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CREDIT RATINGS: A NEW OBJECTIVE METHOD USING THE RASCH MODEL: THE CASE OF CONSUMER DISCRETIONARY

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The purpose of this paper is to understand if the Rasch model can be applied to mimic the credit ratings and can help to develop a simple and objective way to evaluate the creditworthiness of companies and their financial obligations. The research is based on existing data selected with the support of several researches underlined in the paper, but applying the Rasch model to this data has never been done yet in this field. The credit ratings grades for the consumer discretionary, sector of the S&P were estimated using the Rasch model for period from 2004 to 2014. The paper shows that the Rasch model can be applied to estimate a company's credit rating. The model was successfully applied to the Consumer Discretionary sector, where the measures estimated correlate with those of the Bloomberg default risk. Moreover we found that the credit ratings measured by Rasch model are statistically significant in predicting the sign of the stock return, once other rating information, such as Bloomberg default risk, has been taken in account. This paper offers a new approach to credit rating that should be further explored in future researches.

Keywords: Rasch model, Credit ratings, Credit rating agencies, Risk of default, S&P 500.

Aim of the Study

The goal of this paper is to understand if the Rasch model, a measurement tool widely used in psychology and education (Rasch, 1960; Andrich, 1978), can be applied to credit rating. And help to develop a rather simple and objective way to evaluate the creditworthiness of companies and their financial obligations, to be used to anticipate and in addition to what credit rating agencies (CRAs) will publish. The idea is to validate these new credit rating measures by three steps:

a) evaluating the goodness of fit of the data to the model,
b) comparing results obtained by applying this model with those calculated by CRAs and
c) looking if the former may have additional explanatory power of financial phenomena, such as the stock return, once we have taken account of the latter.

The study will be developed as follow: understand which are the main variables used by credit rating agencies to conduct credit rating and what their methodology is. Collect historical data for the S&P 500 companies of the Consumer Discretionary sector, on which the analysis will be conducted over the period

2004-2014. Choose the appropriate variables to undertake the research, and apply the Rasch model to the data collected to obtain credit rating. Understand if the results obtained are in line with the grade given by credit agencies throughout the years, and what is their additional explanatory power.

Introduction and Motivation

A credit rating is defined as "an assessment of an entity's ability to pay its financial obligations" (U.S. Securities and Exchange Commission, 2017). The entity under assessment is called "issuer" or "obligor" and it includes several bodies such as corporations, financial institutions and insurance companies. The rating is determined by a credit rating agency, upon which investors rely in order to understand the creditworthiness of the entity of their interest. A credit rating agency is defined by the Credit Rating Agency Reform Act 2006 (U.S. Government, 2006, page 2) as "any person that:

- Engaged in the business of issuing credit ratings on the Internet or through another readily accessible means, for free or for a reasonable fee, but does not include a commercial credit reporting company;
- Employing either a quantitative or qualitative model, or both, to determine credit ratings; and
- Receiving fees from either issuers, investors, or other market participants, or a combination thereof".

The credit rating agencies (CRAs) usually use different analytical models, expectations and assumptions in their methodologies, which means that their ratings are inherently subjective and include an element of judgement. The final rating provided is usually in a form of an alphabetic and numerical scale, which can vary among different credit rating agencies. Usually, a higher value will correspond a lower risk to default. The credit ratings market is characterized by high entry barriers and it is dominated by three main agencies: Moody's, Standard & Poor's and Fitch ratings, whose ratings are absolutely needed by entities in order to be credible in the eye of investors and other bodies that are interested in their creditworthiness (The Guardian, 2012). In addition, these three agencies are also part of the "NRSROs", the Nationally Recognised Statistical Rating Organizations, which encompass the agencies recognised and permitted by the U.S. Security exchange commission. Even if the term (NRSROs) was first introduced by the U.S Commission for a regulatory purpose, nowadays their ratings became "widely used as benchmarks in federal and state legislation, rules issued by financial and other regulators, foreign regulatory schemes, and private financial contracts" (U.S. Securities and Exchange Commission, 2003). Therefore, being a member of the NRSROs lists has become a necessity for an agency in order to be considered credible and reliable.

The importance of credit ratings stands in the fact that any lender needs to understand if their actual or potential borrowers will be able to repay their debt. Therefore, credit rating agencies, with their options, help to fill this potential asymmetry of information by giving opinion about the credit quality of fixed income securities issued by corporations, governments or mortgages (White, 2010). It has now been more than a century that credit rating agencies have been expressing their judgements and since then their opinions have acquired more and more importance and influence in the market due to several reasons:

- the increase in the number of issuers in the market,
- the introduction of more complex financial products such as asset-backed securities and credit derivatives,
- the globalisation of the financial market world has led to the expansion of credit rating abroad (U.S. Securities and Exchange Commission, 2003),
- The increasing use of credit ratings in financial regulation and contracting (Galil, 2003).

However, credit rating agencies have made several mistakes in the past that have given rise to doubts about their independence and credibility. For instance, during the financial crisis the main credit rating agencies were too slow to downgrade the toxic mortgages-based debt, rated as AAA instead of "junk".

Indeed, one of the reasons why the crisis spread was because CRAs failed to warn bankers, fund managers about the risk involved in backing those mortgages (The Guardian, 2012). The same case was for the Enron scandal in 2001, where the agencies confirmed it as a safe investment until few days before it declared bankruptcy (The Guardian, 2012). Following all these events, CRAs have been questioned on the quality of their opinions and whether they should be more transparent in the processes adopted (U.S. Securities and Exchange Commission, 2003). Particularly, after all these scandals, the CRAs market has become more and more regulated, for instance with the introduction of the "Credit ratings Agency reform act 2006" which aims to protect investors and enhance the quality of the ratings by promoting transparency, accountability and competition. Moreover, the fact that CRAs are financed by the companies they actually need to rate, leads to legitimate concerns about the possibility of conflict of interests and independence.

Therefore, this paper addresses those issues illustrated and tries to solve them. The goal is to create a tool able to predict the outcome of the rating agencies which is objective and independent, and that would therefore help to avoid the concerns cited above. From an academic point of view, this project is innovative as it aims to apply a model which is, at this stage, barely used in the field of finance. The methodology used to this end is that of Rasch models (Rasch, 1960) which have the property of producing interval scale, objective measures of the traits of persons (companies), from ordinal observations (the data used to this end). "Objective measurement is the repetition of a unit amount that maintains its size, within an allowable range of error, no matter which instrument, intended to measure the variable of interest, is used and no matter who or what relevant person or thing is measured" (http://www.rasch.org/define.htm). The Rasch models satisfy such definition thanks to their Specific Objectivity property according to which "comparisons between individuals become independent of which particular instruments -- tests or items or other stimuli -- have been used. Symmetrically, it ought to be possible to compare stimuli belonging to the same class -- measuring the same thing -- independent of which particular individuals, within a class considered, were instrumental for comparison" (Rasch, 1977). Other methods such as Classical Test Theory, Factor Analysis and IRT models do not satisfy these fundamental objectivity criteria.

