantly affected the split between S&P and Moody's in the non-financial sectors. On top of that, her empirical results stongly supported the fact that

the process of assessment of creditworthiness of a particular company is considerably influenced by the prior ratings of other agencies.

The study that inspired our research was introduced by Livingston, et al. (2018) who investigated the nascent but fast-growing Chinese bond market and credit rating industry. As the first part, their study tested directly the information content of Chinese bond ratings. Utilizing an ordered probit model, they tried to test whether common accounting and market-based variables arecorrectly reflected in Chinese bond ratings. In order to test this hypothesis they used data for newly issued Chinese bonds with publicly traded equity in the observed period of 2009-2015. They found that two thirds of the variation in Chinese bond ratings could be explained by simple accounting and market-based variables. In the second part of the study, they examined the factors that might determine Chinese public offering yields expressed as credit spreads. More specifically, they were mostly concerned about the role of credit rating and its correct pricing. Based on the existed literature, they supposed the idea that if Chinese bond ratings confirmed the informative power about default risk, the credit spreads should exhibit adverse relationship with them. Using hunderds of newly issued public bonds with fixed coupon in the observed period 2009-2015, they confirmed the expected adverse relationship between credit spreads and credit ratings. In other words, holding the other bond/market characteristics fixed, the lower the credit rating of the company the higher the credit spread.

Another study that investigated the same relationship was introduced by Livingston & Zhou (2010) who examined the relationship between split bond ratings and bond yields at the notch level for newly issued corporate bonds. Utilizing multivariate regression model and data set of almost 14,000 observations from 1983-2008 they found that the split rated bonds exhibited higher level of risk premium than non-split bonds. These results brought them to the conclusion that investors required higher bond yield in case of split rated bonds to compensate discrepancy of credit rating agencies. Besides, the characteristic of split and non-split credit rates they also confirmed the eadverse relationship between credit spreads and credit ratings was present.

Based on the list of some previously published studies, we confirmed that the use of ordered probit model in terms of credit rating estimation has broad scope of application.

The researchers were able to utilize this methodological approach to examine all credit risk related economic issues. Nevertheless, our study was inspiered by the research of Livingston, et al. (2018). Thus, utilizing the same methodological approach we examined the adverse relationship between credit rating and bond yield on the Czech bond market enviroment.

Czech bond market enviroment

Despite the fact that Czech bond market has been estiblished in 1990s, there is, to our knowledge, few academic studies that investigate the Czech bond market and its credit rating. The researchers are mostly focused on its theoretical desription. None of them analyzed credit risk assessment with respect to bond pricing. Dvořáková (2003) analyzed the Czech bond market from the perspectives of macroeconomic, microeconomic, institutional, historical, and current "financial". She outlined and discussed the broad history of Czech bond market existence and its development in time. Other study of Petr (2020) analyzed Czech bond market of high-yield corporate bonds traded on the Czech over-the-counter (OTC) market. The study provided a comparisson of 25 issuers with respect to their financial performance. Lesák (2020) mapped the corporate bond market in the Czech republic and evaluated their riskiness using the Scorecard 2.0 approach. He concluded that three quarters of the examined bond issues exhibited speculative grade meaning very high credit risk.

3 Methodology and Data

3.1 Methodology

The methodology of this paper is divided into two subsections. The first is focused on the estimation of credit ratings using the set of financial and company specific data in the appropriate model. We try to test whether the basic approach of already existed methodology is replicable. The second part of the study applies the model on the estimation of credit ratings of selected bond issuers. Their bonds are publically traded on the Czech bond market. The estimates are used for examination of the relationship between the credit rating score and bond specific yield metrics i.e., yield to maturity, credit spread and credit margin. Summarizing these two parts, the author defines first three hypotheses focused on a validity and transferability of model estimates and additional two hypothesis that test the relationship between creditworthiness of a company and investor´s risk reward.

Hypothesis #1 (H1): Our credit rating model based on simple financial ratios can be adjusted to measure credit rating on the scale comparable with the scales of credit rating agencies.

H1 basically tests whether the author is able to replicate already existed and approved methodology and use such theoretical approach to estimate the company credit rating.

Inspired by several authors, e.g. Ederington (1985), Blume, et al. (1998), Poon (2003) and Livingston, et al. (2018), we measure the credit rating of a particular company using ordered probit model including key financial variables representing profitability, liquidity and leverage & capital structure ratios. The ordered probit model is defined as follows:

$$Z_{it} = \sum \beta_k X_{k,it} + \alpha_t + \varepsilon_{it}, assuming\ \varepsilon|X \sim Normal\ (0,1)$$
$$E[\varepsilon_{it} \mid X_{it}] = 0 \tag{3.1}$$

$$R_i = \begin{cases} 1\ if\ Z_i \leq \mu_1 \\ 2\ if\ \mu_1 < Z_i \leq \mu_{2,} \\ 3\ if\ \mu_2 < Z_i \leq \mu_{3,} \\ \vdots \\ 5\ if\ \mu_4 < Z_i \leq \mu_{5,} \\ 6\ if\ \mu_5 < Z_i \leq \mu_{6,} \\ 7\ if\ \mu_6 > Z_i \end{cases} \tag{3.2}$$

where for the company i at time t the dependent variable R_{it} is the observed rating category assigned to the company. Ratings are scaled from 1 to 7 while 1 means minimal credit risk and 7 represents the highest risk of bankruptcy. Z_{it} is an unobserved, latent variable representing CRAs´ assessment of the creditworthiness of the company i. Its range is divided into a set of intervals. Independent variable X_{it} represents the set of financial and company-specific variables. The coefficient α_t represents unobserved fixed effects associated with different sector and time. β_k is a vector of slope coefficients. ε_{it} stands for standard normal random variable with a conditional expectation of zero and μ_i are threshold parameters of the intervals defining certain credit rating score.

As defined by Wooldridge in his book Econometric Analysis of Cross Section and Panel Data in 2001, given the standard normal assumption for ε_{it}, it is quite straightforward to derive the conditional distribution R_i given Z_{it} as follows:

$$P(R_i = 1 \mid X_i) = P(Z_i \leq \mu_1 \mid X_i) = P(\beta_k X_{it} + \varepsilon_{it} \leq \mu_1 \mid X_i) = \Phi\left(\mu_1 - \sum \beta_k X_{k,it}\right)$$

$$P(R_i = 2 \mid X_i) = P(\mu_1 < Z_i \leq \mu_{2,} \mid X_i) = \Phi\left(\mu_2 - \sum \beta_k X_{k,it}\right) - \Phi\left(\mu_1 - \sum \beta_k X_{k,it}\right)$$

$$\vdots \tag{3.3}$$

$$P(R_i = 6 \mid X_i) = P(\mu_5 < Z_i \leq \mu_{6,} \mid X_i) = \Phi\left(\mu_6 - \sum \beta_k X_{k,it}\right) - \Phi\left(\mu_5 - \sum \beta_k X_{k,it}\right)$$

$$P(R_i = 7 \mid X_i) = P(Z_i > \mu_6 \mid X_i) = 1 - \Phi\left(\mu_6 - \sum \beta_k X_{k,it}\right)$$

where Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution.

The model parameters β and μ are estimated by maximum likelihood technique more specifically by log-likelihood function[6]. The interpretation itself is not straightforward. As Wooldridge, (2001) pointed out we must remember that estimated β coefficient is of limited interest. We are not interested in $E(\mathrm{Z_{it}}|\mathrm{X_{it}}) = \beta_k X_{it}$ as variable $\mathrm{Z_{it}}$ is a latent, abstract construct. Instead we are looking for the response probabilities defined as $P(R_i = j|\mathrm{X_{it}})$, where j is from 1 to 7. Such response probabilities are defined as follows:

$$\frac{\partial p_1(x)}{\partial x_k} = -\beta_k \phi(\mu_1 - \beta_k X_{it}); \frac{\partial p_j(x)}{\partial x_k} = -\beta_k \phi(\mu_j - \beta_k X_{it})$$
$$\frac{\partial p_j(x)}{\partial x_k} = \beta_k [\phi(\mu_{j-1} - \beta_k X_{it}) - \phi(\mu_j - \beta_k X_{it})], \quad for\ 1 < j < 7 \tag{3.4}$$

In general, we can say two things: the coefficients $\hat{\mu}_j$ are important determinants of the magnitudes of the estimated probabilities and partial effects and $\hat{\beta}_j$ coefficients determines the direction of the effect of x_k on the probabilities. Blume, et al. (1998) outlined the interpretation of single variables as follows: *"In a probit model, there are no natural magnitudes for the linking variable, making it difficult to interpret the economic significance of the size of the estimated coefficients."*

Metrics of model quality:

To evaluate the quality of the estimation we tried to use the basic principles of Machine learning techniques i.e. out-of-sample vs. in-sample estimation and five well-known quality evaluating econometric metrics:

1. Confusion matrix: Ting (2017) defined a confusion matrix as a summary of the classification performance of a classifier with respect to some test data. It is a two-dimensional matrix, indexed in one dimension by the true class of an object and in the other by the class that the classifier assigns/predicts. We are mostly concerned about the accuracy ratio that represents the number of correctly classified data objects over the total number of data. To rate the

[6] Log-likelihood function is defined as: $l_i(\mu, \beta) = 1[R_i = 1]\, log[\Phi(\mu_1 - \beta_k X_{it})] + 1[R_i = 2]\, log[\Phi(\mu_2 - \beta_k X_{it}) - \Phi(\mu_1 - \beta_k X_{it})] + \cdots + 1[R_i = 7]\, log[1 - \Phi(\mu_6 - \beta_k X_{it})]$ (Wooldridge, 2001)

quality of the model based on the accuracy ratio, we set the baseline to 50% which is the flip coin case, given an equal number of classes. So, if we divide the range between 100-50% equally, the classification is defined as follows: 100-87.5% strong predicted power, 87.5-75% semi-strong predicted power, 75-62.5% medium/satisfactory predicted power and 62.5-50% weak predicted power

2. Log-likelihood (LL): is the logarithm of the product of probabilities that the model assigned to each alternative. Normally Log Likelihood is maximized.
3. McFadden´s R-squared: is the most popular goodness-of-fit measure in probabilistic models. The idea of coefficient of determination R-squared (R2), i.e. comparing our model with a constant model, can be translated using likelihoods: log-likelihood function of our model (log L1) and log-likelihood function of a base model with constant probability (log L0). McFadden´s R2 is then calculated as 1 – log L1/log L0.
4. Residual Deviance: shows how well the response is predicted. Deviance of the model is defined as -2*Log Likelihood and it is analogous to the residual sum of squares in OLS models. Residual deviance is minimized.
5. Akaike information criterion (AIC): is an estimator of prediction error. AIC also helps us to compare the quality of each estimated model relative to others within the same data set. AIC is minimized.

Financial and company-specific variables:

As mentioned above the estimation of credit rating is based on the set of financial and company-specific variables. The list of suggested financial ratios is a combination of variables that were used in the previous studies by Altman & Rijken (2004), Poon (2003) and Livingston, et al. (2018). Our set of explanatory variables X covers three key financial fields that are considered by S&P Global Ratings (2020) to be sufficient for the analysis of creditworthiness. These fields include variables explaining profitability, liquidity and the leverage & capital structure. More specifically, the list of pre-considered accounting-based ratios is provided below:

- Profitability: Operating Profit margin, EBITDA margin, Return on Equity, Return on Assets, EBIT/Total Sales, Retained Earnings to Total Assets, Interest Coverage ratio
- Liquidity: Current ratio, Quick ratio, Cash ratio, Working Capital to Total Assets
- Leverage & Capital structure: Net Debt to EBITDA, Total Debt to Total Assets, Long-term Debt to Total Assets, Total Shareholder´s Equity to Total Liabilities

In addition to these variables, Blume, et al. (1998) claimed that there is also a positive relationship between credit ratings and the firm size. Thus we also included logarithm of Total Sales as proxy variable for the size. Following Altman & Rijken (2004) we also added the total assets turnover ratio calculated as Total Sales to Total Assets ratio.

To avoid the possible problem with multicollinearity and overestimation of the model, we aimed to select only key financial variables representing, financial clusters that will significantly contribute to the estimation of the credit rating. Following Havránek (2019) one of the most appropriate methods to select only the most significant variables is model averaging approach. Model averaging method basically runs regression/probit models with different combinations of variables, and then gives these models their weights based on how they fit the data and how parsimonious, and possibly well-specified, they are. (Havránek, 2019). For more detailed theoretical explanation of the model averaging approach and its use in economics see Steel (2020).

As suggested by Metz (2006), we also include categorical variable Sector specifying name of industry according to the Global Industry Classification Standard (GICS) and dummy variable Year which is equal to 1 in a relevant year and zero otherwise. We believe that these two variables may help us to control unobserved fixed effects (FEs) associated with differences corresponding different business sectors and phases of business cycles. On the other hand, we are aware that the best way how to capture FEs corresponding each single company in the company-related models would be to use also variable Company. Such variable is usually constructed as a set of dummy variables according to their tickers. However, in case of our study such construction of FEs is not relevant. Firstly, we aim to apply our model for different market environment which makes it impossible to utilize such information. Secondly, we collected data for hundreds

of firms which would result in hundreds of additional explanatory variables and might cause an overestimation of the model.

As we discussed in the Literature review subsection

Credit rating, the majority of credit rating services is provided by 3 CRAs founded in the US. Market environment and general popularity of credit rating services caused that US is currently the biggest source of credit rating data in the world.

It would be comfortable to use U.S. data for construction of our model. However, we wanted to use our model to estimate credit ratings of Czech companies. We were not sure how strong the expected regional bias might be (i.e. the size of companies, balance sheet structure etc.). To be able to measure it we also collected the EU-based dataset and tested whether U.S. and EU data sets are replaceable. If so, then both models could be used for the Czech market. If not, we would rather use the EU-based model. So we had to test Hypothesis #2 below.

Hypothesis #2 (H2): The credit rating model estimated using EU data is fully transferable to US environment and its estimates are not significantly different and vice versa.

Rejection of this hypothesis would indicate that U.S. and EU-based companies most likely differ in the course of businesses, balance sheet structures or other business related features.

In order to test H2, we used out-of-sample estimation approach. We simply plugged observed financial data for US companies into the EU-based model and predicted credit rating scores and did the same with EU data and US model. Afterwards, we compared confusion matrices and accuracy ratios.

Then we turned our attention to the significance of the variable Sector. As proposed in the subsection Financial and company-specific data, we suppose that variable Sector might help us to filter out the unobserved, clustered effects of selected companies and improve the measure of Goodness-of- Fit. Therefore, we tried to reject the Hypothesis #3.

Hypothesis #3 (H3): The predicted power of estimated credit rating model is not sector specific.

The importance of the Sector is supported by Metz, (2006) who claimed in his study that variable Industry/Sector should be incorporated in the credit rating model to capture unobservable fixed effects.

We tested this hypothesis by runnig two different regressions that included and exluded the sector variable. The results of both models were compared on the level of (Pseudo) R2, Accuracy ratio and AIC.

Based on our findings when testing hypothesis H1 – 3, we selected model with sectors relevant to selected Czech companies. We collected the set of available financial and company-specific variables, plugged them into the EU model and estimated their credit ratings. Then we tried to use them for examination of fair pricing on the Czech bond market.

Fair price should reflect the relationship between the bond yield or credit spread and an estimated rating category. The empirical result of prior studies (e.g. He, Hu, & Lang (2000)) of well-behaved markets, showed that with lower credit rating[7], credit spread becomes wider and upward slopping. In other words, the worse the creditworthiness of a particular company, the higher the credit spread. This statement is also supported by the basic idea defined by Sharpe (1964): *"the higher the risk, the greater the potential return"*.

Bond yield and credit spread are defined as follows:

Yield to Maturity:

Bonds are compared in terms of yields rather than prices due to their different patterns of cash flows. Bond yields are considered as rate of returns earned from holding the bond. The most popular and frequently used measure of the bond return is yield to maturity

[7] Note the odrering of credit rating applied in this study: 1 stands for the best credit rating and 7 for the worst

(YTM). Sharpe, Alexander, & Bailey (1995) defined YTM as a discount rate at which the present value of the discounted cash flows is equal to the current price of the bond. To calculate YTM we have to solve the following equation (**3.5**).

$$P = \sum_{t=1}^{T} \frac{cM}{(1+YTM)^t} + \frac{M}{(1+YTM)^T} \tag{3.5}$$

where P is the fair price of the bond, M is the nominal value of the bond, c is the coupon rate and T represents remaining time to maturity.

Credit spread:

Credit spread is the difference between two yields of two debt instruments with the same maturity. We usually relate YTM of a particular corporate bond to the yield of risk-free government bond. This metric is considered to be the determinant of riskiness of a corporate bond. The credit spread calculation is specified as follows:

$$Credit\ Spread\ = Corporate\ Bond\ Yield - Government\ Bond\ Yield \tag{3.6}$$

To be able to assess whether the Czech bonds are priced in the same way as well-behaved markets mentioned above, i.e. if the price reflects the relationship with credit rating or if the market price is really the fair price we tested our Hypothesis #4.

Hypothesis #4 (H4): Bond yields of Czech companies with higher estimated credit ratings tend to be lower, i.e. yields and ratings are negatively correlated.

Rejection of this hypothesis would mean that the credit risk is not correctly reflected in the price. This would indicate that Czech bonds are not priced in the way as developed markets where the investors are awarded for taking higher risk.

In order to test H4, we simply regressed YTM of a particular bond with estimated credit rating score and the set of control variables as follows:

$$YTM_i = \alpha_0 + \sum_{j=1}^{6} \beta_j R_{j,i} + \sum \gamma_k C_{k,i} + \epsilon_i \tag{3.7}$$

where YTM is a calculated yield to maturity for company i. The explanatory variable R is defined as a series of dummy variables with AAA rated companies as the base case. The variable C represents the set of control variables that we expect to affect the bond yields. They are liquidity, maturity, bond type and volume of the issuance etc. The regression was estimated by the classical OLS estimator.

H4 would be rejected if the error of the model, i.e. the differences of estimated and measured YTM exceed statistical significance. Correlation can be also measured by the correlation coefficient of credit rating and YTM. In addition to that we defined two classical significance metrics as:

- R-squared - (Wooldridge, 2006) defined R-squared as the ratio of the explained variation compared to the total variation, and thus it is interpreted as the fraction of the sample variation in dependent variable y that is explained by independent variable x.

- F-statistic and its p-value to test the overall significance of the regression.

Nevertheless, YTM is not only affected by the credit rating of its issuer (credit risk), but it may also differ with bonds´ maturity. This relationship is reflected in the yield curve[8] of government bonds. It would be expected that bonds with longer maturities reward the investor with higher returns because of higher interest rate risk exposure, i.e. the probability of interest rate changes during longer period of time, and any other kinds of risk such as inflation risk. So the yield curve is expected to be sloped upwards. However, its shape might change. There are even periods when the yields of short term bonds are higher than yields of bonds with longer maturities. Hence, YTM itself may not be the most suitable measure. Except the periods with the flat yield curve, the credit reward would be measured more properly by the difference of the bond YTM and the yield curve.

[8] Yield curve (also called term structure of interest rates) is the relationship between a particular yield measure and a bond's maturity

Using credit spread instead of YTM the Hypothesis #5 would be reformulated in this way:

Hypothesis #5 (H5): Credit spreads, or alternatively, risk margins truly mirror creditworthiness of Czech bond issuer

As it is defined by its nature, risk margin is determined during the process of market placement of bond issuance. Investors, themselves bid for what amount and portion of margin they are willing to buy a particular bond. On the other hand, the issuers decide for what margin they are willing to sell. At some point, investors and issuers find an equilibrium called risk margin which basically reflect the investor´s perception of risk exposure. Thus we can suppose the risk margin as a proxy variable to credit spread in case of bonds with variable coupons that are not frequently traded.

Inspired by Livingston, et al. (2018), we tested the dependence of yield spreads on credit score by means of simple OLS.

$$Yield\ Spread_i = \alpha_0 + \sum_{j=1}^{7} \beta_j R_{j,i} + \sum \gamma_k C_{k,i} + \epsilon_i \tag{3.8}$$

where the Yield Spread is the difference between the YTM of the bond and Czech Government bond yield of similar maturity. The explanatory variables R is as again the series of dummy variables with AAA rated companies as the base case. The variable C represents the set of control variables that are expected to affect the yield spread. We used liquidity, bond type, maturity and volume of issuance.