In the next paragraphs, we are going to explore the relevant literature in support of this paper. In particular, we will investigate the methodology adopted by the credit rating agencies, research conducted in support of the topic and finally studies, which have successfully applied the Rasch model.

Credit Rating Methodology

An initial fundamental research for the scope of this paper is to gain an understanding of the methodology used by CRAs when assessing corporate credit ratings. As the methodologies among the three main credit agencies are very similar, for simplicity, we will mainly focus on the methodology adopted by Standard's and Poor. The corporate credit rating methodology of S&P is based on a common analysis and framework formed by several steps. The graphic below (Fig. 1) summarizes the process for issuing a rating. Once an issuer requests a rating, S&P will create a special committee, which will first assess the company's business risk profile followed by an evaluation of the financial risk profile. The business risk profile is determined by evaluating the risks and the opportunities of a company, its industry with its risks and the country risk, which depends on the different countries in which a company has its functions. Specifically, the industry risk will look at market composition, the competition within the market and the barriers to enter the market and will benchmark the companies against these criteria. The country risk will depend on the weighted average of the presence of the company in the different countries. The business profile is determined based on both qualitative and quantitative information. Qualitative factors are for instance the competitive advantages and disadvantages that a company possess in a particular market. Quantitative information comprise factors like revenue, level of profitability or also volatility of the industry. On the other hand, the financial profile is considered the result of the management decisions. This includes all the action undertaken by management in order to finance the company's operations, the strategy adopted, the composition of its statement of financial position and the relation between the company cash flows and the company leverage. The financial risk profile is mainly based on quantitative information. Particularly, for the cash flow/leverage assessment, Standard and Poor focuses primarily on two core ratio which are “Fund from operation to debt” and “debt to EBITDA (Earnings Before Interest, Taxes, Depreciation and Amortization)”. In addition to this, further supplementary ratios are considered in the analysis, which usually are “cash flows from operation to debt”, “free operating cash flows to debt”, “discretionary cash flows to debt” and “EBITDA to interest”. Finally, these two assessments are put together, and then used to determine the issuer anchor. Usually, for an investment grade rating (BBB or higher) the analysis will weigh more the business profile, while for a speculative grade anchor (below BBB), the financial profile will have more importance. After determining the anchor there might be further elements that could modify the rating. These comprise the company diversification portfolio, the capital structure, the financial policy, liquidity and governance. After this step the rating will be decided.

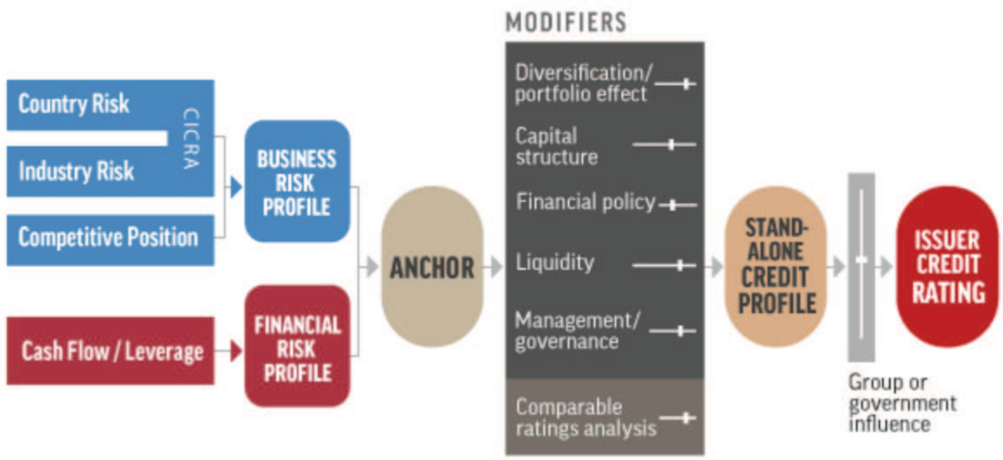


Figure 1. Standard & Poor’s ratings issue process

The rating can be re-considered in case the issuer communicate additional significant information. The rating is then published, unless there are some conditions which require the rating to remain confidential. Standard & Poor’s and Fitch Rating have a scaling methods composed by 10 rating categories that goes from AAA to D, Moody’s uses instead 9 categories from Aaa to C. Bonds with a rating lower than BBB or Baa are called “junk bonds” or “speculative bonds”, while bonds with a rating of BBB or above are “investment grade bonds”. “An investment grade rating is important for certain borrowers to ensure full market access (as some investors are prohibited from investing in sub-investment grade debt), achieving flexible/attractive covenants and terms on debt issues, and in some cases for the prestige value in front of competitors, customers and suppliers. Non-investment grade debt issues tend to require greater operating and financial restrictions and inevitably attract higher pricing”. Credit rating agencies has the opportunity to have access to non-public information when conducting their analysis. However, for big corporation which are required by law to make extended disclosures, the determination of the rating will be mainly based on public available information. Therefore, we can conclude that even if the asymmetry of the information will be obviously an obstacle to the study, the fact that the study will be conducted on large corporation will lighten this limitation.

Credit rating and CRAs activities have been at the center of several academic studies for many years. In the literature, we can observe several models that have tried to predict the bankruptcy risk or mimic the methodology used by the CRAs. These models are mainly based on financial ratios analysis and statistical approaches. One of the most famous model in the literature is the one created by Altman (2000), who developed the so-called "Altman Z-score" model, which aims to predict the risk of bankruptcy based on a 5 accounting ratios and a multiple Discriminant analysis. The analysis took into consideration 22 accounting ratios but 5 in particular among those selected were the most significant in the forecast of corporate bankruptcy. These are: Working capital/total assets, Retained asset/total assets, EBIT /total assets, Market value of equity/ book value of total liabilities, Sales/total asset. This model was very successful as it could predict corporate bankruptcy in the 95% of the cases in the year before bankruptcy. Another important research is the one conducted by Beaver in 1966. Beaver tried to predict the failure of a company, again using accounting ratio analysis. His results showed that cashflow to total debt ratio constitutes an excellent tool to predict corporate bankruptcy up to 5 years prior the failure, while it found that the "predictive power of liquid assets ratios is much weaker". Also Doumpos et al. (2015) tried to forecast the credit rating of European companies using a financial and market data and a cross-country panel data set. In their research they discovered that market capitalization, together with accounting ratios, such as return on asset and interest coverage, has a strong correlation with rating. This has been also confirmed by Hwang (2010) and Agarwal and Taffler (2008). Ohlson (1980) used a logit maximum likelihood method to predict corporate failure using financial ratios. He created 3 models from 9 explanatory variables and he identified 4 major significant factors that affect the possibility of bankruptcy:

1. the size of the company
2. a measure of the financial structure
3. a measure of performance
4. a measure of financial liquidity

These studies revealed to be very effective as they were able to predict corporate failure in more than 90% of the cases. In 2004, Cheng-Ying Wu created a model to predict the bankruptcy of public companies in Taiwan using a combination of financial and non-financial information. The non-financial variables selected were the Board Holding ratio, which showed the ownership structure of the companies, the change in external auditors and the stock price trend, which reflect the company's performance. Cheng Ying constructed a model using these three variables and financial ratios (return on asset, current ratio, long-term capital ratio to fixed asset, Total asset Turnover and Cash reinvestment ratio). He proved that when the non-financial variables were included in the model, the accuracy of the prediction one year prior the failure improved from 79% to 87.10%. Galil (2003) analyzed the methodology of Standard & Poor by using a sample of the S&P 500 corporate ratings and showed how the quality of those ratings can be improved. Again, Kisgen (2006) has investigated how credit ratings affect capital structure decisions. In his research it was found that firms, which are going through a credit rating change, issue less debt relative to equity compared to firms that are not close to a change. Cardoso et al. (2013) offer an additional research. They proposed a model based on financial statement data, which aimed to mimic corporate credit rating for 1400 firms. The study "was able to predict ratings within 3 notches of accuracy for about 90% of the cases". The model was based on 6 financial ratios: Net debt/EBITDA, Interest coverage, ROA, Liabilities/total asset, utilities dummies and size which was measured as ln of total assets. Lee has conducted a more recent investigation in 2007. Lee has tried to predict corporate credit rating by applying a support vector machine model, which is a new learning machine technique, and he compared his results with the most traditional existing methods. In this study he showed that the support vector machine model outperform the other methods. Kamstra et al. (2001) proposed an ordered logit regression combining method to forecast bond rating, using 6 explanatory variables: interest coverage, debt ratio, ROA, total assets and subordination debt status. Figlewski et al. (2011) investigated the effects of macroeconomics factors on firms' credit ratings. They applied a cox model on corporate issuer between 1981 and 2002 and they concluded that by applying macroeconomics variables in the model increased the overall significance of the results. Beaver et al. (2005) conducted a study to test if the ability of financial ratio to predict bankruptcy changed among the years. In this study they demonstrated that when financial ratio are combined with market related variables, the decrease in the prediction ability of financial ratios is offset. The same is valid when the financial information are combined with non-financial statement information. On the same idea, Shumway (1999) developed a hazard model to predict bankruptcy using a model that combined both accounting and market-driven variables as he claimed that a combination of these factors would have given a more accurate result compared to previous studies. Shumway proved that using three market driven variables (firm market size, past stock return and standard deviation of stock return) combined with 2 accounting ratios, the model was given very accurate results.

This research will analyze as well the importance of corporate governance for a company rating. Indeed several researches have demonstrated that a good corporate governance will result in a company having a higher credit rating. In order to understand how corporate governance will influence a firm rating we shall look first at the study conducted by Jensen and Meckling (1976) which is at the basis of the agency theory framework. According to their studies, bondholders faces two different agency conflicts, which can increase the probability that the company will not repay their debt. The first is the conflict between the management and the external shareholders. Indeed the separation of ownership from control rises a problem of information asymmetry which can result in managers prioritizing their short term interests at the expenses of the benefits of shareholders, which will therefore expect lower future cash flows. Therefore is a "firm's expect cash flows decline, the default risk of bondholders increases leading to lower credit ratings" . The second agency conflict is the conflict between bondholders and shareholders. In companies with debt, shareholders could undertake decisions that could benefits their interest and resulting in a transfer of wealth from the bondholders to the shareholders. This can impact the future cash flows of a company increasing bondholders default risk. For instance, shareholders could encourage managers in investing in riskier projects, which could affect the volatility of the firm's future cash flows, and therefore increasing the default risk of shareholders. Skaife et al. (2006) have conducted a study in which they demonstrated a strong relationship between credit ratings and corporate governance variables. They based their analysis on a framework developed by Standard & Poor in 2002 in order to determine companies 'corporate governance structure. This framework is based on 4 main categories: "Ownership structure and influence", "Financial stakeholders rights and relationship", "Financial transparency" and Board Structure and processes". In their research, they conclude that: "Credit ratings are negatively associated with the number of blockholders and CEO power, and positively related to takeover defences, accrual quality, earnings timeliness, board independence, board stock ownership, and board expertise". Aman and Nguyen (2013) have conducted similar research on corporate governance in Japanese firms. In their study they confirmed that the percentage of shares owned by institutional investors, the timeliness of financial reporting and abundance of information provided to investors positively impacts credit ratings, while managerial ownership will result in a lower rating. Sengupta (1998) proved that there is a positive relationship between the quality of corporate disclosure and the ratings of bonds. Indeed governance can influence the rating by indirectly reducing the information risk, which is the risk that managers failed to disclose information that would affect the default risk of the loan. Successively, Bhojaraj and Sengupta (2003) conducted a study aiming to analyze the effect of the role of institutional investors and outside directors on bonds rating. In their research they focused mainly on two dimensions: agency risk and information risk. They stated that a good corporate governance could positively influence these risks and therefore resulting in higher credit rating. The result of their research suggested that bond ratings of new issued debt are positively associated with the percentage of shares hold by institutional investors and the percentage of the board of directors made up of non-officers. They stated that a concentration of ownership is negatively related with bond rating. These results also concluded that a company subjected to higher external monitor over corporate governance would benefit of higher credit ratings.