H5 would be rejected if the error of the model, i.e. the differences of estimated and measured YTM exceed statistical significance. Correlation can be also measured by the correlation coefficient of credit rating and YTM. In addition to that we used again two classical significance metrics R-squared and F-statistic and its p-value.

3.2 Data

This section describes data collection process for both parts of our study. Firstly, we outline how the sample of non-financial companies was acquired and structured for the

purpose of credit rating estimation. Additionally, we preciously define the set of financial variables that were used. Thereafter, we provide discussion about their expected contribution to company performance/creditworthiness using descriptive statistics. In the second part, we move to the Czech bond market environment. We specify the list of selected companies and provide brief introduction of them. Finally, we outline the process of retrieving bond specific and financial data.

Credit rating estimate

The financial and credit rating data used for the modelling of credit rating was retrieved from Thompson Reuters Eikon platform, one of the key provider of financial data of listed companies in the world. The process of data collection was divided into the several steps:

1. Using DATASTREAM function available in Refinitiv Eikon – Microsoft Excel, we selected the list of companies form the U.S. market index S&P 500 and EU market index EURO STOXX 600. The equity market indices are used as benchmarks to gauge the movement and performance of a particular market/segment. They include the most traded companies. We expected that publicly traded companies would be also in focus of credit rating agencies.
2. The companies were selected based on the list of certain criteria;
    a. We decided to exclude companies operating in financial sectors e.g. banks, insurance companies, brokers etc. due to their distinctive financing structure and operating performance drivers;
    b. We also deleted companies that were not rated within the observed period 2008-2019;
    c. Reflecting both criteria we reduced the initial list of 505 (S&P500) and 600 (EURO STOXX 600) companies to 274 and 204, respectively.

We obtained credit rating data and financial variables from the observation period 2008-2019. We downloaded: 1) basic information about company headquarters and industry, 2) its credit ratings assigned by S&P, Fitch and Moody's, and 3) financial variables discussed in the section Methodology.

Credit rating variables

As proposed by Poon (2003), Livingston, et al. (2018) and Kuvíková (2015) we transferred the credit grades to ordinal numbers explained in the Table A.1 in Appendix A.

. The set of retrieved credit ratings was further adjusted according to their types. We focused on senior debt and excluded short-term[9] and junior[10] debt ratings. Short-term credit ratings are scaled and grouped differently than long-term ratings, which would cause difficulties in conversion of credit ratings to ordinal numbers. Junior or subordinated debt is unsecured and more risky than senior debt. The majority of bonds issued on the Czech market belongs to senior category.

Following these adjustments, we made the final selection. As we can see in the Figure 1and Figure 2 the credit ratings for both samples are distributed in the similar way. The most frequent rating score is observed between 3 and 4 meaning A and BBB rating category. However, EU-based dataset does not cover the entire ranting scale. AAA and CCC rating categories are missing. Thus, we merged two credit rating intervals on both tails of the scale.

Figure 1 - Credit rating of US-based companies

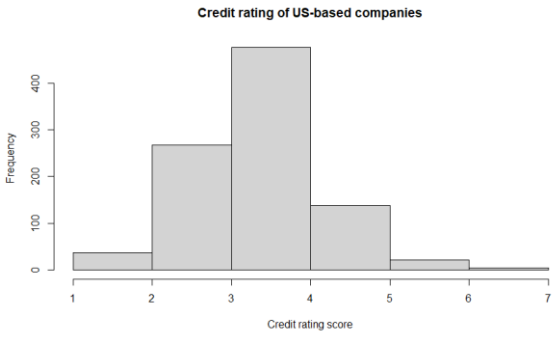
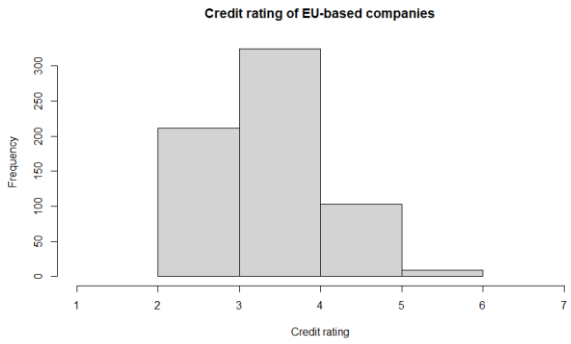


Figure 2 - Credit rating of EU-based companies



3.2.1. Financial and company-specific variables

[9] Short-term credit rating reflects the likelihood that a borrower will default within the year.

[10] Junior credit rating assess the credit risk of junior type of debt. Such type of debt means that in case of default or bankruptcy the creditor will be compensated after more senior entities.

Inspired by the prior research of Altman & Rijken (2004) and Livingston, et al. (2018), we seleceted the set of financial variables in the Table 1 below.

As proposed by S&P Global in their credit rating methodology we used three year moving-averages of collected financial data. The idea of this approach is to ensure the consistency of data with respect to certain credit rating level.

To be able to consider the plausibility of estimates we also tried to gauge the expected influence of variables on the credit rating evaluation. So we marked all variables with the sign by their expected contribution to the assessment of creditworthiness of a company.

Table 1 - Financial variables used for the estimation of credit rating

Variable name [abbreviation]	Expected sign (+/-/unknown)	Definition
Profitability		
Operating profit margin [PM]	(+)	EBIT/Total Sales
Return on Equity [ROE]	(+)	Net Income/Shareholder´s Equity
Interest Coverage ratio_EBIT [Coverage_r_EBIT]	(+)	EBIT/Interest Expense
Retained Earnings to Total Assets [RE_A]	(unknown)	Retained Earnings*/Total Assets
EBIT to Total Assets [EBIT_A]	(+)	EBIT/Total Assets
Liquidity		
Working Capital to Total Assets [W_A]	(+)	Working Capital**/Total Assets
Leverage & Capital structure		
Long-term debt to Total Assets [LngD_A]	(-)	Long-term Debt/Total Assets
Total Debt to Total Assets [D_A]	(-)	Total Debt***/Total Assets
Total Equity to Total Liabilities [E_L]	(-)	Total Equity/Total Liabilities
Size		
Logarithm of Sales [log(Net Sales]	(+)	log of Sales
Efficiency		
Total Sales to Total Assets [S_A]	(+)	Total Sales/Total Assets

Note: *Retained Earnings = Beginning Period Retained Earnings + Net Income/Loss - Cash Dividends - Stock Dividends. **Working Capital = Current Assets - Current Liabilities. ***Total Debt = Short-term Debt + Long-term Debt

Comments of selected financial variables.

- Operating profit margin and EBIT to Total Assets ratio measure profitability that a particular company is able to make from its operations. The higher the profit margin the lower the credit risk exposure.

- Return on Equity measures financial performance of a particular company. The higher the profitability the lower the credit risk exposure.

- Interest Coverage ratio tells us how easy it is for the company to repay interest on its outstanding debt. Creditworthiness of the company will be decreasing with lower ability to repay the interest.

- Retained Earnings to Total Assets measures cumulative profitability. As mentioned by Kuvíková (2015) the ratio effectively reflects the age of the company in terms of its probability of bankruptcy. Companies in their earlier years accumulate relatively low retained earnings and, accordingly, are more exposed to financial difficulties.

- Working capital to Total Assets ratio stands for a measure of liquidity. It describes how well a particular company is able to manage its short-term liabilities by its short-term assets. We assume that more liquid companies will have better credit rating.

- Long-term Debt to Total Assets and Total Debt to Total Assets both measure the financial leverage of a company. It holds generally that more leveraged companies are exposed to greater risk of bankruptcy or default, thus we can assume that the higher the leverage the worse the credit rating.

- Total Equity to Total Liabilities is another measure of solvency or financial leverage of the company. We assume the same relationship as with leverage ratios.

- Logarithm of Total Sales is used as proxy variable of size. Following the statement "too big to fail", we assume that the likelihood of default is lower for bigger companies.

- Total Sales to Total Assets is considered as asset turnover ratio. It helps investors to understand how effectively the company deploys the assets to generate sales. We expect that more efficient companies would have better credit rating.

To verify our expectations about relationship of financial variables and credit rating we calculated the mean values and quartiles in Table 2 in each rating category from EU dataset and looked for any trend with respect to the decreasing rating. The statistics revealed positive trend (the greater the financial metric, the higher the credit rating) for variables: Working Capital to Total Assets, Retained Earnings to Total Assets and Interest Coverage ratio. Variables Total Debt to Total Assets, Long-term Debt to Total Assets and Total Equity to Total Liabilities showed negative relationship (the greater the financial metric, the lower the credit rating). The rest, i.e. 5 variables did not show any visible relationship.

Table 2 - Descriptive statistices of EU financial data

Variable	1st Qu.:	Median:	Mean:	3rd Qu.:	Variable	1st Qu.:	Median:	Mean:	3rd Qu.:
PM					*LngD_A*				
AA	2.653	8.423	9.762	15.700	AA	0.143	0.173	0.165	0.204
A	5.223	8.680	10.622	14.226	A	0.114	0.187	0.198	0.267
BBB	5.803	9.767	12.160	16.357	BBB	0.166	0.242	0.244	0.316
BB	4.245	9.957	11.473	16.363	BB	0.159	0.223	0.243	0.325
B	4.797	9.760	11.204	11.605	B	0.209	0.231	0.263	0.364
ROE					*D_A*				
AA	0.001	0.076	0.062	0.131	AA	0.191	0.260	0.235	0.283
A	0.051	0.113	0.114	0.171	A	0.173	0.239	0.259	0.343
BBB	0.059	0.107	0.140	0.169	BBB	0.201	0.294	0.295	0.390
BB	0.033	0.106	0.090	0.143	BB	0.189	0.284	0.293	0.389
B	0.066	0.120	0.117	0.168	B	0.277	0.299	0.328	0.394
Coverage_r_EBIT					*E_L*				
AA	2.890	5.283	19.584	11.142	AA	0.274	0.926	0.842	1.099
A	3.251	7.117	18.123	15.314	A	0.346	0.507	0.745	0.823
BBB	2.701	6.002	19.408	12.391	BBB	0.324	0.541	0.698	0.893
BB	2.910	6.089	8.207	11.185	BB	0.331	0.561	0.689	0.914
B	2.380	3.490	8.350	7.687	B	0.349	0.503	0.564	0.685
RE_A					*log(Net Sales)*				
AA	0.186	0.273	0.293	0.431	AA	6.782	7.405	7.811	7.890
A	0.145	0.258	0.258	0.361	A	6.785	7.234	7.527	7.644
BBB	0.098	0.228	0.220	0.340	BBB	6.713	7.212	7.601	7.608
BB	0.095	0.237	0.211	0.332	BB	6.728	7.238	7.634	7.558
B	0.093	0.114	0.199	0.320	B	7.189	7.368	7.837	8.170
EBIT_A					*S_A*				
AA	0.019	0.051	0.052	0.065	AA	0.543	0.740	1.008	1.620

A	0.035	0.061	0.062	0.085	A	0.506	0.649	0.759	0.978
BBB	0.041	0.060	0.072	0.092	BBB	0.472	0.630	0.727	0.881
BB	0.031	0.056	0.057	0.080	BB	0.472	0.622	0.738	0.870
B	0.050	0.058	0.062	0.080	B	0.477	0.613	0.810	0.873
W_A									
AA	-0.090	0.022	0.044	0.123					
A	0.004	0.046	0.076	0.132					
BBB	-0.025	0.045	0.066	0.143					
BB	-0.018	0.055	0.062	0.118					
B	-0.030	0.025	0.018	0.055					

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3.2.2. Czech bond market environment

Czech bond market covers almost 60 publicly traded corporate bonds listed on the Prague Stock Exchange (PSE). The issuers are mostly financial companies, real estate investors, and developers. However, the majority of companies issued their bonds through purposeful subsidiaries established solely for issuing of bonds used to finance their mother company or certain project. Therefore, it seems quite complicated for a common investor to distinguish between "true" issuer and "special" entity with own zero operations. For that reasons, our list of companies shrank from almost 60 to roughly 35 companies. Disregarding all financial companies our final sample of selected Czech issuers was reduced to 20 companies in the Table 3 below.

Table 3 - List of Czech bond issuers

Issuer	Sector	Issued bonds
Czechoslovak Group a.s.	Aerospace & Defense	CSG VAR/21
Czechoslovak Group a.s.	Aerospace & Defense	CSG VAR/24
Net4Gas s.r.o.	Gas Utilities	NET4GAS 2,75/25
Net4Gas s.r.o.	Gas Utilities	NET4GAS 2,745/31
Net4Gas s.r.o.	Gas Utilities	NET4GAS VAR/28
Ceska zbrojovka a.s.	Aerospace & Defense	Č.ZBROJOVKA VAR/22
MND a.s.	Oil, Gas & Consumable Fuels	MND VAR/22
Severomoravske Vodovody a Kanalizace Ostrava a.s.	Water Utilities	SMVAK OVA 2,625/22
CEPS a.s.	Electric Utilities	ČEPS 0,25/21
ENERGO-PRO Green Finance s.r.o. /ENERGO-PRO a.s.	Water Utilities	EN.-PRO GF 6,50/23
Teplarna Otrokovice a.s.	Multi-Utilities	TEPL. OTR. VAR/23
Liberty One Methanol LLC	Gas Utilities	LIB. O. M. 5,30/23
Photon Energy N.V.	Multi-Utilities	PHOTON EN. 6,00/23

CD Cargo a.s.	Road & Rail	ČD CARGO 1,26/23
CD Cargo a.s.	Road & Rail	ČD CARGO 2,55/25
AQUAPALACE, a.s.	Hotels, Restaurants & Leisure	AQUAPALACE VAR/34
EPH Financing CZ, a.s.	Electric Utilities	EPH 4,50/25
EPH Financing CZ, a.s.	Electric Utilities	EPH VAR/22
RegioJet Finance a.s. / RegioJet a.s.	Road & Rail	REGIOJET F. VAR/24
EUC a.s.	Health Care Providers & Services	EUC VAR/22
Material & Technology s.r.o.	Manufacturing	MAT.&TECH. 5,20/24
TMR Finance CR, a.s. / Tatry mountain resorts, a.s.	Hotels, Restaurants & Leisure	TMR F. CR 4,50/22
Heureka FinCo CZ a.s. / Heureka Group a.s.	Internet & Direct Marketing Retail	HEUREKA 5,25/25
FIDUROCK Nemovitosti a.s.	Real Estate investments	FIDUR.NMV. 5,60/24
SAZKA Group a.s.	Lottery	SAZKA GR. 5,20/24

Our list of bonds includes mix of quite different businesses. By the sector distribution, 40% of selected companies operate in sector Utilities of any kind, 10% belongs to Aerospace & Defense, Road & Rail and Hotels, Restaurants & Leisure sectors and the rest i.e. 5% each operate in Oil, Gas & Consumable Fuels, Health Care Providers & Services, Manufacturing, Internet & Direct Marketing Retail, Real Estate Investment and Lottery.

On the list there are two types of bonds. Their tickers are showing bonds with variable and fixed coupons. This distinction will be important for further examination. For better understanding of individual business operation, we also prepared a brief introduction of each company.

1. Czechoslovak Group, a.s. (CSG) – *"is a holding that continues in the tradition of Czechoslovak industry. It supports the development of traditional Czech and Slovak companies focusing on military as well as civil production and trade. Its business scope primarily covers the engineering, automotive, rail, aviation and military areas. Product portfolio is varied, and ranges from retail (watches), over rail brakes, radar and navigation systems (both civil and military) to trucks".* (Czechoslovak Group, a.s., 2021)

2. Net4Gas s.r.o. (Net4Gas) – *"is the gas transmission system operator in the Czech Republic. Through their network of almost 4,000 km of pipelines, they transport around 45 billion m^3 of natural gas per year. As a Central European gas transmission system operator, they play an active role in connecting and*

integrating European energy markets to the benefit of Czech and other European customers.“ (Net4Gas, 2021)

3. Česká zbrojovka a.s. (CZG) – *“is a leading European producer of firearms and tactical accessories for military and law enforcement, personal defence, hunting, sport shooting and other civilian uses. Its products are marketed and sold under the Česká zbrojovka, CZ-USA, Dan Wesson, Zbrojovka Brno and 4M Systems brands.”* (Česká zbrojovka Group SE, 2021)

4. MND a.s. (MND) – *“is a European corporation specializing in all areas of crude oil and natural gas production as well as gas and electricity trading. It is a member of strong and stable MND Group AG wherein KKCG Group is the sole shareholder. MND Group companies also focus on the development and operation of underground gas storage facilities and provision of drilling services.”* (MND Group, 2021)

5. Severomoravské Vodovody a Kanalizace Ostrava a.s. (SmVaK Ostrava) – *“is leading and largest water supplier in the Moravian-Silesian region. It also belongs to the largest water suppliers within the Czech market. Its core business focuses on a production and supply of drinking water as well as discharge and treatment of wastewater.”* (Severomoravské Vodovody a Kanalizace Ostrava a.s., 2021)

6. ČEPS a.s. (ČEPS) – *“is the sole Czech Transmission System Operator and holds an exclusive license to that effect granted by the Energy Regulatory Office under the Energy Act. It is responsible for the maintenance and upgrading of 44 substations comprising 79 transformers, which allow electricity to be supplied from the transmission system to the distribution network, as well as 400kV lines with a total length of 3,867 km and 220kV lines with a total length of 1,824 km.”* (ČEPS, 2021)

7. ENERGO-PRO s.r.o. (ENERGO-PRO) – *“operates hydropower plants in Central and Eastern Europe, the Black Sea and the Caucasus. As an originally Czech company, they have gradually expanded to Bulgaria, Georgia and Turkey. Its core*

business is the hydropower sector. They are also engaged in the electricity distribution and power trading." (ENERGO-PRO, 2021)

8. Teplárna Otrokovice a.s. (TEPL. OTR.) – *"is one of the greatest heating plants in the Czech Republic. The main business activities include heat production and distribution and related services and electric power production and trading. The thermal energy for the industrial consumers is supplied in the form of steam and the heat for heating and production of hot water for households is provided in the form of hot water."* (Teplárna Otrokovice, 2021)

9. Liberty One Methanol LLC (LIB. O. M.) – *"is the subsidiary of company US Methanol LLC, which entered the methanol production industry with the acquisition and planned relocation of two methanol production facilities. US Methanol was founded in 2016 with the mission to reliably produce and deliver the highest quality methanol at the lowest delivered price to industrial consumers."* (Liberty One Methanol, 2021)

10. Photon Energy Group (PHOTON EN.) – *"delivers energy and water solutions that are state-of-the-art and sustainable. Its solar power solutions and services cover the entire lifecycle of photovoltaic power plants. Moreover, it also offers comprehensive clean water solutions, from treatment services to the management of wells and other resources."* (Photon Energy, 2021)

11. ČD CARGO a.s. (ČD CARGO) – *"is the largest Czech railway transport provider. It offers the transport of extensive range of goods, from raw materials to products with high added value, transport of containers, exceptional deliveries, lease of railway wagons, spur-line, and other transport services."* (ČD CARGO, 2021)

12. AQUAPALACE a.s. (AQUA) – *"is a subsidiary of GMF Aquapark Prague, a.s. which is joint venture of a Czech company SPGroup, a.s. and of German GMF GmbH& Co KG. GMF GmbH& Co KG is currently running over 20 water resorts and thermal spas all over whole Germany expanding into Czech Republic, Swiss and Poland."* (AQUAPALACE, 2021)

13. Energetický a průmyslový holding a.s. (EPH) – *"is a leading Central European energy group that owns and operates assets in the Czech Republic, the Slovak Republic, Germany, Italy, Ireland, the UK, France and Switzerland. EPH is a vertically integrated energy utility covering the complete value chain ranging from highly efficient cogeneration, power and heat generation, natural gas transmission, gas storage, as well as gas, heat and electricity distribution and supply."* (EPH, 2021)

14. RegioJet a.s. (RegioJet) – "*is leading long distance private bus and train operator in Central Europe, mainly in the Czech Republic, Slovakia, Austria, Germany, Hungary".* (RegioJet, 2021)

15. EUC a.s. (EUC) – "*is a medical group with the largest network of outpatient clinics in the Czech Republic. It is the largest provider of outpatient care, premium care, mamoscreening and medical care for employers."* (EUC, 2021)

16. Material & Technology s.r.o. (M&T) – *"is a Czech based manufacturer of door handles and other door related products. Its main aim is to develop, manufacture and place on the market constant new design, structural and technologically unique products."* (M&T, 2021)

17. Tatry Mountain Resorts (TMR) – *"is the leading operator of mountain resorts and tourist services in the region of Eastern and Central Europe. Its major investments are located in the Tatra region with ambitions to become the largest player in tourism in CEE by means of quality enhancement and extension of the service offer."* (TMR, 2021)

18. Heureka Group (Heureka) – *"is Europe's largest price comparison website and online shopping advisor. It simplifies and facilitates online shopping for millions of customers every day. It operates in 9 countries in Central and Eastern Europe, over 23 million visitors per month and a network of over 55,000 online stores."* (Heureka Group, 2021)

19. FIDUROCK Nemovitosti a.s. (FIDUROCK) – *"is a Czech-Dutch investment boutique founded in 2014. It focuses on investments in real estate, namely in retail*

parks in the Czech Republic and Slovakia and residential real estate in the city center of Prague, Bratislava, Brno or Olomouc. In addition to real estate, it operates a unique audio & cinema showroom VOIX in the center of Prague." (FIDUROCK, 2021)

20. SAZKA Group a.s. (SAZKA) – *"is primarily focused on national lottery games, instant lotteries and online lotteries and has a secondary focus on digital gaming and sports betting. The company is owned by international investment group KKCG. As one of the European lottery leaders, SAZKA Group is also respected on the world lottery market for its iconic and trusted brands and unrivalled distribution networks."* (SAZKA Group, 2021)

This brief business description is showing that companies differ significantly even within the same sector. The small amount of bond issuers and their business diversity may bias our final conclusions.

We collected bond specific data from PSE website and from the bond prospects. We focused primarily on the issue date, maturity, issued size, nominal value, coupon, market price, par value and liquidity[11]. Summary statistics are provided in the Table 4. On average the size of issuance fluctuates around 2.3 bil. which is 5 times lower than in EU or US markets, regardless of currency. It just confirms our expectations that Czech bond market is much smaller. The average maturity of considered bonds is about 6 years which is slightly below average 7-year maturity observed in EU dataset. Nominal value ranges from 1 CZK to 5 mil. CZK with the median value of 3 mil. CZK. Majority of issues is probably focused on corporate investors or financial institutions. Average coupon is slightly below a threshold of 4.88% observed on EU market for unrated bonds issuers. Looking at frequency of trading we see that the Czech bonds in our sample exhibit almost zero liquidity. Bonds with variable coupons were not traded at all. Therefore, we had to split our dataset in two groups of bonds with fixed coupon and with variable coupon.

[11] Liquidity was measured as a number of trades executed per year horizon starting from 2019

Table 4 - Descriptive statistics of bond-specific data of Czech issuers

	Size of issuance	Maturity	Nominal value	Coupon	Liquidity
Min.:	100,000,000	3	1	0.25%	0
1st Qu.:	515,000,000	5	10,000	2.83%	0
Median:	1,500,000,000	5	3,000,000	4.50%	0
Mean:	2,293,632,400	6	2,048,800	4.19%	18
3rd Qu.:	2,921,500,000	7	3,000,000	5.28%	22
Max.:	7,500,000,000	25	5,000,000	6.50%	100

To be able to calculate credit spread we also had to gather YTMs of Czech government bonds. Variable coupons are derived from 6 month Prague InterBank Offered Rate (6M PRIBOR). YTMs of Czech government bonds were retrieved form Thompson Reuters Eikon website in form of time-series for 1Y-15Y maturities. 6M PRIBOR was downloaded from Czech National Bank (CNB) website.

To smooth our study we decided to base all available data in year 2019. The main reason was to mitigate the expected effect of COVID-19 which might cause some distortion on the market and bias our estimation. In addition to that, due to the lack of available data we decided to enlarge our dataset of bonds with fixed coupons by the observations of executed trades within one year horizon. We simply collected market prices of such transactions from PSE website and calculated YTMs for a certain date. These observations helped us to observe the variation of YTM/Credit spread and detect the outliers in our sample.

Financial data was retrieved for observed period 2017-2019 from annual reports of each company. They are available at public source justice.cz[12]. The final dataset was structured in the way as defined in the section Credit rating estimate above. It is: the name of the company, sector specification and financial data.

To calculate appropriate financial metrics we firstly averaged our data on three year basis in line with our methodology of credit rating estimates. The sample statistics are provided in the Table 5 below.

[12] Website justie.cz represents a company register that serves as a source of data about all officially registered entities in the Czech Republic

Table 5 - Descriptive statistics of financial data of Czech bond issuers

	PM	Log(Net Sales)	ROE	EBIT_Interest coverage	Long-term debt to Total Assets	Total Debt to Total Assets	Working Capital to Total Assets	Retained Earnings to Total Assets	EBIT to Total Assets	Equity to Total Liabilities	Total Sales to Total Assets
Min.:	-510.945	4.190	-0.169	-4.828	0.007	0.008	-0.076	-0.045	-0.049	0.260	0.000
1st Qu.:	4.987	5.616	0.006	0.304	0.129	0.242	-0.008	0.001	0.010	0.301	0.147
Median:	12.980	6.564	0.128	4.287	0.342	0.351	0.020	0.038	0.060	0.389	0.466
Mean:	-0.551	6.272	0.122	5.991	0.308	0.367	0.061	0.041	0.052	0.593	0.492
3rd Qu.:	22.458	6.981	0.238	7.032	0.535	0.559	0.119	0.061	0.092	0.736	0.602
Max.:	113.367	7.762	0.391	51.116	0.629	0.657	0.398	0.243	0.151	2.626	3.050

4 Results:

The main objective of this study is focused on creation of simple credit rating model that might be used for examination of basic relationships between creditworthiness of a particular company and its credit risk reward in the Czech bond market environment. The credit risk reward was measured as credit spread, bond yield or risk margin.

4.1. Validity of the model

To be able to examine the credit risk of Czech bond issuers it was necessary to create appropriate tool for credit rates estimates. We used the ordered probit model defined in the section Methodology and tested whether it was possible to obtain statistically significant estimates of credit rating for a particular company using the set of financial and company-specific data.

To estimate the credit rating properly we defined six various types of the models described in the Table 6 below. The models differ by Sector specification, Time and the included financial variables. Two groups of models differ in using time. Models I-III do not include Time variable while, Models IV-VI do. It was expected that estimated credit rating and magnitude of explanatory financial variables may vary in dependence on the economic cycle or another time relevant occasion. We examined whether the significance of the estimation would improve with respect to the Time variable. Another fixed effect may be attributed to the variable Sector. In order, to check such effect in Model III and VI, we created a subset of the datasets based only on industries observed in the set of selected Czech bond issuers. We assumed that sector specification may increase the correctness and applicability of the credit rating estimates for Czech companies. However, for the price of worse overall significance due to decreased number of observations. The selection of variables was inspired by the research of Altman & Rijken (2004) and Livingston, et al. (2018)

As the third attempt to improve statistical significance, model averaging approach was used. This technique selects the most significant ones and helps us to avoid multicollinearity and overestimation.

An important condition for quality estimates is the data size. We were able to acquire an ample data set on the U.S. bond market. Model averaging of U.S. model showed that significant variables were: logarithm of Net Sales, Long-term Debt to Total Asset, Debt to Total Asset, Retained Earnings to Total Assets, EBIT to Total Assets, Total Shareholder's Equity to Total Liabilities and Total Sales to Total Assets ratios.

We applied the same approach on the EU data as well. We found that EU model selected only four significant variables i.e. logarithm of Net Sales, Long-term debt to Total Assets, Total Debt to Total Assets and Working Capital to Total Assets ratios. These two sets of variables were used to estimate parameters of Models II, III, V and VI.

Table 6 - Six various types of model used for estimation of Credit rating

	Sector	Time	Financial variables
Model I	all	not included	Altman&Livingstone
Model II	all	not included	Model averaging
Model III	CZ bond market	not included	Model averaging
Model IV	all	included	Altman&Livingstone
Model V	all	included	Model averaging
Model VI	CZ bond market	included	Model averaging

The estimation of parameters of the ordered probit model was conducted separately for EU and US datasets. The results are summarized in the Table 12 and Table 13 below. The full transcript of results is provided in the Appendix C.

4.1.1 U.S. model estimation

Estimations based on U.S. data showed quite significant and consistent results. They are supported by (McFadden) Pseudo-R2 measure fluctuating between 34% - 35% (Model I-III) and 38%-40% (Model IV-VI), respectively. As expected, Goodness-of-Fit measure is greater in case of models including dummy variable of time owing to the fact that we were able to control better instability of the market over different business cycles.

To illustrate predicting power of each model we used confusion matrix (see Methodology). The matrices of Model I and IV are provided below.

Table 7 - Confusion matrix of U.S. based Model I

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	14	22	0	0	0	0
A	0	0	160	108	0	0	0
BBB	0	0	63	390	22	1	1
BB	0	0	1	75	59	3	0
B	0	0	0	4	14	2	1
CCC	0	0	0	0	2	2	1

(Pseudo) R2 = 35%, AR = 66%

Table 8 - Confusion matrix of U.S. based Model IV

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	14	22	0	0	0	0
A	0	1	163	104	0	0	0
BBB	0	0	60	394	21	2	0
BB	0	0	1	68	65	4	0
B	0	0	0	4	11	5	1
CCC	0	0	0	0	2	3	0

(Pseudo) R2 = 39%, AR = 68%

As we can see, in both cases, the models predicted the credit ratings quite well measured by the Accuracy ratio 66% and 68%, respectively. The best predicted rating categories were at the center with the largest amount of observations. A and BBB covered almost 2/3 of the sample. On the other hand, the weakest predicted power exhibit AAA and CCC with the least number of observed ratings. In general, the predictions of actual credit rating fluctuate within +/- one credit rating grade.

Another measure of model quality is the signs of predicted β coefficients. They are showing in which direction the probability of upgrade and downgrade moves. For instance, it can be assumed that the sign of coefficient of indebtedness would be negative showing that increasing debt worsens the creditworthiness of a particular company.

The signs of 11, out of 25 checked variables were in line with our expectations. The corresponding variables are: Operating profit margin, logarithm of Net Sales, ROE, Long-term Debt to Total Assets, Working capital to Total Assets, Retained Earnings to

Total Assets and EBIT to Total Assets. The discussion of our expectations and all findings are summarized in detail in the section Data. It is all what can be directly judged from the coefficients. As we explained, unlike OLS models there is no natural magnitude of a latent variable Z which makes it difficult to interpret the economic perspective from the size of the estimated coefficients.

On top of estimation of β coefficients, ordered probit model also provides the estimation of threshold parameters. Threshold parameters basically define the set of intervals that relate the latent variable Z to a particular credit rating score. In practice we plugged financial data into our ordered probit model to calculate variable Z. To derive an appropriate credit rating we searched for corresponding interval associated with corresponding credit rating score. In terms of U.S. based Model I the intervals are specified as follows:

Table 9 - Estimation of threshold parameters relating latent variable Z to CR

CR	Boundaries		Std. Error
AAA		< -16.534	-14.3462***
AA	≤ -16.534	< -13.908	-14.5048***
A	≤ -13.908	< -11.722	-12.6496***
BBB	≤ -11.722	< -9.3353	-10.3591***
BB	≤ -9.3353	< -7.5777	-8.474***
B	≤ -7.5777	< -6.3679	-6.9996***
CCC	≤ -6.3679		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.1.2 EU model estimation

In overall, estimation of EU model parameters showed worse results caused likely by smaller amount of data. As described in the section Data, EU dataset does not include firms rated by AAA and CCC credit rating categories, thus we had to merge two credit rating intervals on both sides of the scale.

Goodness-of-Fit measure (McFadden) Pseudo R2 oscillates between 9% and 18% (Model I-III) and 17% and 21% (Model IV-VI), respectively. It is almost 20% slump in the

significance compared to the U.S. model. In addition, the predicted power of EU models declined as well indicating the level of accuracy 60% in case of Model I and 61% for Model IV, respectively. The summary outcomes are shown in the confusion matrices below.

Table 10 - Confusion matrix of EU based Model I

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	2	13	2	0	0
A	1	87	104	2	0
BBB	0	44	274	7	0
BB	0	6	68	28	1
B or below	0	0	3	6	0

(Pseudo) R2 = 18%, Accuracy Ratio = 60%

Table 11 - Confusion matrix of EU based Model IV

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	2	14	1	0	0
A	1	92	99	2	0
BBB	0	47	267	11	0
BB	0	5	61	36	1
B or below	0	0	2	7	0

(Pseudo) R2 = 21%, Accuracy Ratio = 61%

.

The lower significance also affects the signs of predicted β coefficients, just 5 out of 11 met our expectations. These variables are Operating profit margin, ROE, Long-term Debt to Total Assets, Working capital to Total Assets and Total Sales to Total Assets. When we compared U.S. and EU models, we found that financial metrics as Operating profit margin, ROE, Long-term Debt to Total Assets and Working capital to Total Assets affect the assessment of creditworthiness of a particular company identically in line with our expectation. It means that these metrics had the same effect disregarding expected regional differences.

Table 12 - Regression results of Credit rating estimation of Model I-III

EU data	Model I - including all sectors			Model II - including all sectors			Model III - including CZ market sectors		
Explanatory variables	Estimate	Std. Error	z value	Estimate	Std. Error	z value	Estimate	Std. Error	z value
SectorElectric Utilities	0.3162	0.2998	1.0547	0.3974	0.2822	1.4082	0.4177	0.3323	1.2571
SectorGas Utilities	0.4196	0.4689	0.8949	0.4644	0.4442	1.0453	0.6749	0.4990	1.3525
SectorHotels, Restaurants & Leisure	1.2796	0.4660	2.7455**	1.3764	0.4352	1.5868	1.5454	0.4758	3.2476**
SectorInternet & Direct Marketing Retail	1.7497	0.8520	2.0534*	1.8175	0.8409	2.1613*	2.7356	0.9341	2.9284**
SectorMulti-Utilities	0.0279	0.2883	0.0969	0.0681	0.2751	0.2479	0.2570	0.3226	0.7967
SectorOil, Gas & Consumable Fuels	-0.8556	0.3518	-2.4322*	-0.795	0.3098	-2.5661*	-0.1636	0.3753	-0.4359
SectorHealth Care Providers & Services	0.5999	0.0013	1.3097	0.7023	0.4426	1.5868	1.2736	0.5025	2.5341*
SectorWater Utilities	0.6639	1.1835	0.561	0.7425	1.1700	0.6346	0.7146	1.2222	0.5847
Operating profit margin	-0.0068	0.0081	-0.8472						
log(Net_Sales)	0.1737	0.0450	3.8592***	0.1727	0.0411	4.1983***	0.0231	0.0863	0.2684
ROE	-0.0902	0.4189	-0.2154						
Coverage_ratio_EBIT	0.0013	0.0013	0.9869						
Long-term Debt to Total Assets	4.5785	1.3655	3.3528***	4.2436	1.3167	3.2227**	-1.0581	4.0978	-0.2582
Total Debt to Total Assets	-3.5638	1.2367	-2.8817**	-3.6539	1.2108	-3.0177**	0.3942	3.7107	0.1062
Working Capital to Total Assets	-1.2847	0.6035	-2.1287*	-0.9766	0.5663	-1.7246.	-4.7504	1.4870	-3.194**
Retained Earnings to Total Assets	0.2581	0.3047	0.847						
EBIT to Total Assets	0.4116	1.9313	0.2131						
Shareholder´s Equity to Total Liabilities	0.04342	0.1125	0.3858						
Total Sales to Total Assets	-0.0805	0.1736	-0.4638						
AAA									
AA	0.5878	0.8234	0.714	0.5526	0.7175	0.7702	-1.8721	1.4958	-1.2515
A	2.5499	0.8204	3.108**	2.5048	0.7151	3.5026***	0.0040	1.4813	0.0027
BBB	4.3184	0.8289	5.2099***	4.2684	0.7251	5.8863***	1.8994	1.4871	1.2773

BB	5.9970	0.8558	7.0072***	5.9433	0.7522	7.9005***	3.3874	1.5300	2.2139*
B									
CCC									
(McFadden) Pseudo R2:	0.1836			0.1813			0.0931		
log Lik:	-606.00			-612			-165		
Residual Deviance:	1211.85			1224.78			330.54		
AIC:	1341.85			1338.78			362.54		
nobs:	648			648			179		

Table 13 - Regression results of Credit rating estimation of Model IV-VI

EU data	Model IV - including all sectors			Model V - including all sectors			Model VI - including CZ market sectors		
Explanatory variables	Estimate	Std. Error	z value	Estimate	Std. Error	z value	Estimate	Std. Error	z value
SectorElectric Utilities	0.3955	0.3040	1.3008	0.4862	0.2865	0.286509.	0.3713	0.3505	1.0592
SectorGas Utilities	0.5597	0.4757	1.1766	0.6349	0.4510	0.451092	0.8590	0.5303	1.62
SectorHotels, Restaurants & Leisure	1.1852	0.4729	2.5062*	1.2978	0.4416	0.441693**	1.3364	0.5022	2.6611**
SectorInternet & Direct Marketing Retail	1.4261	0.8607	1.6569.	1.4705	0.8501	0.850114.	2.5488	0.9688	2.6308**
SectorMulti-Utilities	0.0941	0.2916	0.3227	0.1538	0.2786	0.278636	0.2808	0.3376	0.8318
SectorOil, Gas & Consumable Fuels	-0.7595	0.3570	-2.1273*	-0.6812	0.3148	0.31487*	0.1122	0.3988	0.2815
SectorHealth Care Providers & Services	0.6596	0.4723	1.3966	0.7785	0.4474	0.447453.	1.4460	0.5226	2.767**
SectorWater Utilities	0.3195	1.1965	0.267	0.4295	1.1826	1.182614	0.2103	1.2781	0.1646
Operating profit margin	-0.0060	0.0082	-0.7288						
log(Net_Sales)	0.1608	0.0457	3.516***	0.1595	0.0418	0.041846***	-0.0273	0.0901	-0.3029
ROE	-0.1233	0.4252	-0.2899						
Coverage_ratio_EBIT	0.0013	0.0013	0.9607						
Long-term Debt to Total Assets	4.1912	1.3940	3.0065**	3.8875	1.3391	1.339196**	-1.0786	4.3275	-0.2493

Total Debt to Total Assets	-3.3694	1.2582	-2.6778**	-3.5384	1.2318	1.231817**	0.6231	3.9214	0.1589
Working Capital to Total Assets	-1.2309	0.6124	-2.0098*	-0.8732	0.5746	0.574676	-5.6383	1.5692	-3.5931***
Retained Earnings to Total Assets	0.1737	0.3092	0.5616						
EBIT to Total Assets	0.8083	1.9812	0.408						
Shareholder´s Equity to Total Liabilities	0.0650	0.1143	0.5687						
Total Sales to Total Assets	-0.0242	0.1765	-0.1375						
Year_2019	-0.3651	0.1778	-2.0535*	-0.3597	0.1762	0.176234*	-0.1937	0.4022	-0.4816
Year _2018	-0.5534	0.1924	-2.876**	-0.5431	0.1911	0.191196**	-0.0336	0.3942	-0.0852
Year _2017	-0.7428	0.1901	-3.906***	-0.7225	0.1889	0.188958***	-0.8039	0.3683	-2.1827*
Year _2016	-0.6326	0.1574	-4.016***	-0.6392	0.1566	0.156613***	-0.8431	0.3176	-2.6539**
Year _2015	-0.2382	0.1879	-1.2675	-0.2391	0.1864	0.186465	0.0944	0.3482	0.2712
Year _2014	-0.4711	0.1928	-2.4435*	-0.4682	0.1910	0.191071*	-0.4390	0.3651	-1.2023
Year _2013	-0.3359	0.2045	-1.6422	-0.3468	0.1997	0.199798.	-0.6000	0.3622	-1.6566.
Year _2012	-0.4818	0.2593	-1.8579.	-0.4866	0.2553	0.255388.	-0.1632	0.4001	-0.408
Year _2011	-0.9888	0.2557	-3.865***	-0.9855	0.2540	0.254081***	-1.2727	0.4871	-2.6125**
Year _2010	-0.6125	0.3006	-2.0377*	-0.6311	0.2956	0.295615*	-2.1487	0.5536	-3.8813***
AAA									
AA	-0.0523	0.8475	-0.0617	-0.1516	0.7423	0.742341	-3.4114	1.5994	-2.1329*
A	1.9755	0.8423	2.3453*	1.8676	0.7372	0.737271*	-1.2236	1.5663	-0.7812
BBB	3.7966	0.8496	4.4687***	3.6835	0.7456	0.745611***	0.8563	1.5671	0.5464
BB	5.5166	0.8760	6.2976***	5.3980	0.7722	0.772295***	2.3285	1.6006	1.4547
B									
CCC									
(McFadden) Pseudo R2	0.2048			0.2025			0.1741		
log Lik	-595.00			-597.00			-151.00		
Residual Deviance:	1189.66			1193.10			301.02		
AIC:	1337.66			1327.10			353.02		
nobs:	648			648			179		

4.2. Transferability of the estimated models

The magnitude of U.S. data is bigger and the estimates are statistically more significant than those of EU estimates. However, we suspected that data and models were not transferable between both regions. So we tried to verify whether the estimates were significantly different.