The literature above has showed how financial ratio, or model combining both financial and non-financial information, have been successfully used to predict credit rating or the probability of default of a company. Additional studies have also demonstrated how corporate governance can influence the decision over a company credit rating. Given the relevance of these studies on the topic in question, we can choose some financial ratios belonging to different categories (e.g. profitability ratios, liquidity ratios, leverage ratios, solvency ratios) which are going to be likely to fit in our model. Particularly, we expect that leverage ratios will be negatively associated with the rating. Indeed, an increase in the level of debt would imply higher interest costs for a company and this could be a risk in the company especially when the company has no high liquidity. Moreover, an increase in leverage could also increase the risk that the company won't be able to repay its debt and therefore the risk of default would be higher. Profitability ratios can also be used to create an indicator of the rating of companies. For instance, a high return on asset is a sign that the company is generating cash, which is fundamental for the long-term activity of the company. Therefore, we expect that higher profitability will imply a higher credit rating. Finally, liquidity ratios will be selected, as they are another good prediction for the company default, especially in a short-term period. Particularly, looking at the bankruptcy regulation, a creditor can file a company for bankruptcy if the company fails to meet its financial obligations six months prior the filing date. Therefore, we would expect that companies with liquidity issues will have a higher risk to default and a lower credit rating. Looking instead at other variables, we would expect that good corporate governance will correspond to a higher rating. To conclude our hypothesis, as our analysis covers the period of the financial crisis, we would expect the estimated ratings to show a decrease in the period of the crisis. The variables selected will be discussed in more details later.

The Rasch Model in the Credit Rating Literature

Several studies can also be found on the Rasch model. The Rasch model is an objective measurement model, which has already been successfully applied to a wide range of disciplines, including health studies, education, psychology, marketing, economics and social sciences. For instance Pallant et al. (2007), have showed how the Rasch model can be used as a measure of psychological distress while Golia et al. (2011) have successfully applied the Rasch Model to assess the quality of work in the Italian social cooperatives. Similar studies have been conducted by Salini et al. (2003) to examine the quality of university teaching. Zheng (2013) used the Rasch model in order to develop a scale to measure individual financial risk tolerance. However, the application of the Rasch model to finance is still at its beginning. Indeed the only Rasch analysis in finance is given by Ridzak (2011), which ranks banks by their strictness in classifying risk and by Schellhorn et al. (2013) which have applied the Rasch model to rank firm based on managerial abilities. Schellhorn et al. (2013) applied the dichotomous Rasch model to 13 financial rations in order to measure the performance of the food and aerospace industry of the S&P. The ratios selected covered five areas of financial performance and are: Current ratio, Quick ratio, Sales divided by receivables, Gross margin, Net margin, Times-interest earned ratio, Equity ratio, Asset to debt ratio, ROE, Retained earnings/equity, Price to book ratio, Price earnings ratio. These financial ratios not only have been used in different studies to predict the corporate credit risks but they have been proved to be compatible with the dichotomous Rasch model and therefore they will be selected in this research. Another interesting research is the one proposed by Raileanu (2008), who encourages researchers to apply IRT measurement models, in order to measure the bankruptcy risk of companies. Indeed in this study Raileanu (2008) states that one of the main advantages of the IRT models compared to other statistical models (such as the Altman Z score model) is that "they calculate the Z score of bankruptcy risk, taking into account the measurement errors and the latent nature of bankruptcy." Lehmann (2004) used the Rasch model on German SME credit data in order to assess if it is possible to "improve the quality of subjective information in the credit rating system by considering information about rating patterns or strategies that it is contained in questionnaire data". This paper is therefore clearly based on an exploratory research as it aims to present a new and innovative way of credit rating. The research is based on existing data selected with the support of several researches underlined above but applying this data to the Rasch model has never been done yet in this field. The Rasch model, as seen before, has already been proven effective in different areas such as education or even management abilities of firm, but the application to finance is limited. This study will try to demonstrate that the Rasch model can be used successfully in this field as well.

Data

This paragraph will walk the reader through the method used in order to select the sample, the data and finally the limitations encountered in the collection of the data. In order to carry out our analysis, we have built a sample of 44 companies from S&P 500 belonging to the sector of Consumer Discretionary. In order to select the companies, the historical components of the S&P from 2004 to 2014 were downloaded from the Bloomberg terminal and only the companies included in the index for all the 11-years period were shortlisted. We chose a period of analysis of 11 years from 2004 to 2014 to be able to obtain significant results and also to cover the financial crisis during which the CRAs has been criticized to have wrongly evaluate the rating of several companies. Companies in the Consumer Discretionary sector manufacture goods or provide services that people want but don't necessarily need, such as high-definition televisions, new cars and family vacations. The main reasons to consider such sector are (Fidelity, 2016): performance is closely related to the health of the overall economy; tends to perform well at the beginning of a recovery, when interest rates are low, but can lag during economic slowdowns; offers potential exposure to growth in high-end, luxury brand. The main source used for the data collection is the Bloomberg terminal where we were able to download the necessary financial statements data and market data of all companies. When data were missing from the Bloomberg database or qualitative data were needed, we have researched the single companies 10-k using EDGAR on the US Security and exchange commission website (U.S. Security and Exchange Commission, 2016). Yahoo finance was also used in order to collect the stock prices for 2004 as several data were missing for this year in the Bloomberg database. We have collected 17 variables of which 13 are financial ratios while the remaining ones consists of market data and qualitative variables. The variables were collected according to the popularity in the literature and according to the resources available to the author for the extraction of the data. In order to have a complete dataset, variables from different categories have been selected. This can be summaries as follows.

Profitability - A higher profitability indicates that a company is able to generate cash, which is fundamental for the company long-term survival. Therefore, companies with higher profitability will expected to have a higher credit rating (Dumpos et al., 2015). In order to summarize profitability, the following variables have been selected:

	Variable	Calculation	Rationale
1	Return on Asset	Net income/ total assets	Return on asset measures the efficiency of a company in creating profit by using its assets. A high ROA will be associated with better performance as it means that a company is able to generate higher earnings with a lower level of investments.
2	Return on total asset	Earnings before interest and taxes/total asset	Return on total asset measures how productive the asset of a company is independently of any tax or interest payable. This ratio is expected to be relevant for this analysis as the existence of a company is based on its ability to generate positive earnings. In addition, "failure in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets with the value determined by the earning power of the assets" (Altman, 2000).
3	Capital turnover ratio	Total sales/ Total assets	This ratio is another profitability ratio which aims to measure the company ability of generating revenue from its assets. It is also a measure of the company ability in dealing with competition. We will expect that a higher capital turnover ratio will be associated to a better performance and therefore to a higher credit rating.
4	Inverse of Interest coverage (INT_COV_INV)	Interest expenses/ Earnings before interest and taxes	The interest coverage obligation measures the ability of a company to pay interest on its debt outstanding. The lower is the ratio the higher will be the probability of the default as higher will be the debt burden for the company. In our analysis we have computed the inverse of the interest coverage ratio in order to avoid the problem of a denominator equal to zero. Therefore, a lower coverage ratio will be a sign of a higher default risk.
5	Return on Equity (ROE)	Earnings before interest and taxes/ total equity	The return on equity is another profitability ratio which indicates the profit generated by the company compared to the money that the shareholders have invested. Therefore higher ROE is expected to result in a higher credit score.
6	Stock return	(Stock price P1 - Stock Price P0)/Stock price P0	The stock return is the gain or loss made on an investment on a particular stock over a period. In order to calculate the stock return we have downloaded from Bloomberg the stock prices of the companies selected at the closest day to 31 December and we have compared the price to the price stock in the previous year. The missing prices from the database were researched using Yahoo finance. The stock return is expected to be positively related to credit ratings.