In order to test the transferability of the model we plugged observed financial data for U.S. companies into the EU based models and predicted credit rating scores and vice versa with EU data and models. The results of confusion matrices provided below suggest the level of accuracy, 38% in case of EU data and 40% in case of U.S., respectively. This accuracy is much worse than 60% for regional models. Thus, we rejected the hypothesis that financial data from U.S. are transferable to EU model and vice versa.

Even if the magnitude of U.S. dataset and quality of estimates in the U.S. model are better than in case of EU models and data, our comparison within the hypothesis H2 persuaded us to estimate credit rating of Czech companies rather by means of the EU model and its estimated parameters based on the EU dataset.

Table 14 - Credit rating estimates of EU model based on U.S. data

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AAA	0	0	1	0	0
AA	0	9	17	8	0
A	2	64	137	43	1
BBB	0	118	253	67	1
BB	0	36	71	19	0
B	0	5	13	2	0
CCC	0	0	4	0	0

Accuracy Ratio = 38%

Table 15 - Credit rating estimates of U.S. model based on EU data

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AA or above	0	1	6	4	0	0	0
A	1	3	63	84	17	2	0
BBB	2	12	83	155	37	4	0
BB	0	2	25	53	11	1	1
B or below	0	0	1	7	1	0	0

Accuracy Ratio = 40%

4.3. Prediction power of company specific variable Sector

Companies are divided based on their primary business activities into sectors. Each sector varies by its way of operation, balance sheet structure, customer base etc. However, we were not sure if such differences were relevant for the estimation of credit rating. So, we checked whether the predicted power of estimated credit rating model were indifferent on company specific-variable sector.

In order to test the hypothesis about importance of the sector we run two EU based models that included and excluded the sector variable. We can see, from the Table 16 and Table 17 below that the prediction power of the models significantly differs. The model with the sector variable shows the accuracy ratio of 62% with (Pseudo) R2 of 21%. On the other hand, the model without sector variable exhibits the accuracy ratio of 50% with (Pseudo) R2 of only 4%. Thus, we are able to reject hypothesis about insignificance of the variable Sector. So we included this variable in our model.

Table 16 - Confusion matrix of EU based model without variable Sector

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	0	4	13	0	0
A	0	35	159	0	0
BBB	0	20	304	1	0
BB	0	5	98	0	0
B or below	0	0	9	0	0

(Pseudo) R2 = 4%, Accuracy Ratio = 50%

Table 17 - Confusion matrix of EU based model with variable Sector

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	2	14	1	0	0
A	1	92	99	2	0
BBB	0	47	267	11	0
BB	0	5	61	36	1
B or below	0	0	2	7	0

(Pseudo) R2 = 21%, Accuracy Ratio = 62%

4.4. Selection of a suitable model for the Czech environment

Equipped with the model we estimated credit rating of the Czech bonds, or that of their issuers. The rate estimates are summarized in the Table 18 below. The results are divided into two parts according to the Time specification.

Table 18 - Credit rating estimates of Czech bond issuers

EU model	Estimation without time variable			Estimation with time variable		
	Model I	Model II	Model III	Model IV	Model V	Model VI
CSG VAR/21	AA or above	AA or above	A	A	A	BBB
CSG VAR/24	AA or above	AA or above	A	A	A	BBB
NET4GAS 2,75/25	A	A	BBB	A	BBB	BBB
NET4GAS 2,745/31	A	A	BBB	A	BBB	BBB
NET4GAS VAR/28	A	A	BBB	A	BBB	BBB
Č.ZBROJOVKA VAR/22	A	A	AA or above	A	A	A
MND VAR/22	AA or above	AA or above	A	AA or above	A	BBB
SMVAK OVA 2,625/22	A	A	A	A	A	BBB
ČEPS 0,25/21	A	A	A	A	A	BBB
EN.-PRO GF 6,50/23	A	A	A	A	A	BBB
TEPL. OTR. VAR/23	A	A	BBB	A	A	BBB
LIB. O. M. 5,30/23	A	AA or above	A	A	A	BBB
PHOTON EN. 6,00/23	AA or above	AA or above	A	AA or above	AA or above	BBB
ČD CARGO 1,26/23	A	A	BBB	A	A	BBB
ČD CARGO 2,55/25	A	A	BBB	A	A	BBB
AQUAPALACE VAR/34	A	A	AA or above	A	A	BBB
EPH 4,50/25	A	A	BBB	A	A	BBB
EPH VAR/22	A	A	BBB	A	A	BBB
REGIOJET F. VAR/24	A	A	BBB	A	A	BBB
EUC VAR/22	A	A	BBB	A	A	BB
MAT.&TECH. 5,20/24	A	A	A	A	A	BBB
TMR F. CR 4,50/22	BBB	BBB	BBB	BBB	BBB	BBB
HEUREKA 5,25/25	BBB	BBB	BB	BBB	BBB	B or below
FIDUR.NMV. 5,60/24	AA or above	A	BBB	A	A	BBB
SAZKA GR. 5,20/24	BB	A	A	BB	A	BBB

The Table 19 shows the distribution of bonds by credit rating category. Each model detected at least three different credit rates. The range of estimates seems to be similar across all models. However, ratings are strongly concentrated around one rating category except Model III. We suspect that the way of structuring depends on the value of the fixed effect. While the proportions of Model I and Model II are nearly the same Model III shifted estimated ratings downward and distinguished clearly the central group splitting it in two. Following our aim to examine the dependence of yields of Czech bonds and credit scores of we decided to use the Model III for our further examination. This model is also adjusted for the selection of Czech relevant sectors.

Table 19 - Distribution of bonds by credit rating category

Credit rating score	Model I	Model II	Model III	Model IV	Model V	Model VI
AA or above	20%	20%	8%	8%	4%	N/A
A	68%	72%	40%	80%	76%	4%
BBB	8%	8%	48%	8%	20%	88%
BB	4%	N/A	4%	4%	N/A	4%
B or below	N/A	N/A	N/A	N/A	N/A	4%
Total	100%	100%	100%	100%	100%	100%

4.5. Bonds yield vs. Credit rating

Before we move on to the findings regarding the Czech bond market, we have to mention that selected Czech companies exhibit very low liquidity. Only 11 of 25 selected bonds were traded at least once within 1 year horizon starting in 2019. We discussed this problem in detail in the section Methodology. We are aware that lack of data could lead to biased conclusions.

Missing market prices also limit the interpretation of YTM. Therefore, we had to split our dataset in two parts: bonds with variable coupon and the bonds with fixed coupon. The reason was that we registered trading just with 9 fixed coupon bonds unlike the variables with zero trading. So we knew only credit margins for them.

According our hypothesis H4, we were interested in the relationship between the bond yields and estimated credit ratings checking the simple risk-return tradeoff defined by Sharpe (1964) that the higher the risk, the higher the reward. So we were curious

whether this relationship holds also in the Czech bond market environment or more specifically whether bond yields of Czech companies are negatively correlated with increasing credit rating.

4.5.1. Bonds with fixed coupon

Our simplified model uses primarily credit scores as the main source of yield diversity, but we looked for other significant variables. For example, it may be higher liquidity that persuades the investor to be satisfied with lower risk premiums. The sign of estimated coefficient confirmed that investor in the corporate bond market would expect additional premium for lower liquidity. (Landschoot (2004)) The Table 20 reports the outcomes of Equation (3.7) where we regressed YTM on credit ratings of bonds with fixed coupons, liquidity and size of the issuance. Thus, if the liquidity or more specifically the number of trades increases by 1, holding other factors fixed, YTM decreases by 0.017%. It might be also the issue size that increases the apetite for investment. So we added this factor in CZK billion to see whether the variable Size of the issue also relates to YTM. Supoorting our expectations, the coefficient showed that, holidng other factors fixed, if the issue size increases by one billion, YTM increses by 0.03%.

In the part of our model with credit rating dummies, we used credit rate A as a reference base case. Thus minus sign of β coefficient for BBB (-0.76%) and plus sign for BB (0.82%) are showing lower and higher return compared with score A. So β coefficient for BBB suggests that credit rating grades and YTM of bonds used in this study do not exhibit expected relationship. It means that estimated YTM for bonds rated by BBB would be on average lower by 0.76% than for A rated bonds with higher rating while BB bonds are showing yield premium +0.82% over A rated bonds and +1,58% over BBB rated bonds. In other words, investors who purchased BBB rated bonds were not rewarded for taking higher risk with respect to less risky A rated investment. On the other hand, BB yield premium is in line with our expectation.

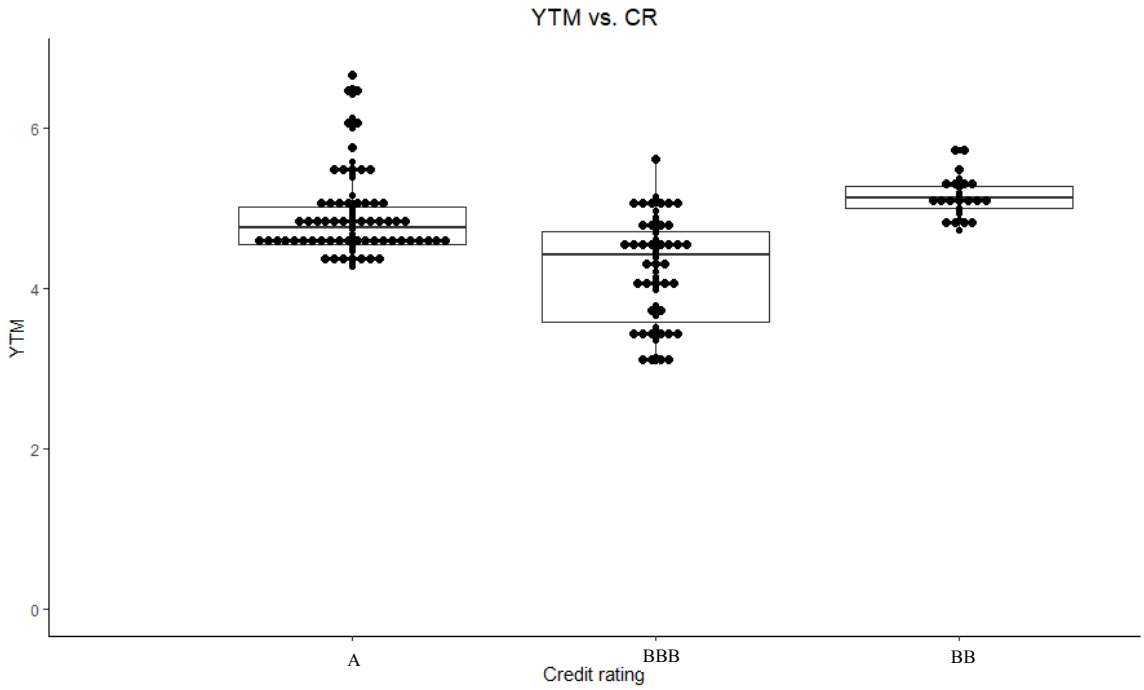
Table 20 - Regression results of bonds with fixed coupons (YTM)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.831%	1.01E-03	57.72	< 2e-16	***
CR_BBB	-0.766%	8.13E-04	-9.423	6.59E-16	***
CR_BB	0.823%	1.19E-03	6.943	2.58E-10	***
Liquidity	-0.017%	1.62E-05	-10.587	< 2e-16	***
Issue size	0.026%	1.67E-13	1.561	0.121	

Multiple R2 = 66%. RSE = 0.003941, Degrees of Freedom = 113, F-statistic: 54.67, p-value: < 2.2e-16.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

The Figure 3 with box plots for each credit score displays the range of observed YTM values for each trade in each rating category. The points represent number of trades with a particular level of yield. The median of YTM values for bonds rated by our model as BBB grade is lower than the YTM value in adjacent rating categories. Hence, the outcomes of our model are consistent with empirical observations but in contradiction with our expectation. If the relationship of the credit rating and YTM really holds the Czech companies with BBB financials should have been rated higher. As expected linear correlation between credit scores and YTM is very low and statistically insignificant.

Figure 3 - YTM vs. Credit rating score of bonds with fixed coupon

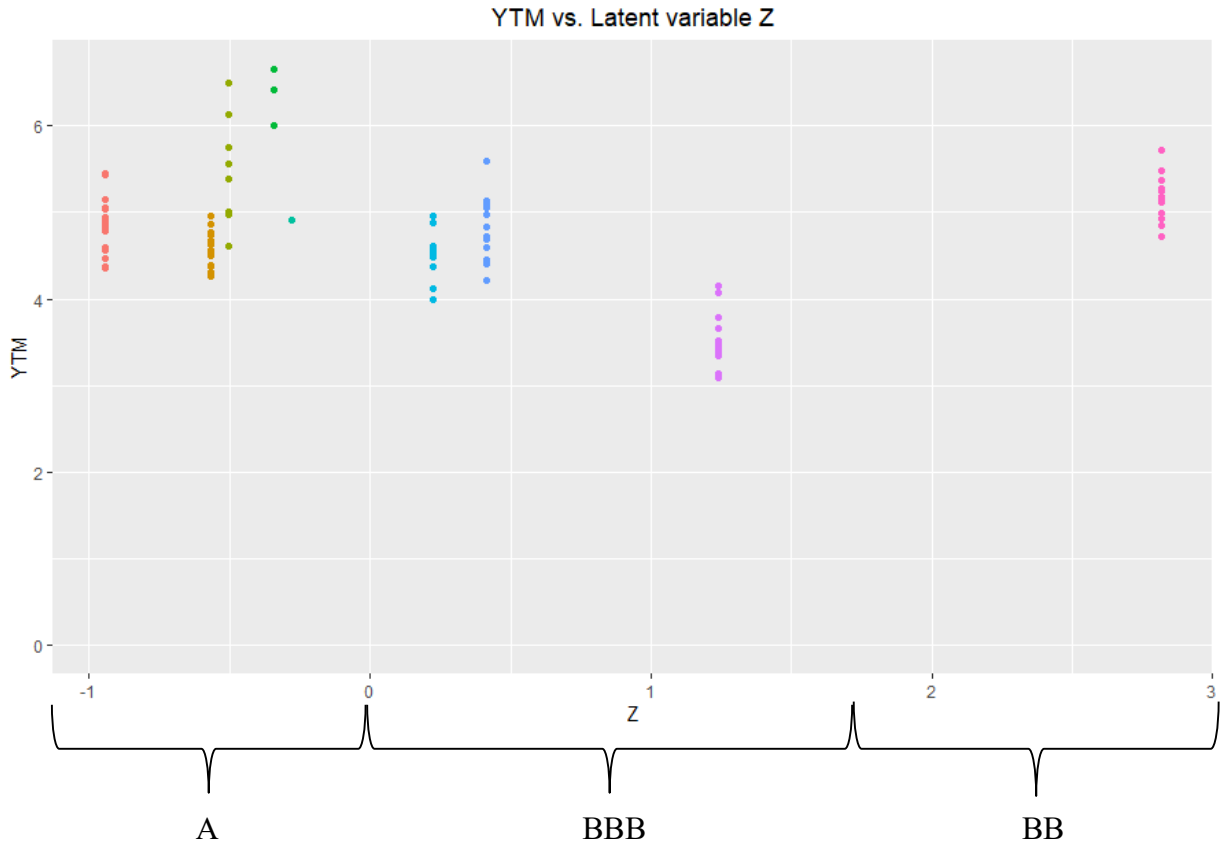


Another explanation why the estimated ratings do not fit our expectations might be the business diversity of explored companies. We discussed this problem in detail in the chapter Data. Due to the lack of data we were not able to apply adjustment technique such as winsorizing to get rid of outliers. Instead, we decided to go one step back and explore the distribution of YTM on the level of individual firms using estimated values of the latent variable Z. Variable Z as proposed in the Methodology allocates the credit score of a particular company based on the Z-value which belongs to the corresponding credit interval. In other words, it tells us the individual position/value of a particular company in the corresponding credit interval.

The Figure 4 outlines the relationship between variable Z and YTM. It surprisingly shows that YTM of each company´s bonds vary quite a lot[13] in the period of time less than one year. This variability of YTM cannot be explained by the creditworthiness and may be the source of bias. The variance of YTM for different trades with the same bond may be affected by other factors like interest rate, inflation expectation and liquidity risk but more likely by the purpose of the trade and by low liquidity in the selected segment of the Czech bond market.

[13] Standard deviation of YTM of A rated bonds = 0.54, Standard deviation of YTM of BBB rated bonds = 0.68, Standard deviation of YTM of BB rated bonds = 0.29

Figure 4 - YTM vs. latent variable Z



The firms that significantly deviate from the expected upward trend are companies like Photon Energy N.V. (light-green/the third from the right), ENERGO-PRO s.r.o (dark-green/the fourth from the right) and TMR CR, a.s (purple/the second from the left). So, basically firms with completely different business structure and operations. It is also operational heterogeneity that affects our estimation.

4.5.2. Bonds with variable coupon:

The relationship between credit score and yield premium of bonds with variable coupons is very similar to the fixed bond findings. Unlike the bonds with fixed coupons we did not observe any trading activity within our selected sample of variable bonds. Based on this fact, we were not able to calculate YTMs correctly and used only the margin values as described in Methodology. So we expect that our results might be biased.

The Table 21 below is showing the estimates. All coefficients of dummy variables have positive values with decreasing trend. Thus bonds rated by A pay significantly higher

yield premium (+2.36%) than AA or higher rated bonds. On the other hand, BBB bonds pay slightly lower yield premium i.e. (+2.18%) with respect to AA or higher rated bonds. The coefficient of determination R2 about 44% indicates that we explained again quite significant portion of YTM variability.