Liquidity ratios - The aim of the liquidity ratio is to determine if a company has enough liquidity in order to cover its short-term obligations. This ratio will therefore be relevant in the determination of the rating at least in the short term as lack of liquidity is one of the main factors of default. The following variables have been selected:

	Variable	Calculation	Rationale
7	Current ratio	Current asset/Current Labilities	The current ratio is a liquidity ratio which measures the ability of a company to cover its short-term financial obligations. Higher ratio corresponds to higher liquidity and therefore it will be associated to greater credit score as the company will have enough liquidity to pay its short term debts.
8	Quick ratio	Current asset – inventories/Current liabilities	The quick ratio is as well a liquidity ratio to measure a company's ability to meet its short term obligation with its most liquid asset. This ratio is very similar to the current ratio but it doesn't take into the calculation the inventories.
9	Working capital to total asset	(Current asset-Current liabilities)/ total assets	This ratio aims to measure the ability of a company to meet its short-term financial obligations. The ratio has been taken into consideration as usually a company having consequently operating losses will have dwindling current assets compared to total assets.
10	Percentage of Free-float	Directly extracted from the Bloomberg terminal	The free float is defined as those shares that can be publicly traded by public investors without being locked by regulatory requirements like those shares held by institutional investors, controlling interest investors or government. This variables is a liquidity measures as a stock with a lower float will have lower liquidity. Therefore, we would expect this variable to be positively related with credit ratings.

Leverage - Increase in the level of debts increases the risk that the company will not be able to pay back its obligation. Moreover, higher level of debt will also increase the interest expenses of a company. Therefore, the following ratios have been considered of fundamental interest for the purpose of our analysis:

	Variable	Calculation	Rationale
11	Debt to equity ratio	Total liabilities/total assets	The debt to equity ratio is one of the most relevant ratio when analysing a company financial health and default risk. This ratio indicates the portion of debt of a company compared to its equity and therefore it indicates if a company is overly depending on debt to finance its operations. This ratio is also taken into consideration by lenders as if the debt is expected to increase compared to equity, lenders could be reluctant to further finance a company.
11	Capitalization ratio	Long term debt/(Long term debt+ Equity)	The capitalisation ratio is another leverage ratio which indicates the portion of long term debt of a company compared to its equity. As for the debt to equity ratio, a company with a higher capitalisation ratio will be considered to be riskier than those with lower leverage and therefore we will expect this variable to be negatively related to credit ratings.
13	Retained earnings to total assets	Retained earnings/Total asset	This ratio is one of the ratio used in the Altman Z-score model to predict bankruptcy. This ratio aims to explain the amount of reinvested earnings of a firm over its life. Therefore, this is a ratio which is expected to increase with the firm life. Moreover this ratio is also a measure of leverage as it indicates that a firm with high Retained earnings to total asset is able to finance its assets by using its profits and not by taking additional debt (Altman, 2000).

Solvency - These ratios has been selected as they underline the ability of a company to meet both its long term and short term financial liabilities.

	Variable	Calculation	Rationale
14	Solvency ratio	(Net Income + Amortization and depreciation)/ total liabilities	This is one of the main solvency ratio and it indicates if a company has enough cash flows in order to repay both its long-term and short-term debts. The lower this ratio is, the highest is the probability of default.
15	Market value of equity to total liabilities	Market value of equity/ Total liabilities	This ratio measures how much the asset of a company can decrease before the value of the liabilities is greater than the value of the assets and therefore when the company will become insolvent. The market value of equity was downloaded directly from the Bloomberg terminal and as in Altman Z score model is a proxy for the firms' asset values.

Corporate governance - As seen in the literature review, several studies have demonstrated that corporate governance influences credit ratings. Particularly, good corporate governance is positively related to credit scores (Aman and Nguyen, 2013). In order to include a corporate governance factor in our analysis, we have selected the variable "CEO power". The reason why only one corporate governance variable has been selected is the limited resources available.

#	Variable	Calculation	Rationale
16	CEO power	Dummy variable 0/1	This is a dummy variable which is a determinant of the corporate governance of a company. This variable assumes value 0 if the CEO is not as well the chairman of the board of directors, while it will have value equal to 1 in the opposite scenario. As we didn't have access to a corporate governance specialised database, in order to obtain this variable we had to research each company financial statement for the 11 year period. This variable will be expected to be negatively associated with the credit rating as if a CEO is also the chairman of a board it will "reduce the board's disciplining opportunistic management" (Skaife et al., 2006).

Bloomberg default risk - In order to assess the validity of the credit rating measures produced by the Rasch model, they need to be compared to results published by the credit ratings agencies. Due to the limitation of resources available, it was not possible to obtain the historical credit ratings of the major credit ratings agencies. The Bloomberg terminal provides the latest credit rating and the same is for the credit rating agencies website. Therefore, after considering these limitation, we have decided to use as a proxy of the credit rating scores: the Bloomberg default risk (DRSK), which is a credit scale created by Bloomberg in order to determine companies' default risk and the default probabilities. The Bloomberg scale is computed by using both market data and fundamental analysis and constitutes an independent judgement of the financial health of a company.

The Bloomberg default scale is composed of 3 categories:

1. IG, Investment grade group: which comprises the equities with highest rating. The investment grade category can assume values between 1 and 10 with 1 corresponding to the highest credit score.
2. HY, High Yield group: this group is the middle group with values ranging from 1 to 7.

3. Distressed group: this group comprises all the company with the lowest credit ratings. None of the companies selected in our sample have been rated as "distressed" (Bloomberg, 2015).

The other variable selected to assess the validity of the credit rating measures is the Stock return, already discussed above: in particular, we will analyze the relation between the sign of the stock return and the variations of the credit rating measures calculated by the Rasch model.

The main limitation encountered while collecting the data was the scarcity of resources. The Bloomberg terminal was an excellent tool in order to find market and financial ratios data. However, except for the CEO power, no other sources were identified in order to collect corporate governance variables, which would have provided a more complete analysis in order to determine how good a company's corporate governance is. Access to BoardEx database would have been a great tool to fill this gap. Unfortunately, the access to the database is limited and was not available to the authors. In addition, it was not possible to obtain the historical credit ratings of the main CRAs. Indeed, Bloomberg and the CRAs websites provide only the updated credit ratings for 2016, but not the historical data back to 2004. The same is for the CRAs websites, which offer only the last updated ratings. Finally, another limitation encountered is related to some data which were unavailable on the Bloomberg terminal. This was particularly the case for the data relating to 2004. We have tried to find the missing data in the companies' 10-ks in the Edgar database, by inspecting each financial statement one by one, but for some data like "market value of equity" this was not possible. Therefore we should consider in the analysis that some data was missing from the database. But this is not a problem for Rasch models.

Methods: the Rasch Models

The Rasch models are measurement models, which use dichotomous or ordinal data in order to construct a measure of the latent quantity of interest (credit rating) for the unity under observation (in this case companies). In order to apply the Rasch models, the variables, which are continuous, as the majority of the one chosen for the analysis, must be transformed to dichotomous or ordinal: but this point will be discussed later. The optimal property of Rasch models arises from the fact that they satisfy the fundamental measurement axioms, in particular "concatenation" (Campbell, 1920), as shown by Wright (1988), and "specific objectivity" (Rasch, 1960, 1977). This last property states that the comparison between two stimuli should be independent of which particular individuals were instrumental for the comparison; and it should also be independent of which other stimuli within the considered class were or might also have been compared. Symmetrically, a comparison between two individuals should be independent of which particular stimuli within the class considered were instrumental for the comparison; and it should also be independent of which other individuals were also compared, on the same or some other occasion. Given the optimal theoretical properties of the Rasch models the main problem in the analysis will be to actually understand how good the data fit the model. There are several Rasch models according to the nature of the variables. For two ordered categories the Dichotomous Rasch model is provided (Rasch, 1960), while for higher ordered categories the Rating Scale model (Andrich, 1978) and the Partial Credit model (Masters, 1982) can be used. Below is a summary of these models:

(1) Dichotomous Rasch model: $\left(\dfrac{P(X_{ij}=1)}{P(X_{ij}=0)} \right) = \alpha_i - \beta_j, X_{ij} \in \{0,1\}$,

where X_{ij} is the response of person I to item j, α_i is the ability" of the person (level of the latent trait), and β_j is the difficulty of the item (expressed on the same scale of the latent trait).

(2) Rating Scale model: $\ln \left(\dfrac{P(X_{ij}=k)}{P(X_{ij}=k-1)} \right) = \alpha_i - \beta_j - \tau_k, X_{ij} \in \{0,1,2,...K\}$,

where τ_k is a "threshold" that measures the difficulty to reach category k, identical for every item

(3) Partial Credit model: $\ln\left(\frac{P(X_{ij}=k)}{P(X_{ij}=k-1)}\right)=\alpha_i-\beta_j-\tau_{jk}, X_{ij}\in\{0,1,2,...K\}$

where τ_{jk} is a "threshold" that measures the difficulty to reach category *k* for the item *j*.

In the case under study, what can be assumed is that a latent variable exists such as "solidity in corporate governance", that can be related to some important aspects in determining the solvency of a company. Therefore, variables (Item) such as CEO power can be used to undertake the research and if the firm score 1 (yes) in such aspects that means that the firm has a higher level of "solidity in corporate governance". If instead the firm scores 0 in these aspects, it has a lower level of the latent variable of interest. In the final stage, all the responses of a person to each item will be summarized by a "measure" and the person with the highest measure is going to be the one deemed to show more of the variables assessed. Looking to the research objectives, the higher measure will be associated to higher credit rating. It has to be also underlined that the measures obtained with the Rasch models consider that during the process errors can be made, and therefore in the calculation of the measure this is taken into account by automatically calculating the standard deviation of these errors. Usually this standard deviation is not calculated in the traditional measurement methods, and this can create a distortion in the result obtained, especially if we use the constructed variable as explanatory in regression models. Therefore the Rasch model is of fundamental importance as it offsets the drawbacks of these traditional methods, and provides us a way to correct the bias that we may face when the estimate of the latent variable is used as an explanatory variable in regression models (Battauz et al., 2011).

The first step in applying the Rasch model will be to understand if the data is compatible with the model and satisfies its assumptions. First of all we will look at the correlation coefficient between the items observed and the estimated Rasch measure in order to assess how much the responses to the items are correlated to the results obtained. This first assessment will be generally very helpful also to check if there are some coding errors and to identify items with negative or zero correlation. Indeed this could be a sign that items do not agree with the latent variables and therefore the item will need to be removed from the analysis or their coding need to be reversed. In addition, when using Rating Scale model for continuous variables, another analysis to be performed will be to understand if the categories created assuming value 0,1,2,3 etc. have an actual meaning and therefore can be interpreted. This issue will appear immediately once the model has been applied and after obtaining the first observation as the results obtained will not be in a consequently order. The indicator used to understand if the measures obtained are ordered or disordered is the Andrich Threshold (Linacre 2001). In case the Andrich Threshold will be disordered, the solution is usually to reduce the number of categories put into place. Another important aspect of fit is possible violation of local independence hypothesis (Lord and Novick, 1968) and multidimensionality (Linacre. 2011). For what it concerns the first problem, using Winsteps (Linacre, 2016), one of the most famous software for Rasch Analysis (Bond & Fox, 2007), we may look at the correlation for the standardized residuals: if this is low (<0.70) we may conclude that the local independence hypothesis is not violated (http://www.winsteps.com/winman/table23_99.htm). Regarding the second problem, in a dataset, fitting the Rasch model, we have a variability that is due to the model and a residual variability due to randomness. Rasch "Principal Component Analysis (PCA) of residuals" looks for patterns in the part of the data due to randomness. This eventual pattern is the "unexpected" part of the data that may be due, among other reasons (Smith, 2002), to the presence of multiple dimensions in the data. In the Rasch PCA of residuals, we are looking for groups of items sharing the same patterns of unexpectedness. In particular, the matrix of item correlations based on residuals is decomposed to identify possible "contrasts" (the principal components) that may be affecting response patterns. Usually the contrast needs to have the strength (eigenvalue) of at least two items to be above the noise level: if the largest eigenvalue of PCA is around 2 or less the latent measure under investigation may be considered unidimensional (https://www.rasch.org/rmt/rmt191h.htm). Once these issue has been investigated and resolved, we can look at the a fit statistics which will give an estimation to which degree the persons (the companies) and items (the variables) are responding according to our expectations based on the model. This fit statistics will be therefore a summary of all the residuals (the difference between what is actually observed and what was expected) of each item for each person. In this paper, the fit statistics that we will use is the square mean deviation, which can assume values between zero and infinite. Values above 1 will indicate that there is a greater variation than the one expected while values less than 1 will indicate a lower variation than actually estimated. This fit statistics will be divided in two categories, weighted called INFIT and unweighted, called OUTFIT. Values around 1 can be deemed to be acceptable. For suggestions regarding good practice interval see Bond and Fox (2007, p. 243). The items and the person that do not fit will be removed from the model to increase the validity of the results obtained. In order to apply the Rasch models we will use a software called Winsteps (http://www.winsteps.com/index.htm).