Table 21 - Regression results of bonds with variable coupons (YTM)

Model III	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.95%	1.47E-02	3.366	0.0151	*
CR_A	2.36%	1.62E-02	1.462	0.194	
CR_BBB	2.18%	1.54E-02	1.421	0.2052	
Size	-0.11%	6.10E-12	-1.86	0.1122	

Multiple R2 = 44%. RSE = 0.01736, Degrees of Freedom = 6, F-statistic: 1.58, p-value: 0.28.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

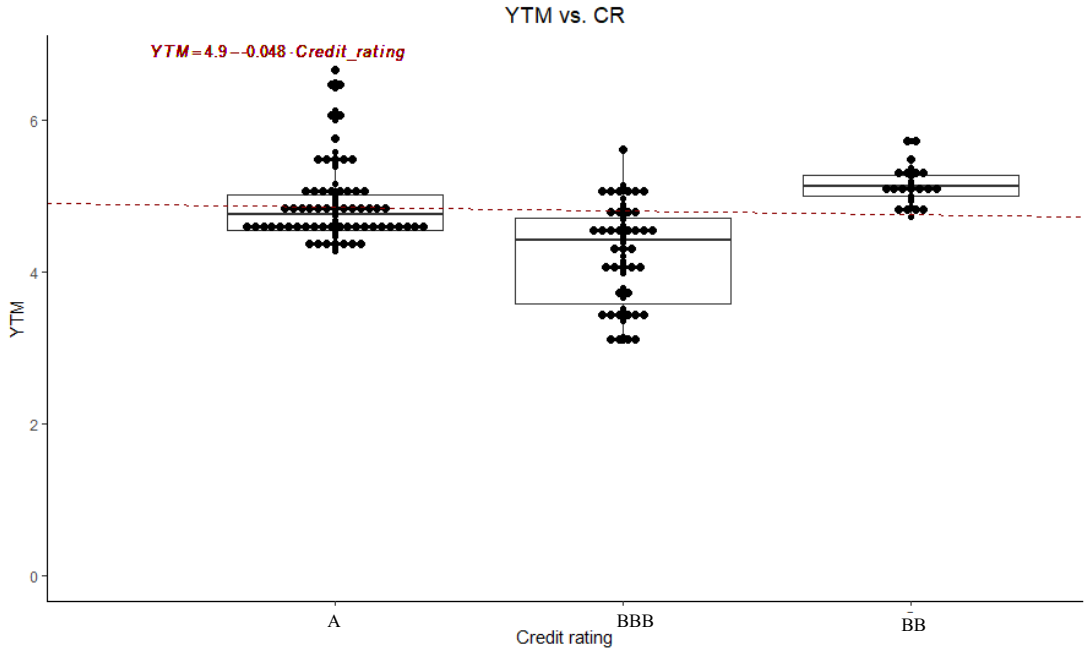
4.5.3. Conclusions

The results of both linear regressions showed that selected Czech bonds do not exhibit negative linear relationship between their YTMs and credit ratings. Statistical significance of estimates and the p-value for R2 of the model for YTM of bonds with fixed coupons lower than 0.005% justify rejection of our hypothesis H4 that *bond yields of Czech companies with higher estimated credit ratings tend to be lower, i.e. yields and ratings are negatively correlated.*

This result is also supported by the weak level of correlation in the observed data. However, as we discussed earlier our results might be biased by at least two factors such as lack of data and overall business heterogeneity of issuers of selected bonds.

Different reason why YTM declined in case of BBB rated bonds might be incorrect pricing. We suggest that the bonds are mispriced and they do not reflect correctly the riskiness of the investment. In this case the investors are not fairly rewarded for taking higher risk.

Figure 5 - YTM vs. Credit rating with displayed linear dependence



4.6. Credit spread vs. Credit rating

Although, YTM is considered as a suitable measure of bond returns, its calculation depends on its sufficient liquidity. If the bond is not traded there is no fair market price and YTM cannot be properly determined. However, as we explained in the Methodology, YTM itself may be influenced by the shape of the yield curve of risk free bonds. It is rather the distance from the yield curve, or the credit spread, than the value of YTM itself that should reflect the creditworthiness of bond issuers. Thus, we decided to replace YTM by credit spreads and explore whether they truly mirror creditworthiness of selected Czech bond. To test our last hypothesis H5 we used again estimates of credit ratings assigned by the Model III and regressed them with credit spreads following equation (3.8). We added again the variables liquidity and size of the issue.

4.6.1. Bonds with fixed coupon:

We started again with fixed coupon bonds. For modelling the spread we used similar equation as for YTM case. The spreads were calculated as a difference of YTM and government yield of the same maturity.

As can be seen in the Table 22 we received similar results with regard credit ratings.

Based on estimates from the Model III bonds rated by BBB show Credit spread lower by 0.89% than A rated bonds. Only bonds rated by BB show significant credit spread premium (+1.49%) over A rated bonds. The Liquidity coefficient confirmed with its negative sign that higher liquidity may decrease the required risk premium. In case of variable Size, we can observe the positive sign meaning higher issue size increase credit spread. The coefficient of determination R2 68% is again showing statistical significance.

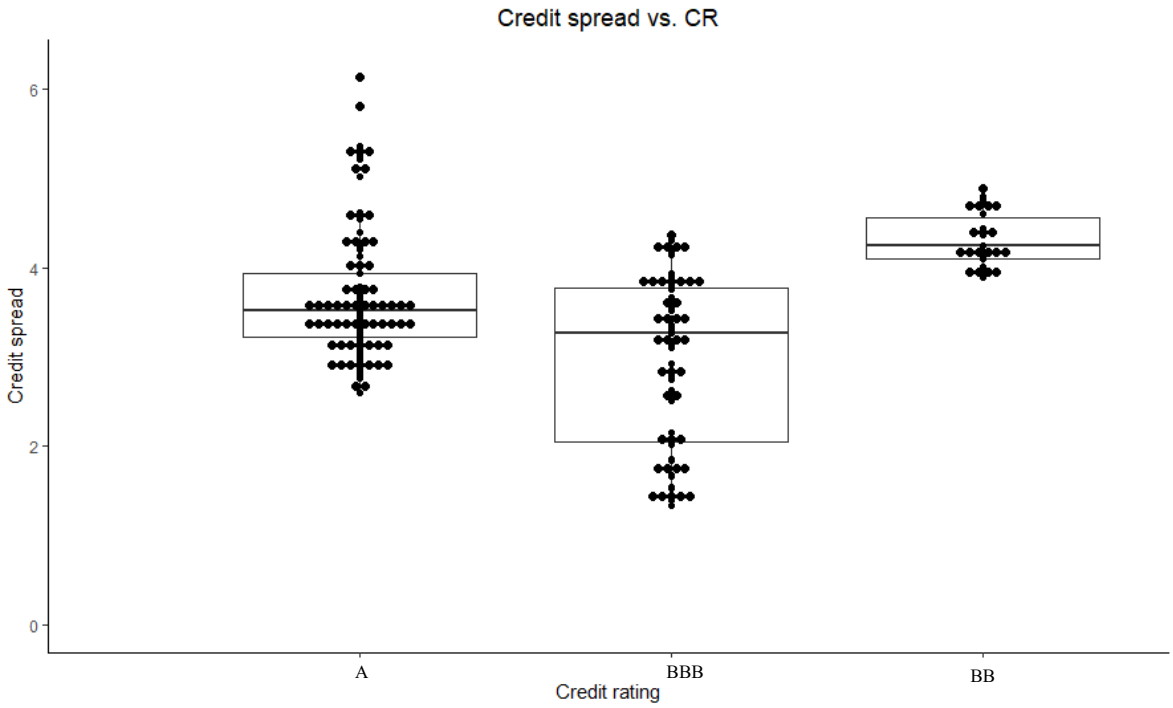
Table 22 - Regression results of bonds with fixed coupons (Credit spread)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.967%	1.33E-03	37.244	< 2e-16	***
CR_BBB	-0.894%	1.07E-03	-8.327	2.17E-13	***
CR_BB	1.493%	1.57E-03	9.539	3.56E-16	***
Liquidity	-0.027%	2.13E-05	-12.686	< 2e-16	***
Issue size	0.108%	2.21E-13	4.936	2.78E-06	***

Multiple R2 = 68%. RSE = 0.0052, Degrees of Freedom = 113, F-statistic: 63.9, p-value: < 2.2e-16.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Lack of linear correlation between decreasing credit rating and increasing credit spread see Figure 6, or no visible trend confirms the value of correlation coefficient equal to 0.0497.

Figure 6 – Credit spread vs. Credit rating score of bonds with fixed coupon



4.6.2. Bonds with variable coupon:

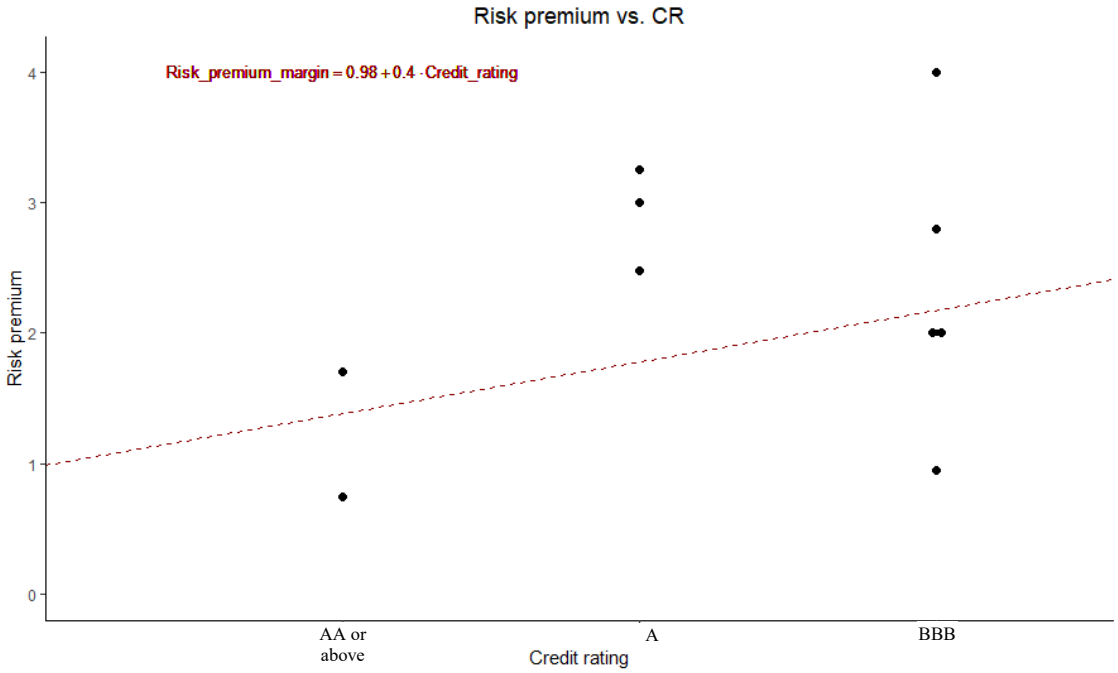
As in the previous case we observed zero liquidity, so we were forced to use only risk premiums instead of real YTM values. We considered a risk margin as a proxy variable to credit spread. In the Table 23, we can see that coefficients are all positive again. Hence, our results showed that bonds with variable coupons rated as BBB were issued with lower risk margin than companies with rating A. In other words, it means that investors were willing to buy the riskier type of bonds for lower reward. In theory, such situation reflects mispricing of risk. Nevertheless, the Figure 7 shows weak linear positive dependence supported by the correlation coefficient which is equal to 0.3209.

Table 23 - Regression results of bonds with variable coupons (Credit spread)

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.81%	7.17E-03	2.526	0.0449	*
CR_A	1.91%	7.88E-03	2.428	0.0513	.
CR_BBB	1.49%	7.49E-03	1.985	0.0944	.
Size	0.00%	2.97E-12	-1.487	0.1875	

Multiple R2 = 53%. RSE = 0.0085, Degrees of Freedom = 6, F-statistic: 2.33, p-value: 0.17.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Figure 7 – Risk margin vs. Credit rating score of bonds with variable coupon



4.6.3. Conclusions

The findings regarding credit spread and credit rating showed again mixed relationship. The results of both linear regressions showed that selected Czech bonds do not exhibit negative linear relationship between their credit spreads and credit ratings. Statistical significance of estimates, the p-value for F stat of the model for credit spreads of bonds with fixed coupons lower than 0.005% justify rejection of our hypothesis H5 that *credit spreads, or alternatively, risk margins truly mirror creditworthiness of Czech bond issuer.*

5 Conclusion

There is a widespread belief among the academics that the bond investors are sufficiently rewarded for taking higher credit risk in their investments. In other words, that the basic risk-return relationship defined by Sharpe (1964) holds. They are persuaded that such basic relationship should hold anytime and anywhere regardless of country and business cycle. Employing the estimated credit ratings of Czech companies, this is the first empirical study that analyzes the relationship between credit rating and bond yield or alternatively that of credit spread on the Czech bond market.

Our study demonstrates that financial and company specific data are sufficient to estimate the credit rating by means of ordered probit model. This model was also applied to the Czech market to determine credit scores of Czech bond issuers. These credit scores were employed to examine the mentioned relationship between credit risk exposure (credit rating) and bond yield and credit spread. The research did not confirm strong linear relationship between credit risk and return and suggests that there are other factors included in the risk feeling of the Czech investors.

Our study was performed in two steps. First we had to develop appropriate tool how to measure the expected dependence i.e. to create suitable model for credit rating measurement. Following previously published literature we decided for the ordered probit model technique. Due to the lack of data on the Czech bond market we tried to estimate its parameters using financial and company-specific variables of 274 US and 204 EU companies. The data was structured as pooled panel data observed in 2008-2019.

When searching for a suitable model, our results confirmed that the basic set of financial and company specific variables is sufficient to estimate the credit rating score. Moreover, they supported the evidence that significance of credit rating estimates is highly dependent on variables that control unobserved variability such as different business cycles (Time) and clustered characters of a particular company (Sector).

Furthermore, we identified that the significance of results differs with US and EU datasets. Employing robust source of data, the US based model showed more significant and consistent results than EU based model. To be able to select an appropriate model for

Czech data we performed the test of transferability between both datasets and models. We basically compared the quality of credit score estimates of the US model for EU dataset and vice versa. The quality of estimates worsened to the extent that persuaded us to select the EU model. Difficult transferability between the two regions can be probably attributed to the different market and business characteristics, as the size of companies, balance sheet structure or other factors. Nonetheless, research in this direction is out of the scope of our thesis.

In the second step, we decided to employ EU based model and utilized its credit rating estimates based on the character of Czech bond issuers. Equipped with these ratings we examined the relationship between credit ratings and bond yield and credit spread of Czech issuers by means of classical linear regression.

Selecting the most suitable model for the Czech data we used different options with different sectors and time perspective (the influence of time variable). As a consequence of short period of time covered by our Czech data we finally decided to employ the model without the time variable but applied the estimates only for sectors where the Czech issuers operate (Model III). Estimation of credit ratings of Czech bond issuers split bonds into four different categories. It was important for further examination of analyzed relationships that the selected model distinguished clearly the central group splitting it in two.

As we estimated the credit ratings of Czech companies we moved on to the examination of the relationship between credit rating and bond yield or credit spread. In other words we checked if the broadly accepted adverse relationship of bond credit quality and required bond yield holds in the Czech market environment as well. Nevertheless, it is important to mention that Czech market for corporate bonds exhibits very low liquidity. Only less than half of 20 available corporate bonds were traded at least once within our focused horizon of the year 2019. (We excluded bonds of financial institutions in our research.) Missing market prices limit the interpretation of YTM. Therefore, we were forced to split our dataset in two parts: bonds with fixed coupon that recorded at least some trading activity and bonds with variable coupon with zero trading. Then we tested the searched relationship separately.

The statistically significant results for fixed coupon bonds confirmed that selected Czech bonds did not exhibit expected adverse relationship between their YTMs and estimated credit ratings. Measured by linear correlation the yields were not actually influenced by the credit rating at all. Even if the YTM for credit rating of the group BBB was lower than that of BB its value was also lower than the yields in the group A.

Unlike the bonds with fixed coupons we did not observe any trading activity within our selected sample of variable bonds. So we were not able to calculate YTMs and were forced to use only the margin values. But credit rating did not show to be the most influential part of the risk reward. The correlation between credit rating and the margin was also very weak.

However, our conclusions might have been biased as a result of lack of data and overall business heterogeneity of issuers of selected bonds. Another reason might be incorrect pricing. This was confirmed by the variance and range of measured YTMs for the same bond. Thus, we suggest that Czech bonds are mispriced and do not reflect correctly the riskiness of the investment. This finding also means that Czech investors are not fairly rewarded for taking higher credit risk. However, it does not mean that the risk reward does not function. We expected that the Czech investors appreciate also other factors like liquidity or volume of issue size. As our results confirmed estimates of these variables in our regression were statistically significant. However they did not explain other reasons for trading with so different yields of the same bonds.

We are aware that YTM may also differ with maturity of the bond and changes in relation to the market yield curve. Therefore it is rather the distance from the yield curve, or in other words the credit spread, than the value of YTM itself that should reflect dependence of yield on the creditworthiness of bond issuers. Calculation of the spread basically means the adjustment of the YTM values for the yield of risk-free investment.

Our findings regarding the relationship of credit spread and credit rating confirmed again that selected Czech bonds exhibit neither linear relationship between their credit spreads and credit ratings.

To sum it up, even if our study demonstrates that financial and company specific data are sufficient to estimate the credit rating by means of ordered probit model and such

model was applied to Czech bond issuers to determine their credit scores we were not able to prove the expected adverse relationship between credit risk exposure (credit rating) and bond yield or credit spread. It suggests incorrect pricing. In this way the Czech bond market differs from developed or global markets where this strong influence was observed and confirmed.

We are aware that our study has some limitations that should be taken into account when interpreting our final results. It is mainly the lack of appropriate data that limits the statistical significance of results. In terms of credit rating estimation, we dealt with the problem of regional diversity which curbs usability of the model used for credit score estimation. We expect however, that more thorough data collection, focus on selection of comparable regions, and economically more similar sectors would support our finding in further development of the study.

In terms of Czech bond market environment, we noticed very low liquidity of corporate bonds traded on the Prague Stock Exchange. Thus, it would be beneficial to enhance the data sample by bonds that are traded on the over-the-counter market. This additional source could provide additional trade records and increase statistical significance of estimates.

Despite the mentioned limitations, our study contributes to the existing literature about the relationship of credit risk and bond yield in several ways. To our best knowledge, this is the first study that analyzes the relationship between credit risk and bond yield on the Czech corporate bond market. We proved that there is strong dependence of the model and its usability on the economic region. We answered the question whether publicly traded bonds on the PSE are fairly priced with regard credit rating of the issuer. Our study showed that there must be other strong factors that influence the bond yield than only those explored in our study. Our ambitions was to develop a sophisticated and easily accessible tool for retail investors to use if they are going to invest in bonds of companies without official credit rating. Our study showed that so far such simplified model based only on credit ratings is difficult to use in the Czech market environment.

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Appendix A

In our study we are working with adjusted credit rating scales. The Table A**.1** below presents original rating scales of S&P, Fitch and Moody´s, defines their features and propose the transformation to numerical scale from letter scale as suggested by e.g. (Kuvíková, 2015), (Poon, 2003).

Table A.1 – Credit rating interpretation and numeric transformation

Original rating grades		Interpretation	New rating grades	
			Wide scale	
S&P/Fitch	Moody´s		Numeric	Letter
		Investment grades		
AAA	AAA	Extremely strong capacity to meet financial commitments	1	AAA
AA+	Aa1	Very strong capacity to meet financial commitments	2	AA
AA	Aa2		2	AA
AA-	Aa3		2	AA
A+	A1	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and change in circumstances	3	A
A	A2		3	A
A-	A3		3	A
BBB+	Baa1	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions. Considered lowest investment grade by market participants	4	BBB
BBB	Baa2		4	BBB
BBB-	Baa3		4	BBB
		Non-investment (speculative) grades		
BB+	Ba1	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions	5	BB
BB	Ba2		5	BB
BB-	Ba3		5	BB
B+	B1	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments	6	B
B	B2		6	B
B-	B3		6	B
CCC+	Caa1	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments	7	CCC
CCC	Caa2		7	CCC
CCC-	Caa3		7	CCC
CC	Ca	Currently highly vulnerable obligations and other defined circumstances	7	CCC
C	C		7	CCC
SD/D		Payment default on financial commitments	7	CCC

Source: (Kuvíková, 2015)

Appendix B

In Appendix B, we present full definitions of credit rating metric retrieved from three main CRAs.