Preliminary Analysis with the Rasch Models

In order to apply the Rasch models, the data must be transformed into an ordinal scale: this is done by using the percentiles. To this end, the main issue will be to determine how many categories need to be used. A solution is to perform empirical analysis starting from two categories and growing the number of categories until a satisfactory model is find. In this study, we have performed 9 different analysis using respectively 2 to10 percentile categories. We are going to synthesize the results obtained, starting from the two category model. The table 1 contains the label assigned to each variable in the analysis. As a first step, we have started dichotomizing the data into 0 = below median, 1= above median, and we have then applied a simple Rasch dichotomous model (1). Where β_n are the "ability" parameters that in this case may be interpreted as a sort of rating of the equity (company) *n* (it measures its goodness and therefore the higher the measure the better it will be). δ_i are the "difficulty" parameters that represent how difficult is to get a high value in the indicator *i*, which is represented by the variables selected. From the first run of the program, we obtained negative correlations between categories and measures for item 3, 9 and 10: this fact was expected, given the nature of the indicators. We then proceed to reverse the categories and rerun the program. **2.1**

The reliability indices obtained from the model was 0.96 for the items (the variables) and 0.76 for the persons (the equity), while the difficulties δ_i of the items ranged between -1.40 and 1.00. We can also notice that some items show a poor fit (represented by INFIT and OUTFIT measures) as the results lie outside the range of 0.5-1.7 suggested by the literature (Bond and Fox, 2007, p. 243). In addition, the PCA of standardized residuals revealed a level of 2.65 for the unexplained variance in the first contrast, which is a bit higher compared to the level 2 suggested for unidimensionality. However, after a closer inspection of the largest standardized residual correlation, we have noticed that this higher value of 2.65 is mainly due to two items with a correlation of 0.77, above the advice limit of 0.70, which implies a violation of Local Independence hypothesis of the Rasch Model.

Table 1. Label used for the analysis

Key	Variable name
01ROA_	Return on asset
02AROA	Altman Return on asset
03INCR	Interest Coverage reversed
04ROEC	Return on Equity
05SATA	Sales to Total Asset
06CURA	Current ratio
07QURA	Quick Ratio
08SORA	Solvency Ratio
09DERC	Debt equity ratio com
10CARA	Cap Ratio
11WCTA	Working cap to total asset
12RETT	Retained earn to total
13MVTL	Market value equity to tot liabilities

Table 2. Fit indices and difficulty measures for the dichotomous model

ITEM STATISTICS: MISFIT ORDER

ENTRY NUMBER	TOTAL SCORE	TOTAL COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD	PTMEASUR-AL CORR.	PTMEASUR-AL EXP.	EXACT MATCH OBS%	EXACT MATCH EXP%	ITEM
4	249	484	-.30	.12	1.39	6.1	1.69	7.3	A .51	.65	64.7	75.0	04ROEC
9	218	484	.17	.12	1.37	5.4	1.45	4.3	B .55	.67	62.9	76.1	09DERC
5	321	484	-1.37	.13	1.25	4.2	1.34	2.3	C .51	.60	69.3	75.3	05SATA
3	171	484	.94	.13	1.01	.2	1.18	1.3	D .67	.68	82.5	79.7	03INCR
10	188	484	.65	.13	1.16	2.3	1.14	1.2	E .63	.68	75.1	78.2	10CARA
11	214	484	.23	.12	1.13	2.1	1.11	1.1	e .63	.67	70.6	76.4	11WCTA
13	194	438	.14	.13	.71	-5.1	.56	-5.2	d .77	.67	85.4	75.8	13MVTL
2	257	484	-.42	.12	.66	-6.8	.55	-6.0	c .76	.65	85.5	74.8	02AROA
8	229	484	.00	.12	.63	-7.2	.55	-6.1	b .78	.66	89.6	75.4	08SORA
1	233	484	-.06	.12	.61	-7.6	0.50	-7.0	a .78	.66	89.1	75.4	01ROA_
MEAN	227.4	479.4	.00	.13	.99	-.6	1.02	-.7			77.5	76.2	
P.SD	40.3	13.8	.60	.00	.30	5.2	.43	4.7			9.6	1.5	

These are items, 6 and 11, respectively "Current ratio" and "Working capital/Total asset". In order to avoid this high correlation, we have omitted item 6 (Current ratio), and this reduced the unexplained variance to 2.3. We then excluded from the analysis the indicator with INFIT or OUTFIT indices outside the range 0.5-1.7. We ended up excluding from the analysis the indicators 6, 7 and 12. At this point, we rerun the program. The reliability of the items remained constant at 0.96 while the one of the equities is now 0.71. In addition, we have observed that the items difficulties range from -1.37 to 0.94 with acceptable fit indices (table 2). The unexplained variance in the first contrast was reduced to 2.23 but all the correlations between equities measures determined on the base of the tentatively different item clusters of items was 1, meaning that we are dealing with the same dimension. Therefore, we may say that this first run of the Rasch model was quite successful and we may go on to analyze data with a greater number of categories. In this second part of the analysis we have transformed the data in an ordinal scale with *m* levels using *m* classes defined by equally spaced percentiles and the Minimum and Maximum. The model applied was therefore the Rasch rating Scale model (2), where β_n are again the "ability" parameters, δ_i are the "average difficulty" parameters, while τ_k is the difficulty to reach the level (category) *k*. The model (3) did not improve the analysis with respect the main indicators of fit and therefore was not applied here.

In order to decide which number of categories was the most adequate, we need to consider three main indicators:

- The Reliability indices
- The fit of the model, determined by the measures of INFIT and OUTFIT
- The Andrich Thresholds: this is a parameter which shows if a Rasch rating is disordered.