Credit rating definitions:

S&P Global:

"An S&P Global Ratings issue credit rating is a forward-looking opinion about the creditworthiness of an obligor with respect to a specific financial obligation, a specific class of financial obligations, or a specific financial program (including ratings on medium-term note programs and commercial paper programs). It takes into consideration the creditworthiness of guarantors, insurers, or other forms of credit enhancement on the obligation and takes into account the currency in which the obligation is denominated. The opinion reflects S&P Global Ratings' view of the obligor's capacity and willingness to meet its financial commitments as they come due, and this opinion may assess terms, such as collateral security and subordination, which could affect ultimate payment in the event of default." (S&P Global Ratings, 2020)

Fitch:

"Fitch's credit ratings relating to issuers are an opinion on the relative ability of an entity to meet financial commitments, such as interest, preferred dividends, repayment of principal, insurance claims or counterparty obligations. Credit ratings relating to securities and obligations of an issuer can include a recovery expectation. Credit ratings are used by investors as indications of the likelihood of receiving the money owed to them in accordance with the terms on which they invested." (FitchRating, 2020)

Moody's:

"Moody's assigns ratings to long-term and short-term financial obligations. Long-term ratings are assigned to issuers or obligations with an original maturity of one year or more and reflect both on the likelihood of a default on contractually promised payments and the expected financial loss suffered in the event of default. Short-term ratings are assigned to obligations with an original maturity of thirteen months or less and reflect both on the likelihood of a default on contractually promised payments and the expected financial loss suffered in the event of default." (Moody's Investors Service, 2020)

Appendix C

Appendix C listed full transcript of empirical results of EU dataset collected from statistical program R studio.

Table 24 - Regression results Model I on EU data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-0.902	0.477	-1.889	0.059	.
SectorAirlines	1.147	0.395	2.902	0.004	**
SectorAuto Components	1.986	0.510	3.894	0.000	***
SectorAutomobiles	0.186	0.351	0.529	0.597	
SectorBeverages	0.781	0.347	2.248	0.025	*
SectorBiotechnology	2.572	0.736	3.492	0.000	***
SectorBuilding Products	1.083	0.610	1.774	0.076	.
SectorCommercial Services & Supplies	2.045	0.462	4.426	0.000	***
SectorCommunications Equipment	1.645	0.535	3.078	0.002	**
SectorConstruction & Engineering	0.601	0.356	1.692	0.091	.
SectorConstruction Materials	0.955	0.374	2.551	0.011	*
SectorContainers & Packaging	2.168	0.703	3.084	0.002	**
SectorDiversified Telecommunication Services	0.396	0.348	1.136	0.256	
SectorElectric Utilities	0.316	0.300	1.055	0.292	
SectorElectrical Equipment	-1.153	0.371	-3.105	0.002	**
SectorEnergy Equipment & Services	0.778	1.174	0.663	0.508	
SectorEntertainment	0.695	0.841	0.827	0.408	
SectorFood & Staples Retailing	0.101	0.416	0.242	0.809	
SectorFood Products	-1.216	0.403	-3.018	0.003	**
SectorGas Utilities	0.420	0.469	0.895	0.371	
SectorHealth Care Equipment & Supplies	1.021	0.536	1.906	0.057	.
SectorHealth Care Providers & Services	0.612	0.467	1.310	0.190	
SectorHotels, Restaurants & Leisure	1.280	0.466	2.746	0.006	**
SectorHousehold Durables	-0.808	0.711	-1.136	0.256	
SectorChemicals	0.317	0.327	0.970	0.332	
SectorIndustrial Conglomerates	-0.505	0.731	-0.690	0.490	
SectorInteractive Media & Services	2.702	1.173	2.303	0.021	*
SectorInternet & Direct Marketing Retail	1.750	0.852	2.053	0.040	*
SectorIT Services	1.394	0.887	1.572	0.116	
SectorMachinery	0.211	0.310	0.682	0.495	
SectorMarine	0.714	0.627	1.140	0.254	
SectorMedia	0.235	0.467	0.503	0.615	
SectorMetals & Mining	1.252	0.328	3.818	0.000	***
SectorMulti-Utilities	0.028	0.288	0.097	0.923	
SectorMultiline Retail	1.734	0.516	3.362	0.001	***
SectorOil, Gas & Consumable Fuels	-0.856	0.352	-2.432	0.015	*

SectorPaper & Forest Products	0.777	0.498	1.558	0.119	
SectorPersonal Products	-3.041	0.802	-3.793	0.000	***
SectorPharmaceuticals	-0.684	0.325	-2.101	0.036	*
SectorProfessional Services	-0.515	0.491	-1.049	0.294	
SectorSemiconductors & Semiconductor Equipment	1.412	0.576	2.451	0.014	*
SectorSoftware	-1.515	0.752	-2.015	0.044	*
SectorSpecialty Retail	1.838	0.570	3.224	0.001	**
SectorTextiles, Apparel & Luxury Goods	-0.564	0.403	-1.400	0.161	
SectorTobacco	-0.209	0.679	-0.309	0.758	
SectorTrading Companies & Distributors	0.404	1.193	0.338	0.735	
SectorTransportation Infrastructure	0.499	0.437	1.142	0.254	
SectorWater Utilities	0.664	1.184	0.561	0.575	
SectorWireless Telecommunication Services	0.294	0.534	0.551	0.581	
Operating profit margin	0.174	0.045	3.859	0.000	***
log(Net_Sales)	-0.007	0.008	-0.847	0.397	
ROE	-0.090	0.419	-0.215	0.829	
Coverage_ratio_EBIT	0.001	0.001	0.987	0.324	
Long-term Debt to Total Assets	4.579	1.366	3.353	0.001	***
Total Debt to Total Assets	-3.564	1.237	-2.882	0.004	**
Working Capital to Total Assets	-1.285	0.604	-2.129	0.033	*
Retained Earnings to Total Assets	0.258	0.305	0.847	0.397	
EBIT to Total Assets	0.412	1.931	0.213	0.831	
Shareholder´s Equity to Total Liabilities	0.043	0.113	0.386	0.700	
Total Sales to Total Assets	-0.081	0.174	-0.464	0.643	
2|3	0.588	0.823	0.714	0.475	
3|4	2.550	0.820	3.108	0.002	**
4|5	4.318	0.829	5.210	0.000	***
5|6	5.997	0.856	7.007	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.184
log Lik	-611.00
Residual Deviance:	1221.42
AIC:	1349.42
nobs:	648

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	2	13	2	0	0
A	1	87	104	2	0
BBB	0	44	274	7	0
BB	0	6	68	28	1
B or below	0	0	3	6	0

Table 25 - Regression results of Model II on EU data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-0.875	0.438	-1.998	0.046	*
SectorAirlines	1.188	0.386	3.074	0.002	**
SectorAuto Components	2.036	0.481	4.234	0.000	***
SectorAutomobiles	0.237	0.339	0.698	0.485	
SectorBeverages	0.774	0.328	2.357	0.018	*
SectorBiotechnology	2.597	0.715	3.631	0.000	***
SectorBuilding Products	1.105	0.594	1.861	0.063	.
SectorCommercial Services & Supplies	2.069	0.455	4.546	0.000	***
SectorCommunications Equipment	1.600	0.510	3.135	0.002	**
SectorConstruction & Engineering	0.624	0.350	1.784	0.074	.
SectorConstruction Materials	0.979	0.358	2.732	0.006	**
SectorContainers & Packaging	2.236	0.691	3.235	0.001	**
SectorDiversified Telecommunication Services	0.452	0.314	1.441	0.150	
SectorElectric Utilities	0.397	0.282	1.408	0.159	
SectorElectrical Equipment	-1.123	0.360	-3.116	0.002	**
SectorEnergy Equipment & Services	0.828	1.164	0.711	0.477	
SectorEntertainment	0.637	0.833	0.764	0.445	
SectorFood & Staples Retailing	0.190	0.368	0.517	0.605	
SectorFood Products	-1.133	0.368	-3.076	0.002	**
SectorGas Utilities	0.464	0.444	1.045	0.296	
SectorHealth Care Equipment & Supplies	1.005	0.498	2.017	0.044	*
SectorHealth Care Providers & Services	0.702	0.443	1.587	0.113	
SectorHotels, Restaurants & Leisure	1.376	0.435	3.162	0.002	**
SectorHousehold Durables	-0.779	0.695	-1.120	0.263	
SectorChemicals	0.365	0.303	1.206	0.228	
SectorIndustrial Conglomerates	-0.529	0.707	-0.749	0.454	
SectorInteractive Media & Services	2.715	1.168	2.325	0.020	*
SectorInternet & Direct Marketing Retail	1.818	0.841	2.161	0.031	*
SectorIT Services	1.694	0.831	2.040	0.041	*
SectorMachinery	0.213	0.297	0.717	0.474	
SectorMarine	0.768	0.618	1.242	0.214	
SectorMedia	0.290	0.454	0.640	0.522	
SectorMetals & Mining	1.247	0.295	4.235	0.000	***
SectorMulti-Utilities	0.068	0.275	0.248	0.804	

SectorMultiline Retail	1.618	0.446	3.631	0.000	***
SectorOil, Gas & Consumable Fuels	-0.795	0.310	-2.566	0.010	*
SectorPaper & Forest Products	0.855	0.481	1.777	0.076	.
SectorPersonal Products	-2.754	0.772	-3.569	0.000	***
SectorPharmaceuticals	-0.641	0.308	-2.083	0.037	*
SectorProfessional Services	-0.217	0.400	-0.542	0.588	
SectorSemiconductors & Semiconductor Equipment	1.343	0.557	2.411	0.016	*
SectorSoftware	-1.533	0.736	-2.083	0.037	*
SectorSpecialty Retail	1.918	0.550	3.486	0.000	***
SectorTextiles, Apparel & Luxury Goods	-0.444	0.378	-1.173	0.241	
SectorTobacco	-0.183	0.640	-0.286	0.775	
SectorTrading Companies & Distributors	0.376	1.162	0.323	0.746	
SectorTransportation Infrastructure	0.548	0.423	1.294	0.196	
SectorWater Utilities	0.743	1.170	0.635	0.526	
SectorWireless Telecommunication Services	0.239	0.480	0.497	0.619	
log(Net_Sales)	0.173	0.041	4.198	0.000	***
Longterm Debt to Total Assets	4.244	1.317	3.223	0.001	**
Total Debt to Total Assets	-3.654	1.211	-3.018	0.003	**
Working Capital to Total Assets	-0.977	0.566	-1.725	0.085	.
2|3	0.553	0.718	0.770	0.441	
3|4	2.505	0.715	3.503	0.000	***
4|5	4.268	0.725	5.886	0.000	***
5|6	5.943	0.752	7.901	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.181
log Lik	-612
Residual Deviance:	1224.79
AIC:	1338.79
nobs:	648

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	6	10	0	1	0
A	1	95	93	5	0
BBB	0	65	239	21	0
BB	0	13	62	26	2
B or below	0	1	4	4	0

Table 26 - Regression results of Model III on EU data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorElectric Utilities	0.418	0.332	1.257	0.209	
SectorGas Utilities	0.675	0.499	1.353	0.176	
SectorHealth Care Providers & Services	1.274	0.503	2.534	0.011	*
SectorHotels, Restaurants & Leisure	1.545	0.476	3.248	0.001	**
SectorInternet & Direct Marketing Retail	2.736	0.934	2.928	0.003	**
SectorMulti-Utilities	0.257	0.323	0.797	0.426	
SectorOil, Gas & Consumable Fuels	-0.164	0.375	-0.436	0.663	
SectorWater Utilities	0.715	1.222	0.585	0.559	
log(Net_Sales)	0.023	0.086	0.268	0.788	
Longterm Debt to Total Assets	-1.058	4.098	-0.258	0.796	
Total Debt to Total Assets	0.394	3.711	0.106	0.915	
Working Capital to Total Assets	-4.750	1.487	-3.195	0.001	**
2|3	-1.872	1.496	-1.252	0.211	
3|4	0.004	1.481	0.003	0.998	
4|5	1.899	1.487	1.277	0.202	
5|6	3.387	1.530	2.214	0.027	*

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.093
log Lik	-165
Residual Deviance:	330.55
AIC:	362.55
nobs:	179

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	0	3	0	0	0
A	1	20	36	0	0
BBB	0	23	72	5	0
BB	0	1	11	6	0
B or below	0	0	1	0	0

Table 27 - Regression results of Model IV on EU data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-0.917	0.484	-1.8967.	0.058	.
SectorAirlines	1.177	0.401	2.937**	0.003	**
SectorAuto Components	1.943	0.515	3.7724***	0.000	***
SectorAutomobiles	0.324	0.356	0.9086	0.364	
SectorBeverages	0.853	0.352	2.4263*	0.015	*
SectorBiotechnology	2.741	0.743	3.6877***	0.000	***
SectorBuilding Products	1.181	0.619	1.9081.	0.056	.
SectorCommercial Services & Supplies	2.069	0.467	4.4306***	0.000	***
SectorCommunications Equipment	1.787	0.542	3.2993***	0.001	***
SectorConstruction & Engineering	0.797	0.362	2.2047*	0.027	*
SectorConstruction Materials	1.099	0.379	2.8969**	0.004	**
SectorContainers & Packaging	2.176	0.711	3.0613**	0.002	**
SectorDiversified Telecommunication Services	0.477	0.353	1.3531	0.176	
SectorElectric Utilities	0.396	0.304	1.3008	0.193	
SectorElectrical Equipment	-1.166	0.377	-3.0916**	0.002	**
SectorEnergy Equipment & Services	1.125	1.195	0.942	0.346	
SectorEntertainment	0.708	0.850	0.8335	0.405	
SectorFood & Staples Retailing	0.147	0.421	0.35	0.726	
SectorFood Products	-1.306	0.405	-3.2207**	0.001	**
SectorGas Utilities	0.560	0.476	1.1766	0.239	
SectorHealth Care Equipment & Supplies	0.803	0.541	1.4839	0.138	
SectorHealth Care Providers & Services	0.660	0.472	1.3966	0.163	
SectorHotels, Restaurants & Leisure	1.185	0.473	2.5062*	0.012	*
SectorHousehold Durables	-0.898	0.723	-1.2415	0.214	
SectorChemicals	0.353	0.332	1.0636	0.288	
SectorIndustrial Conglomerates	-0.749	0.745	-1.0065	0.314	
SectorInteractive Media & Services	2.376	1.184	2.0071*	0.045	*
SectorInternet & Direct Marketing Retail	1.426	0.861	1.6569.	0.098	.
SectorIT Services	1.007	0.897	1.1226	0.262	
SectorMachinery	0.229	0.313	0.7308	0.465	
SectorMarine	0.731	0.634	1.1522	0.249	
SectorMedia	0.239	0.471	0.5074	0.612	
SectorMetals & Mining	1.297	0.333	3.9***	0.000	***
SectorMulti-Utilities	0.094	0.292	0.3227	0.747	
SectorMultiline Retail	1.622	0.523	3.099**	0.002	**
SectorOil, Gas & Consumable Fuels	-0.760	0.357	-2.1273*	0.033	*
SectorPaper & Forest Products	0.961	0.519	1.8525.	0.064	.
SectorPersonal Products	-3.187	0.841	-3.790***	0.000	***
SectorPharmaceuticals	-0.729	0.329	-2.2185*	0.027	*
SectorProfessional Services	-0.628	0.498	-1.2617	0.207	
SectorSemiconductors & Semiconductor Equipment	1.301	0.583	2.232*	0.026	*
SectorSoftware	-1.514	0.765	-1.9796*	0.048	*
SectorSpecialty Retail	1.953	0.578	3.3779***	0.001	***

SectorTextiles, Apparel & Luxury Goods	-0.755	0.411	-1.8352.	0.066	.
SectorTobacco	-0.257	0.684	-0.3765	0.707	
SectorTrading Companies & Distributors	0.071	1.206	0.0591	0.953	
SectorTransportation Infrastructure	0.415	0.443	0.9368	0.349	
SectorWater Utilities	0.320	1.197	0.267	0.789	
SectorWireless Telecommunication Services	0.469	0.542	0.865	0.387	
Operating profit margin	0.161	0.046	3.516***	0.000	***
log(Net_Sales)	-0.006	0.008	-0.7288	0.466	
ROE	-0.123	0.425	-0.2899	0.772	
Coverage_ratio_EBIT	0.001	0.001	0.9607	0.337	
Long-term Debt to Total Assets	4.191	1.394	3.0065**	0.003	**
Total Debt to Total Assets	-3.369	1.258	-2.6778**	0.007	**
Working Capital to Total Assets	-1.231	0.612	-2.0098*	0.044	*
Retained Earnings to Total Assets	0.174	0.309	0.5616	0.574	
EBIT to Total Assets	0.808	1.981	0.408	0.683	
Shareholder´s Equity to Total Liabilities	0.065	0.114	0.5687	0.570	
Total Sales to Total Assets	-0.024	0.177	-0.1375	0.891	
Year_2019	-0.365	0.178	-2.0535*	0.040	*
Year _2018	-0.553	0.192	-2.876**	0.004	**
Year _2017	-0.743	0.190	-3.906***	0.000	***
Year _2016	-0.633	0.157	-4.016***	0.000	***
Year _2015	-0.238	0.188	-1.2675	0.205	
Year _2014	-0.471	0.193	-2.4435*	0.015	*
Year _2013	-0.336	0.205	-1.6422	0.101	
Year _2012	-0.482	0.259	-1.8579.	0.063	.
Year _2011	-0.989	0.256	-3.865***	0.000	***
Year _2010	-0.613	0.301	-2.0377*	0.042	*
2|3	-0.052	0.848	-0.0617	0.951	
3|4	1.976	0.842	2.3453*	0.019	*
4|5	3.797	0.850	4.4687***	0.000	***
5|6	5.517	0.876	6.2976***	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.205
log Lik	-595.00
Residual Deviance:	1189.66
AIC:	1337.66
nobs:	648

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	2	14	1	0	0
A	1	92	99	2	0
BBB	0	47	267	11	0
BB	0	5	61	36	1
B or below	0	0	2	7	0

Table 28 - Regression results of Model V on EU data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-0.836	0.443	0.442858.	0.059	.
SectorAirlines	1.242	0.391	0.391492**	0.002	**
SectorAuto Components	2.034	0.485	0.485175***	0.000	***
SectorAutomobiles	0.395	0.345	0.344796	0.252	
SectorBeverages	0.869	0.333	0.332709**	0.009	**
SectorBiotechnology	2.804	0.722	0.722229***	0.000	***
SectorBuilding Products	1.223	0.602	0.601705*	0.042	*
SectorCommercial Services & Supplies	2.114	0.459	0.459471***	0.000	***
SectorCommunications Equipment	1.755	0.517	0.517192***	0.001	***
SectorConstruction & Engineering	0.817	0.356	0.355816*	0.022	*
SectorConstruction Materials	1.141	0.363	0.363316**	0.002	**
SectorContainers & Packaging	2.243	0.699	0.698745**	0.001	**
SectorDiversified Telecommunication Services	0.573	0.318	0.318172.	0.072	.
SectorElectric Utilities	0.486	0.287	0.286509.	0.090	.
SectorElectrical Equipment	-1.131	0.366	0.366004**	0.002	**
SectorEnergy Equipment & Services	1.185	1.184	1.184296	0.317	
SectorEntertainment	0.627	0.842	0.842223	0.456	
SectorFood & Staples Retailing	0.290	0.373	0.372778	0.436	
SectorFood Products	-1.188	0.371	0.370505**	0.001	**
SectorGas Utilities	0.635	0.451	0.451092	0.159	
SectorHealth Care Equipment & Supplies	0.831	0.502	0.502048.	0.098	.
SectorHealth Care Providers & Services	0.779	0.447	0.447453.	0.082	.
SectorHotels, Restaurants & Leisure	1.298	0.442	0.441693**	0.003	**
SectorHousehold Durables	-0.827	0.707	0.70693	0.242	
SectorChemicals	0.416	0.307	0.307355	0.176	
SectorIndustrial Conglomerates	-0.719	0.717	0.717472	0.317	
SectorInteractive Media & Services	2.384	1.178	1.178253*	0.043	*
SectorInternet & Direct Marketing Retail	1.471	0.850	0.850114.	0.084	.
SectorIT Services	1.340	0.840	0.839778	0.111	
SectorMachinery	0.249	0.300	0.299826	0.406	
SectorMarine	0.821	0.625	0.625295	0.189	
SectorMedia	0.309	0.458	0.457662	0.499	
SectorMetals & Mining	1.315	0.299	0.298785***	0.000	***
SectorMulti-Utilities	0.154	0.279	0.278636	0.581	

SectorMultiline Retail	1.613	0.450	0.44992***	0.000	***
SectorOil, Gas & Consumable Fuels	-0.681	0.315	0.31487*	0.030	*
SectorPaper & Forest Products	1.052	0.501	0.500863*	0.036	*
SectorPersonal Products	-2.885	0.811	0.811381***	0.000	***
SectorPharmaceuticals	-0.669	0.311	0.310658*	0.031	*
SectorProfessional Services	-0.220	0.404	0.404375	0.586	
SectorSemiconductors & Semiconductor Equipment	1.295	0.562	0.561517*	0.021	*
SectorSoftware	-1.532	0.749	0.749339*	0.041	*
SectorSpecialty Retail	2.063	0.559	0.558608***	0.000	***
SectorTextiles, Apparel & Luxury Goods	-0.595	0.385	0.385309	0.122	
SectorTobacco	-0.221	0.646	0.645512	0.733	
SectorTrading Companies & Distributors	0.058	1.175	1.175081	0.960	
SectorTransportation Infrastructure	0.473	0.429	0.429464	0.271	
SectorWater Utilities	0.430	1.183	1.182614	0.716	
SectorWireless Telecommunication Services	0.478	0.489	0.488804	0.328	
log(Net_Sales)	0.160	0.042	0.041846***	0.000	***
Long-term Debt to Total Assets	3.888	1.339	1.339196**	0.004	**
Total Debt to Total Assets	-3.538	1.232	1.231817**	0.004	**
Working Capital to Total Assets	-0.873	0.575	0.574676	0.129	
Year_2019	-0.360	0.176	0.176234*	0.041	*
Year _2018	-0.543	0.191	0.191196**	0.004	**
Year _2017	-0.723	0.189	0.188958***	0.000	***
Year _2016	-0.639	0.157	0.156613***	0.000	***
Year _2015	-0.239	0.186	0.186465	0.200	
Year _2014	-0.468	0.191	0.191071*	0.014	*
Year _2013	-0.347	0.200	0.199798.	0.083	.
Year _2012	-0.487	0.255	0.255388.	0.057	.
Year _2011	-0.986	0.254	0.254081***	0.000	***
Year _2010	-0.631	0.296	0.295615*	0.033	*
2|3	-0.152	0.742	0.742341	0.838	
3|4	1.868	0.737	0.737271*	0.011	*
4|5	3.684	0.746	0.745611***	0.000	***
5|6	5.398	0.772	0.772295***	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.203
log Lik	-597.00
Residual Deviance:	1193.10
AIC:	1327.10
nobs:	648

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	2	14	1	0	0
A	1	95	97	1	0
BBB	0	43	273	9	0
BB	0	5	62	35	1
B or below	0	0	2	7	0

Table 29 - Regression results of Model VI on EU data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorElectric Utilities	0.371	0.351	1.0592	0.289	
SectorGas Utilities	0.859	0.530	1.62	0.105	
SectorHealth Care Providers & Services	1.446	0.523	2.767**	0.006	**
SectorHotels, Restaurants & Leisure	1.336	0.502	2.6611**	0.008	**
SectorInternet & Direct Marketing Retail	2.549	0.969	2.630**	0.009	**
SectorMulti-Utilities	0.281	0.338	0.8318	0.406	
SectorOil, Gas & Consumable Fuels	0.112	0.399	0.2815	0.778	
SectorWater Utilities	0.210	1.278	0.1646	0.869	
log(Net_Sales)	-0.027	0.090	-0.3029	0.762	
Long-term Debt to Total Assets	-1.079	4.328	-0.2493	0.803	
Total Debt to Total Assets	0.623	3.921	0.1589	0.874	
Working Capital to Total Assets	-5.638	1.569	-3.593***	0.000	***
Year_2019	-0.194	0.402	-0.4816	0.630	
Year _2018	-0.034	0.394	-0.0852	0.932	
Year _2017	-0.804	0.368	-2.1827*	0.029	*
Year _2016	-0.843	0.318	-2.6539**	0.008	**
Year _2015	0.094	0.348	0.2712	0.786	
Year _2014	-0.439	0.365	-1.2023	0.229	
Year _2013	-0.600	0.362	-1.6566.	0.098	.
Year _2012	-0.163	0.400	-0.408	0.683	
Year _2011	-1.273	0.487	-2.6125**	0.009	**
Year _2010	-2.149	0.554	-3.881***	0.000	***
2|3	-3.411	1.599	-2.1329*	0.033	*
3|4	-1.224	1.566	-0.7812	0.435	
4|5	0.856	1.567	0.5464	0.585	
5|6	2.329	1.601	1.4547	0.146	

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.174
log Lik	-151.00
Residual Deviance:	301.02
AIC:	353.02
nobs:	179

	Prediction				
Truth	AA or above	A	BBB	BB	B or below
AA or above	0	2	1	0	0
A	0	18	39	0	0
BBB	0	24	76	0	0
BB	0	3	12	3	0
B or below	0	0	1	0	0

Appendix D

Appendix D listed full transcript of empirical results of U.S. dataset collected from statistical program R studio.

Table 30 - Regression results of Model I on U.S. data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-0.855	0.493	-1.734	0.083	.
SectorAirlines	2.052	0.344	5.965	0.000	***
SectorAuto Components	0.580	0.560	1.037	0.300	
SectorAutomobiles	3.102	0.445	6.964	0.000	***
SectorBeverages	-0.228	0.365	-0.625	0.532	
SectorBiotechnology	0.313	0.360	0.868	0.385	
SectorBuilding Products	0.199	0.369	0.539	0.590	
SectorCommercial Services & Supplies	-0.464	0.397	-1.168	0.243	
SectorCommunications Equipment	-0.305	0.464	-0.657	0.511	
SectorConstruction & Engineering	-1.826	0.750	-2.436	0.015	*
SectorConstruction Materials	0.043	0.402	0.107	0.915	
SectorContainers & Packaging	0.116	0.368	0.315	0.753	
SectorDistributors	0.786	0.599	1.312	0.190	
SectorDiversified Telecommunication Services	0.698	0.429	1.627	0.104	
SectorElectric Utilities	-0.468	0.273	-1.711	0.087	.
SectorElectrical Equipment	-0.736	0.459	-1.605	0.108	
SectorElectronic Equipment, Instruments & Components	0.248	0.366	0.677	0.498	
SectorEnergy Equipment & Services	0.205	0.477	0.430	0.667	
SectorEntertainment	0.870	0.376	2.317	0.021	*
SectorFood & Staples Retailing	-0.819	0.432	-1.897	0.058	.
SectorFood Products	-0.070	0.281	-0.250	0.803	
SectorGas Utilities	-2.114	0.594	-3.562	0.000	***
SectorHotels, Restaurants & Leisure	0.795	0.317	2.509	0.012	*
SectorHousehold Durables	0.839	0.372	2.258	0.024	*
SectorHousehold Products	0.175	0.450	0.390	0.697	
SectorChemicals	-0.118	0.273	-0.432	0.666	
SectorIndependent Power and Renewable Electricity Producer	0.856	0.560	1.527	0.127	
SectorIndustrial Conglomerates	0.178	0.421	0.422	0.673	
SectorInteractive Media & Services	0.084	0.600	0.140	0.889	
SectorInternet & Direct Marketing Retail	-0.404	0.364	-1.110	0.267	
SectorLeisure Products	0.747	0.672	1.111	0.267	
SectorLife Sciences Tools & Services	-0.489	0.521	-0.938	0.348	
SectorMachinery	-0.153	0.286	-0.533	0.594	
SectorMedia	0.714	0.304	2.345	0.019	*
SectorMetals & Mining	0.885	0.415	2.131	0.033	*

SectorMulti-Utilities	-0.520	0.305	-1.708	0.088	.
SectorMultiline Retail	0.371	0.376	0.985	0.325	
SectorOil, Gas & Consumable Fuels	0.264	0.257	1.025	0.305	
SectorPersonal Products	-0.286	0.901	-0.317	0.751	
SectorProfessional Services	0.853	0.410	2.084	0.037	*
SectorRoad & Rail	0.289	0.338	0.857	0.392	
SectorSemiconductors & Semiconductor Equipment	0.263	0.299	0.879	0.379	
SectorSpecialty Retail	0.632	0.302	2.090	0.037	*
SectorTextiles, Apparel & Luxury Goods	0.653	0.340	1.922	0.055	.
SectorTobacco	1.712	0.520	3.292	0.001	***
SectorWater Utilities	-1.406	0.665	-2.114	0.035	*
SectorWireless Telecommunication Services	1.877	0.702	2.675	0.007	**
Operating profit margin	-0.691	0.052	-13.30	< 0.005	***
log(Net_Sales)	-0.007	0.007	-1.016	0.310	
ROE	-0.041	0.034	-1.213	0.225	
Coverage_ratio_EBIT	0.000	0.001	0.306	0.760	
Long-term Debt to Total Assets	9.160	1.413	6.485	0.000	***
Total Debt to Total Assets	-4.798	1.329	-3.611	0.000	***
Working Capital to Total Assets	-0.101	0.458	-0.221	0.825	
Retained Earnings to Total Assets	-0.815	0.190	-4.284	0.000	***
EBIT to Total Assets	-10.071	1.161	-8.677	< 0.005	***
Shareholder´s Equity to Total Liabilities	-0.165	0.119	-1.392	0.164	
Total Sales to Total Assets	0.529	0.140	3.783	0.000	***
1|2	-16.534	1.153	-14.34	< 0.005	***
2|3	-13.908	0.959	-14.50	< 0.005	***
3|4	-11.722	0.927	-12.65	< 0.005	***
4|5	-9.335	0.901	-10.35	< 0.005	***
5|6	-7.578	0.894	-8.474	< 0.005	***
6|7	-6.368	0.910	-7.000	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.354
log Lik	-749
Residual Deviance:	1498.97
AIC:	1626.97
nobs:	946

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	14	22	0	0	0	0
A	0	0	160	108	0	0	0
BBB	0	0	63	390	22	1	1

BB	0	0	1	75	59	3	0
B	0	0	0	4	14	2	1
CCC	0	0	0	0	2	2	1

Table 31 - Regression results of Model II on U.S. data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-0.860	0.492	-1.748	0.080	.
SectorAirlines	2.059	0.333	6.182	0.000	***
SectorAuto Components	0.588	0.559	1.052	0.293	
SectorAutomobiles	3.097	0.443	6.992	0.000	***
SectorBeverages	-0.238	0.364	-0.654	0.513	
SectorBiotechnology	0.264	0.351	0.751	0.453	
SectorBuilding Products	0.204	0.369	0.554	0.579	
SectorCommercial Services & Supplies	-0.445	0.395	-1.127	0.260	
SectorCommunications Equipment	-0.354	0.455	-0.777	0.437	
SectorConstruction & Engineering	-1.835	0.750	-2.448	0.014	*
SectorConstruction Materials	0.078	0.400	0.196	0.845	
SectorContainers & Packaging	0.135	0.366	0.368	0.713	
SectorDistributors	0.804	0.597	1.347	0.178	
SectorDiversified Telecommunication Services	0.684	0.427	1.603	0.109	
SectorElectric Utilities	-0.497	0.265	-1.873	0.061	.
SectorElectrical Equipment	-0.722	0.458	-1.577	0.115	
SectorElectronic Equipment, Instruments & Components	0.253	0.366	0.691	0.490	
SectorEnergy Equipment & Services	0.200	0.474	0.422	0.673	
SectorEntertainment	0.869	0.372	2.333	0.020	*
SectorFood & Staples Retailing	-0.874	0.416	-2.103	0.035	*
SectorFood Products	-0.060	0.276	-0.216	0.829	
SectorGas Utilities	-2.103	0.589	-3.571	0.000	***
SectorHotels, Restaurants & Leisure	0.820	0.312	2.629	0.009	**
SectorHousehold Durables	0.830	0.368	2.254	0.024	*
SectorHousehold Products	0.054	0.431	0.124	0.901	
SectorChemicals	-0.110	0.273	-0.404	0.687	
SectorIndependent Power and Renewable Electricity Producers	0.85099	0.559	1.523	0.128	
SectorIndustrial Conglomerates	0.155	0.420	0.369	0.712	
SectorInteractive Media & Services	0.087	0.578	0.150	0.881	
SectorInternet & Direct Marketing Retail	-0.414	0.363	-1.139	0.255	
SectorLeisure Products	0.725	0.663	1.094	0.274	
SectorLife Sciences Tools & Services	-0.501	0.521	-0.962	0.336	
SectorMachinery	-0.162	0.285	-0.570	0.569	
SectorMedia	0.688	0.302	2.281	0.023	*
SectorMetals & Mining	0.857	0.413	2.075	0.038	*
SectorMulti-Utilities	-0.526	0.301	-1.750	0.080	.

SectorMultiline Retail	0.379	0.374	1.013	0.311	
SectorOil, Gas & Consumable Fuels	0.239	0.252	0.947	0.344	
SectorPersonal Products	-0.291	0.902	-0.323	0.747	
SectorProfessional Services	0.829	0.400	2.074	0.038	*
SectorRoad & Rail	0.234	0.325	0.720	0.472	
SectorSemiconductors & Semiconductor Equipment	0.235	0.281	0.839	0.402	
SectorSpecialty Retail	0.679	0.299	2.272	0.023	*
SectorTextiles, Apparel & Luxury Goods	0.640	0.334	1.917	0.055	.
SectorTobacco	1.594	0.501	3.182	0.001	**
SectorWater Utilities	-1.489	0.653	-2.281	0.023	*
SectorWireless Telecommunication Services	1.924	0.699	2.752	0.006	**
log(Net_Sales)	-0.684	0.051	-13.39	< 0.005	***
Long-term Debt to Total Assets	9.106	1.399	6.510	0.000	***
Total Debt to Total Assets	-4.830	1.321	-3.655	0.000	***
Retained Earnings to Total Assets	-0.780	0.188	-4.138	0.000	***
EBIT to Total Assest	-10.896	0.884	-12.33	< 0.005	***
Shareholder´s Equity to Total Liabilities	-0.172	0.113	-1.527	0.127	
Sales to Total Assets	0.591	0.119	4.954	0.000	***
1|2	-16.355	1.140	-14.34	< 0.005	***
2|3	-13.732	0.942	-14.57	< 0.005	***
3|4	-11.543	0.909	-12.70	< 0.005	***
4|5	-9.160	0.883	-10.37	< 0.005	***
5|6	-7.414	0.877	-8.452	< 0.005	***
6|7	-6.208	0.894	-6.947	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.353
log Lik	-751
Residual Deviance:	1501.58
AIC:	1621.58
nobs:	946

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	14	22	0	0	0	0
A	0	0	156	112	0	0	0
BBB	0	0	65	389	21	1	1
BB	0	0	1	75	60	2	0
B	0	0	0	4	14	2	1
CCC	0	0	0	0	2	3	0

Table 32 - Regression results of Model III on U.S. data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorElectric Utilities	-0.506	0.298	-1.695	0.090	.
SectorGas Utilities	-2.191	0.630	-3.478	0.001	***
SectorHotels, Restaurants & Leisure	0.696	0.359	1.938	0.053	.
SectorInternet & Direct Marketing Retail	-0.459	0.382	-1.201	0.230	
SectorMulti-Utilities	-0.610	0.344	-1.775	0.076	.
SectorOil, Gas & Consumable Fuels	0.497	0.313	1.587	0.112	
SectorRoad & Rail	0.052	0.375	0.138	0.890	
SectorWater Utilities	-1.643	0.692	-2.374	0.018	*
log(Net_Sales)	-0.797	0.099	-8.043	0.000	***
Long-term Debt to Total Assets	9.807	4.927	1.990	0.047	*
Total Debt to Total Assets	-5.120	4.722	-1.084	0.278	
Retained Earnings to Total Assets	-0.442	0.427	-1.035	0.301	
EBIT to Total Assest	-9.409	1.697	-5.544	0.000	***
Shareholder´s Equity to Total Liabilities	-0.609	0.316	-1.928	0.054	.
Sales to Total Assets	0.733	0.197	3.722	0.000	***
1|2	-17.418	2.039	-8.542	< 0.000	***
2|3	-15.348	1.867	-8.219	< 0.000	***
3|4	-13.382	1.809	-7.399	0.000	***
4|5	-10.768	1.759	-6.123	0.000	***
5|6	-9.155	1.726	-5.304	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘’ 1

(McFadden) Pseudo R2	0.342
log Lik	-222
Residual Deviance:	444.11
AIC:	484.11
nobs:	292

	Prediction					
Truth	AAA	AA	A	BBB	BB	B
AAA	0	1	0	0	0	0
AA	0	2	9	0	0	0
A	0	2	34	37	0	0
BBB	0	0	20	138	7	1
BB	0	0	0	18	15	0
B	0	0	0	1	4	3

Table 33 - Regression results of Model IV on U.S. data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-1E+00	5E-01	-2.1336*	3E-02	*
SectorAirlines	2E+00	3E-01	6.0873***	1E-09	***
SectorAuto Components	6E-01	6E-01	1.0203	3E-01	
SectorAutomobiles	3E+00	5E-01	6.8282***	9E-12	***
SectorBeverages	-3E-01	4E-01	-0.8047	4E-01	
SectorBiotechnology	3E-01	4E-01	0.8639	4E-01	
SectorBuilding Products	2E-01	4E-01	0.5234	6E-01	
SectorCommercial Services & Supplies	-5E-01	4E-01	-1.2178	2E-01	
SectorCommunications Equipment	-4E-01	5E-01	-0.9209	4E-01	
SectorConstruction & Engineering	-2E+00	8E-01	-2.2523*	2E-02	*
SectorConstruction Materials	-1E-01	4E-01	-0.2614	8E-01	
SectorContainers & Packaging	1E-01	4E-01	0.2679	8E-01	
SectorDistributors	7E-01	6E-01	1.1502	3E-01	
SectorDiversified Telecommunication Services	8E-01	4E-01	1.8846.	6E-02	.
SectorElectric Utilities	-5E-01	3E-01	-1.7393.	8E-02	.
SectorElectrical Equipment	-8E-01	5E-01	-1.7344.	8E-02	.
SectorElectronic Equipment, Instruments & Components	2E-01	4E-01	0.5787	6E-01	
SectorEnergy Equipment & Services	2E-01	5E-01	0.5177	6E-01	
SectorEntertainment	9E-01	4E-01	2.393*	2E-02	*
SectorFood & Staples Retailing	-9E-01	4E-01	-2.0205*	4E-02	*
SectorFood Products	-1E-01	3E-01	-0.3897	7E-01	
SectorGas Utilities	-2E+00	6E-01	-3.7575***	2E-04	***
SectorHotels, Restaurants & Leisure	7E-01	3E-01	2.1165*	3E-02	*
SectorHousehold Durables	6E-01	4E-01	1.5754	1E-01	
SectorHousehold Products	-1E-01	5E-01	-0.3001	8E-01	
SectorChemicals	-1E-01	3E-01	-0.4489	7E-01	
SectorIndependent Power and Renewable Electricity Producers	8E-01	6E-01	1.3203	2E-01	
SectorIndustrial Conglomerates	-3E-02	4E-01	-0.0595	1E+00	
SectorInteractive Media & Services	1E-01	6E-01	0.2337	8E-01	
SectorInternet & Direct Marketing Retail	-5E-01	4E-01	-1.451	1E-01	
SectorLeisure Products	5E-01	7E-01	0.7636	4E-01	
SectorLife Sciences Tools & Services	-8E-01	5E-01	-1.4953	1E-01	
SectorMachinery	-3E-01	3E-01	-1.1641	2E-01	
SectorMedia	6E-01	3E-01	1.9692*	5E-02	*
SectorMetals & Mining	9E-01	4E-01	2.1483*	3E-02	*
SectorMulti-Utilities	-7E-01	3E-01	-2.2557*	2E-02	*
SectorMultiline Retail	3E-01	4E-01	0.8558	4E-01	
SectorOil, Gas & Consumable Fuels	1E-01	3E-01	0.5537	6E-01	
SectorPersonal Products	-3E-01	9E-01	-0.3575	7E-01	

SectorProfessional Services	7E-01	4E-01	1.5963	1E-01	
SectorRoad & Rail	8E-02	3E-01	0.2162	8E-01	
SectorSemiconductors & Semiconductor Equipment	2E-01	3E-01	0.5164	6E-01	
SectorSpecialty Retail	4E-01	3E-01	1.4302	2E-01	
SectorTextiles, Apparel & Luxury Goods	6E-01	3E-01	1.6733.	9E-02	.
SectorTobacco	2E+00	5E-01	3.2011**	1E-03	**
SectorWater Utilities	-2E+00	7E-01	-2.5777**	1E-02	**
SectorWireless Telecommunication Services	2E+00	7E-01	3.0815**	2E-03	**
Operating profit margin	-7E-01	5E-02	-13.806***	< 0.000	***
log(Net_Sales)	-9E-03	7E-03	-1.2583	2E-01	
ROE	-3E-02	3E-02	-0.8986	4E-01	
Coverage_ratio_EBIT	6E-04	9E-04	0.6276	5E-01	
Long-term Debt to Total Assets	9E+00	1E+00	6.5631***	5E-11	***
Total Debt to Total Assets	-5E+00	1E+00	-3.4713***	5E-04	***
Working Capital to Total Assets	-1E-01	5E-01	-0.3118	8E-01	
Retained Earnings to Total Assets	-8E-01	2E-01	-3.9314***	8E-05	***
EBIT to Total Assets	-1E+01	1E+00	-8.8073***	< 0.000	***
Shareholder´s Equity to Total Liabilities	-2E-01	1E-01	-1.5809	1E-01	
Total Sales to Total Assets	6E-01	1E-01	3.8789***	1E-04	***
Year_2019	-4E-01	2E-01	-2.4836*	1E-02	*
Year _2018	-6E-01	2E-01	-3.4841***	5E-04	***
Year _2017	-1E+00	2E-01	-5.6793***	1E-08	***
Year _2016	-9E-01	2E-01	-5.3927***	7E-08	***
Year _2015	-7E-01	2E-01	-3.9567***	8E-05	***
Year _2014	-5E-01	2E-01	-3.1611**	2E-03	**
Year _2013	-1E-01	2E-01	-0.5898	6E-01	
Year _2012	3E-01	3E-01	1.0557	3E-01	
Year _2011	-3E-02	2E-01	-0.1442	9E-01	
Year _2010	-8E-01	3E-01	-3.0282**	2E-03	**
1|2	-2E+01	1E+00	-15.001***	< 0.000	***
2|3	-2E+01	1E+00	-15.241***	< 0.000	***
3|4	-1E+01	1E+00	-13.471***	< 0.000	***
4|5	-1E+01	9E-01	-11.271***	< 0.000	***
5|6	-9E+00	9E-01	-9.394***	< 0.000	***
6|7	-8E+00	1E+00	-7.940***	2E-15	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’1

(McFadden) Pseudo R2	0.384
log Lik	-715.00
Residual Deviance:	1430.64
AIC:	1578.64
nobs:	946

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	14	22	0	0	0	0
A	0	1	163	104	0	0	0
BBB	0	0	60	394	21	2	0
BB	0	0	1	68	65	4	0
B	0	0	0	4	11	5	1
CCC	0	0	0	0	2	3	0

Table 34 – Regression results of Model V on U.S. data set

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorAir Freight & Logistics	-1.091	0.504	-2.1649*	0.030	*
SectorAirlines	2.142	0.338	6.3307***	0.000	***
SectorAuto Components	0.588	0.569	1.034	0.301	
SectorAutomobiles	3.107	0.452	6.8752***	0.000	***
SectorBeverages	-0.319	0.371	-0.8598	0.390	
SectorBiotechnology	0.241	0.357	0.6753	0.500	
SectorBuilding Products	0.206	0.373	0.5533	0.580	
SectorCommercial Services & Supplies	-0.469	0.400	-1.1749	0.240	
SectorCommunications Equipment	-0.509	0.469	-1.0858	0.278	
SectorConstruction & Engineering	-1.751	0.770	-2.2739*	0.023	*
SectorConstruction Materials	-0.071	0.411	-0.1741	0.862	
SectorContainers & Packaging	0.120	0.372	0.3218	0.748	
SectorDistributors	0.718	0.606	1.1851	0.236	
SectorDiversified Telecommunication Services	0.803	0.433	1.8555.	0.064	.
SectorElectric Utilities	-0.525	0.270	-1.945.	0.052	.
SectorElectrical Equipment	-0.807	0.467	-1.7266.	0.084	.
SectorElectronic Equipment, Instruments & Components	0.216	0.372	0.5795	0.562	
SectorEnergy Equipment & Services	0.233	0.478	0.4875	0.626	
SectorEntertainment	0.919	0.378	2.4305*	0.015	*
SectorFood & Staples Retailing	-0.955	0.421	-2.2681*	0.023	*
SectorFood Products	-0.100	0.280	-0.3567	0.721	
SectorGas Utilities	-2.296	0.608	-3.7739***	0.000	***
SectorHotels, Restaurants & Leisure	0.712	0.318	2.2417*	0.025	*
SectorHousehold Durables	0.584	0.379	1.5421	0.123	
SectorHousehold Products	-0.226	0.442	-0.5122	0.609	
SectorChemicals	-0.118	0.277	-0.4244	0.671	
SectorIndependent Power and Renewable Electricity Producers	0.7469381	0.570	1.3113	0.190	
SectorIndustrial Conglomerates	-0.060	0.429	-0.1396	0.889	

SectorInteractive Media & Services	0.145	0.587	0.2466	0.805	
SectorInternet & Direct Marketing Retail	-0.556	0.372	-1.4964	0.135	
SectorLeisure Products	0.487	0.675	0.7212	0.471	
SectorLife Sciences Tools & Services	-0.816	0.532	-1.5327	0.125	
SectorMachinery	-0.360	0.292	-1.2341	0.217	
SectorMedia	0.578	0.307	1.8802.	0.060	.
SectorMetals & Mining	0.869	0.421	2.0633*	0.039	*
SectorMulti-Utilities	-0.709	0.306	-2.3138*	0.021	*
SectorMultiline Retail	0.331	0.381	0.8688	0.385	
SectorOil, Gas & Consumable Fuels	0.111	0.256	0.4329	0.665	
SectorPersonal Products	-0.345	0.922	-0.3747	0.708	
SectorProfessional Services	0.630	0.404	1.5578	0.119	
SectorRoad & Rail	0.002	0.335	0.0057	0.995	
SectorSemiconductors & Semiconductor Equipment	0.117	0.287	0.4074	0.684	
SectorSpecialty Retail	0.489	0.306	1.5999	0.110	
SectorTextiles, Apparel & Luxury Goods	0.559	0.342	1.6341	0.102	
SectorTobacco	1.560	0.512	3.0453**	0.002	**
SectorWater Utilities	-1.878	0.675	-2.7837**	0.005	**
SectorWireless Telecommunication Services	2.259	0.713	3.1658**	0.002	**
log(Net_Sales)	-0.736	0.053	-13.854***	< 0.000	***
Long-term Debt to Total Assets	9.397	1.430	6.5723***	0.000	***
Total Debt to Total Assets	-4.725	1.346	-3.5114***	0.000	***
Retained Earnings to Total Assets	-0.730	0.193	-3.7814***	0.000	***
EBIT to Total Assest	-11.416	0.908	-12.571***	< 0.000	***
Shareholder´s Equity to Total Liabilities	-0.200	0.116	-1.721.	0.085	.
Sales to Total Assets	0.632	0.123	5.1489***	0.000	***
Year_2019	-0.418	0.166	-2.5206*	0.012	*
Year _2018	-0.612	0.171	-3.5862***	0.000	***
Year _2017	-0.962	0.168	-5.7254***	0.000	***
Year _2016	-0.868	0.162	-5.3575***	0.000	***
Year _2015	-0.699	0.174	-4.0073***	0.000	***
Year _2014	-0.538	0.168	-3.2148**	0.001	**
Year _2013	-0.126	0.207	-0.6115	0.541	
Year _2012	0.292	0.282	1.0371	0.300	
Year _2011	-0.038	0.236	-0.162	0.871	
Year _2010	-0.741	0.251	-2.951**	0.003	**
1|2	-17.962	1.201	-14.959***	< 0.000	***
2|3	-15.283	1.001	-15.264***	< 0.000	***
3|4	-12.955	0.961	-13.481***	< 0.000	***
4|5	-10.456	0.930	-11.241***	< 0.000	***
5|6	-8.607	0.922	-9.3325***	< 0.000	***
6|7	-7.347	0.936	-7.8518***	0.000	***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’1

(McFadden) Pseudo R2	0.383
log Lik	-717.00
Residual Deviance:	1433.41
AIC:	1573.41
nobs:	946

	Prediction						
Truth	AAA	AA	A	BBB	BB	B	CCC
AAA	0	1	0	0	0	0	0
AA	0	14	22	0	0	0	0
A	0	2	161	105	0	0	0
BBB	0	0	64	388	23	2	0
BB	0	0	1	69	65	3	0
B	0	0	0	4	11	5	1
CCC	0	0	0	0	2	3	0

Table 35 - Regression results of Model VI on U.S. dataset

	Estimate	Std. Error	z value	Pr(>|z|)	
SectorElectric Utilities	-0.639	0.312	-2.0501*	0.040	*
SectorGas Utilities	-2.530	0.674	-3.7513***	0.000	***
SectorHotels, Restaurants & Leisure	0.558	0.376	1.4855	0.137	
SectorInternet & Direct Marketing Retail	-0.579	0.399	-1.4492	0.147	
SectorMulti-Utilities	-0.804	0.361	-2.2275*	0.026	*
SectorOil, Gas & Consumable Fuels	0.324	0.329	0.9844	0.325	
SectorRoad & Rail	-0.301	0.399	-0.7551	0.450	
SectorWater Utilities	-2.117	0.742	-2.8536**	0.004	**
log(Net_Sales)	-0.854	0.106	-8.0454***	0.000	***
Long-term Debt to Total Assets	10.518	5.227	2.0121*	0.044	*
Total Debt to Total Assets	-5.109	4.997	-1.0224	0.307	
Retained Earnings to Total Assets	-0.425	0.447	-0.9506	0.342	
EBIT to Total Assest	-10.782	1.866	-5.778***	0.000	***
Shareholder´s Equity to Total Liabilities	-0.467	0.334	-1.3967	0.163	
Sales to Total Assets	0.766	0.205	3.7417***	0.000	***
Year_2019	-0.677	0.310	-2.1841*	0.029	*
Year _2018	-0.888	0.306	-2.9057**	0.004	**
Year _2017	-0.997	0.296	-3.3686***	0.001	***
Year _2016	-1.012	0.304	-3.3276***	0.001	***
Year _2015	-0.813	0.301	-2.7025**	0.007	**
Year _2014	-0.508	0.296	-1.7183.	0.086	.
Year _2013	0.188	0.370	0.5083	0.611	
Year _2012	0.355	0.522	0.6807	0.496	
Year _2011	0.530	0.509	1.0399	0.298	
Year _2010	0.582	0.545	1.0677	0.286	
1|2	-19.130	2.221	-8.6129***	< 2.2e-16	***

2|3	-17.005	2.050	-8.2953***	< 2.2e-16	***
3|4	-14.892	1.979	-7.5246***	0.000	***
4|5	-11.961	1.915	-6.2456***	0.000	***
5|6	-10.136	1.878	-5.3976***	0.000	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(McFadden) Pseudo R2	0.39797
log Lik	-203.00
Residual Deviance:	406.28
AIC:	466.28
nobs:	292

	Prediction					
Truth	AAA	AA	A	BBB	BB	B
AAA	0	1	0	0	0	0
AA	0	3	8	0	0	0
A	0	0	42	31	0	0
BBB	0	0	17	141	7	1
BB	0	0	0	19	13	1
B	0	0	0	0	4	4

Appendix E

In the Appendix E we present the results of test of hypothesis H2 i.e. the transferability between U.S. and EU regions.

Table 36 - Confusion matrix of U.S. data on EU model

	Predition				
Truth	AA or above	A	BBB	BB	B or below
AAA	0	0	1	0	0
AA	0	9	17	8	0
A	2	64	137	43	1
BBB	0	118	253	67	1
BB	0	36	71	19	0
B	0	5	13	2	0
CCC	0	0	4	0	0

Table 37 - Confusion matrix of EU data on U.S. model

				Predition			
Truth	AAA	AA	A	BBB	BB	B	CCC
AA or above	0	1	6	4	0	0	0
A	1	3	63	84	17	2	0
BBB	2	12	83	155	37	4	0
BB	0	2	25	53	11	1	1
B or below	0	0	1	7	1	0	0

Appendix F

Appendix F shows the estimation of credit rating of Czech bond issuers. We present results for both included regions EU and U.S.

Table 38 - Estimation of credit rating of Czech bond issuers using EU model

EU model	Estimation without time			Estimation with time		
	Model I	Model II	Model III	Model IV	Model V	Model VI
CSG VAR/21	AA or above	AA or above	A	A	A	BBB
CSG VAR/24	AA or above	AA or above	A	A	A	BBB
NET4GAS 2,75/25	A	A	BBB	A	BBB	BBB
NET4GAS 2,745/31	A	A	BBB	A	BBB	BBB
NET4GAS VAR/28	A	A	BBB	A	BBB	BBB
Č.ZBROJOVKA VAR/22	A	A	AA or above	A	A	A
MND VAR/22	AA or above	AA or above	A	AA or above	A	BBB
SMVAK OVA 2,625/22	A	A	A	A	A	BBB
ČEPS 0,25/21	A	A	A	A	A	BBB
EN.-PRO GF 6,50/23	A	A	A	A	A	BBB
TEPL. OTR. VAR/23	A	A	BBB	A	A	BBB
LIB. O. M. 5,30/23	A	AA or above	A	A	A	BBB
PHOTON EN. 6,00/23	AA or above	AA or above	A	AA or above	AA or above	BBB
ČD CARGO 1,26/23	A	A	BBB	A	A	BBB
ČD CARGO 2,55/25	A	A	BBB	A	A	BBB
AQUAPALACE VAR/34	A	A	AA or above	A	A	BBB
EPH 4,50/25	A	A	BBB	A	A	BBB
EPH VAR/22	A	A	BBB	A	A	BBB
REGIOJET F. VAR/24	A	A	BBB	A	A	BBB
EUC VAR/22	A	A	BBB	A	A	BB
MAT.&TECH. 5,20/24	A	A	A	A	A	BBB
TMR F. CR 4,50/22	BBB	BBB	BBB	BBB	BBB	BBB
HEUREKA 5,25/25	BBB	BBB	BB	BBB	BBB	B or below
FIDUR.NMV. 5,60/24	AA or above	A	BBB	A	A	BBB
SAZKA GR. 5,20/24	BB	A	A	BB	A	BBB

Table 39 - Estimation of Credit rating of Czech bond issuers using U.S. model

US model	Estimation without time			Estimation with time		
	Model I	Model II	Model III	Model IV	Model V	Model VI
CSG VAR/21	CCC	CCC	CCC	CCC	CCC	B or below
CSG VAR/24	CCC	CCC	CCC	CCC	CCC	B or below
NET4GAS 2,75/25	CCC	CCC	CCC	CCC	CCC	B or below
NET4GAS 2,745/31	CCC	CCC	CCC	CCC	CCC	B or below
NET4GAS VAR/28	CCC	CCC	CCC	CCC	CCC	B or below
Č.ZBROJOVKA VAR/22	CCC	CCC	CCC	CCC	CCC	B or below

MND VAR/22	CCC	CCC	CCC	CCC	CCC	B or below
SMVAK OVA 2,625/22	CCC	CCC	CCC	CCC	CCC	B or below
ČEPS 0,25/21	CCC	CCC	CCC	CCC	CCC	B or below
EN.-PRO GF 6,50/23	CCC	CCC	CCC	CCC	CCC	B or below
TEPL. OTR. VAR/23	CCC	CCC	CCC	CCC	CCC	B or below
LIB. O. M. 5,30/23	CCC	CCC	CCC	CCC	CCC	B or below
PHOTON EN. 6,00/23	CCC	CCC	CCC	CCC	CCC	B or below
ČD CARGO 1,26/23	CCC	CCC	CCC	CCC	CCC	B or below
ČD CARGO 2,55/25	CCC	CCC	CCC	CCC	CCC	B or below
AQUAPALACE VAR/34	CCC	CCC	CCC	CCC	CCC	B or below
EPH 4,50/25	CCC	CCC	CCC	CCC	CCC	B or below
EPH VAR/22	CCC	CCC	CCC	CCC	CCC	B or below
REGIOJET F. VAR/24	CCC	CCC	CCC	CCC	CCC	B or below
EUC VAR/22	CCC	CCC	CCC	CCC	CCC	B or below
MAT.&TECH. 5,20/24	CCC	CCC	CCC	CCC	CCC	B or below
TMR F. CR 4,50/22	CCC	CCC	CCC	CCC	CCC	B or below
HEUREKA 5,25/25	CCC	CCC	CCC	CCC	CCC	B or below
FIDUR.NMV. 5,60/24	CCC	CCC	CCC	CCC	CCC	B or below
SAZKA GR. 5,20/24	CCC	CCC	CCC	CCC	CCC	B or below

Appendix G

Appendix G summarizes regression results of bonds with fix coupon and variable coupon.

Table 40 - Regression results of bonds with fix. coupon (Credit spread)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.97%	1.33E-03	37.244	< 2e-16	***
CR_BBB	-0.89%	1.07E-03	-8.327	2.17E-13	***
CR_BB	1.49%	1.57E-03	9.539	3.56E-16	***
Liquidity	-0.03%	2.13E-05	-12.686	< 2e-16	***
Size	0.00%	2.21E-13	4.936	2.78E-06	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.005203 on 113 degrees of freedom
Multiple R-squared: 0.6934, Adjusted R-squared: 0.6826
F-statistic: 63.9 on 4 and 113 DF, p-value: < 2.2e-16

Table 41 - Regression results of bonds with fix. coupon (YTM)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	5.83%	1.01E-03	57.72	< 2e-16	***
CR_BBB	-0.77%	8.13E-04	-9.423	6.59E-16	***
CR_BB	0.82%	1.19E-03	6.943	2.58E-10	***
Liquidity	-0.02%	1.62E-05	-10.587	< 2e-16	***
Size	0.00%	1.67E-13	1.561	0.121	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.003941 on 113 degrees of freedom
Multiple R-squared: 0.6593,
Adjusted R-squared: 0.6473
F-statistic: 54.67 on 4 and 113 DF, p-value: < 2.2e-16

Table 42 - Regression results of bonds with variable coupon (Credit spread)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	2.98%	1.49E-02	2.003	0.092	.
CR_A	2.40%	1.63E-02	1.469	0.192	
CR_BBB	2.28%	1.55E-02	1.471	0.192	
Size	0.00%	6.16E-12	-1.58	0.165	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01755 on 6 degrees of freedom
Multiple R-squared: 0.3997,
Adjusted R-squared: 0.09959
F-statistic: 1.332 on 3 and 6 DF, p-value: 0.349

Table 43 - Regression results of bonds with variable coupon (YTM)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	4.95%	1.47E-02	3.366	0.0151	*
CR_A	2.36%	1.62E-02	1.462	0.194	
CR_BBB	2.18%	1.54E-02	1.421	0.2052	
Size	0.00%	6.10E-12	-1.86	0.1122	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.01736 on 6 degrees of freedom
Multiple R-squared: 0.4415,
Adjusted R-squared: 0.1622
F-statistic: 1.581 on 3 and 6 DF, p-value: 0.2893

Table 44 - Regression results of bonds with variable coupon (Credit margin)

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	1.81%	7.17E-03	2.526	0.0449	*
CR_A	1.91%	7.88E-03	2.428	0.0513	.
CR_BBB	1.49%	7.49E-03	1.985	0.0944	.
Size	0.00%	2.97E-12	-1.487	0.1875	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.008469 on 6 degrees of freedom
Multiple R-squared: 0.5387,
Adjusted R-squared: 0.3081
F-statistic: 2.336 on 3 and 6 DF, p-value: 0.1733