We have summarized these three indicators in the following tables and figures. Figure 1 illustrates that with the increase of the number of categories, the person's reliability grows sensibly reaching levels of 0.90. The item reliability is constantly over 0.95. Also the Cronbach alpha and index of the goodness of the scale is always over 0.85. We can notice that the reliability remains constant after reaching 7 categories.

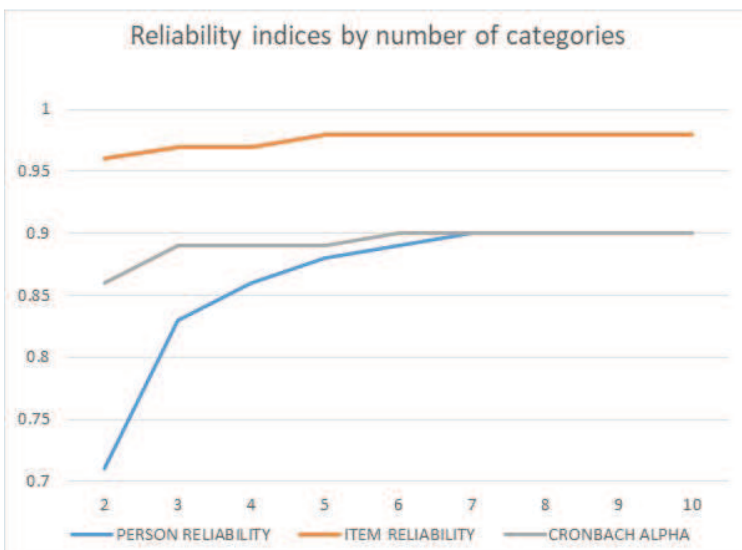


Figure 1. Reliability indices by number of categories of the variables used in the model

From Table 3 we can also see that INFIT and OUFIT indices lie between the limit of 0.5 and 1.7, with fit indices lower than 0.5 for some item. This is not such a big issue for the goodness of the scale as it would be in the opposite case (with INFIT and OUTFIT greater than 1.7). Indeed a measure greater than 1.7 would imply a high variability than expected, which would damage the validity of the measure obtained with the model.

Table 3. Fit indices for different number of categories

	NUMBER OF CATEGORIES								
	2	3	4	5	6	7	8	9	10
MAX INFIT	1.39	1.45	1.58	1.52	1.62	1.62	1.64	1.61	1.64
MIN INFIT	0.61	0.46	0.43	0.4	0.4	0.38	0.38	0.38	0.37
MAX OUTFIT	1.69	1.59	1.74	1.7	1.69	1.66	1.66	1.61	1.61
MIN OUTFIT	0.5	0.44	0.44	0.42	0.42	0.41	0.41	0.4	0.4

Finally, from Table 4, we can observe that the Andrich Thresholds tends to be unordered as the number of categories grow. Andrich Disordered Thresholds are evidence of bad fit of the data to the model and should be avoided. We can see in the table that the Andrich Threshold becomes disordered when the number of categories is equal to 9 and that for 8 categories some threshold are too near. Therefore, considering these results, we have deemed that the optimal results is obtained when we limit the categories to 7. The final models will be presented now.

Table 4. Andrich thresholds for the ranting scale models

	CATEGORIES							
	3	4	5	6	7	8	9	10
0	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
1	-0.67	-0.76	-0.81	-0.81	-0.78	-0.74	-0.7	-0.64
2	0.67	-0.11	-0.21	-0.32	-0.37	-0.38	-0.41	-0.43
3		0.87	0.01	-0.09	-0.14	-0.22	-0.23	-0.22
4			1.01	0.17	-0.05	-0.04	-0.06	-0.11
5				1.05	0.31	0.01	-0.05	-0.07
6					1.03	0.38	0.09	-0.06
7						0.99	0.42	0.16
8							0.93	0.41
9								0.96

Before to show these results we must say that the inclusion of the variable CEO power produced the following results. Once entered into the model (with 7 categories for the other indicators), with the original coding (0 = CEO is not the chairman, 1 = CEO is the chairman: the Rasch model (2) is able to deal with indicators with different coding) the variable was misfitting and negatively correlated with the measure. We then reversed the codes and we obtained positive correlation with the measure and good fit indices (INFIT = 1.21, OUTFIT = 1.32). This means that this variable represents an indicator compatible with the latent variable measured by the other items. In addition, we must say that this variable shows the highest difficulty (0.52): this means that it is useful in measuring the latent dimension at high levels. Despite these good results, we decided to exclude her from the model, in order to produce a measure based on the indicators most used in literature, but in future application of Rasch model it will be good choice to include her into the model. As we will see, this variable is negatively correlated (in his original coding) with the credit rating produced by Rasch model, confirming what expected and, therefore, contributing to validate the measure.

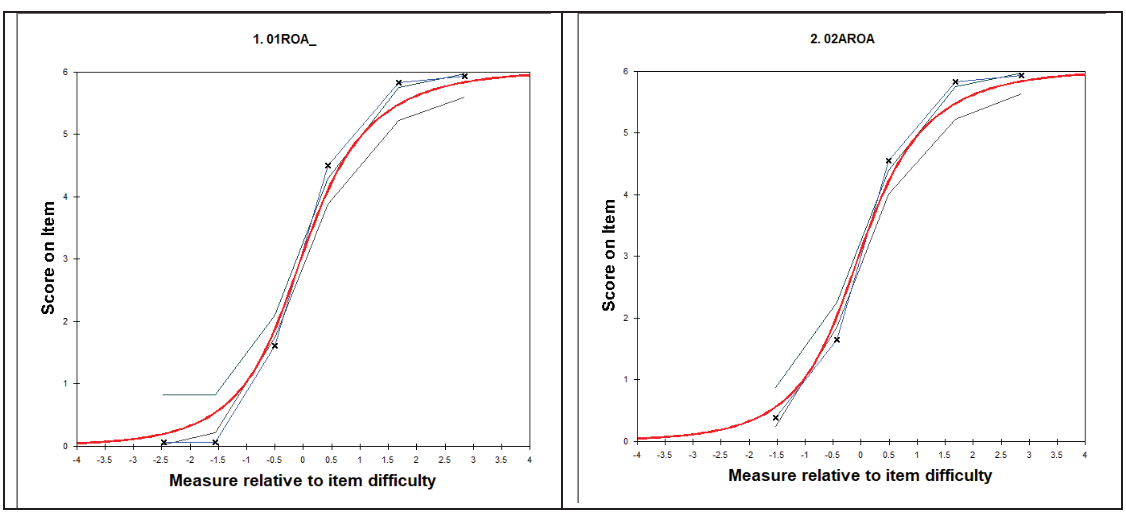
Final Results

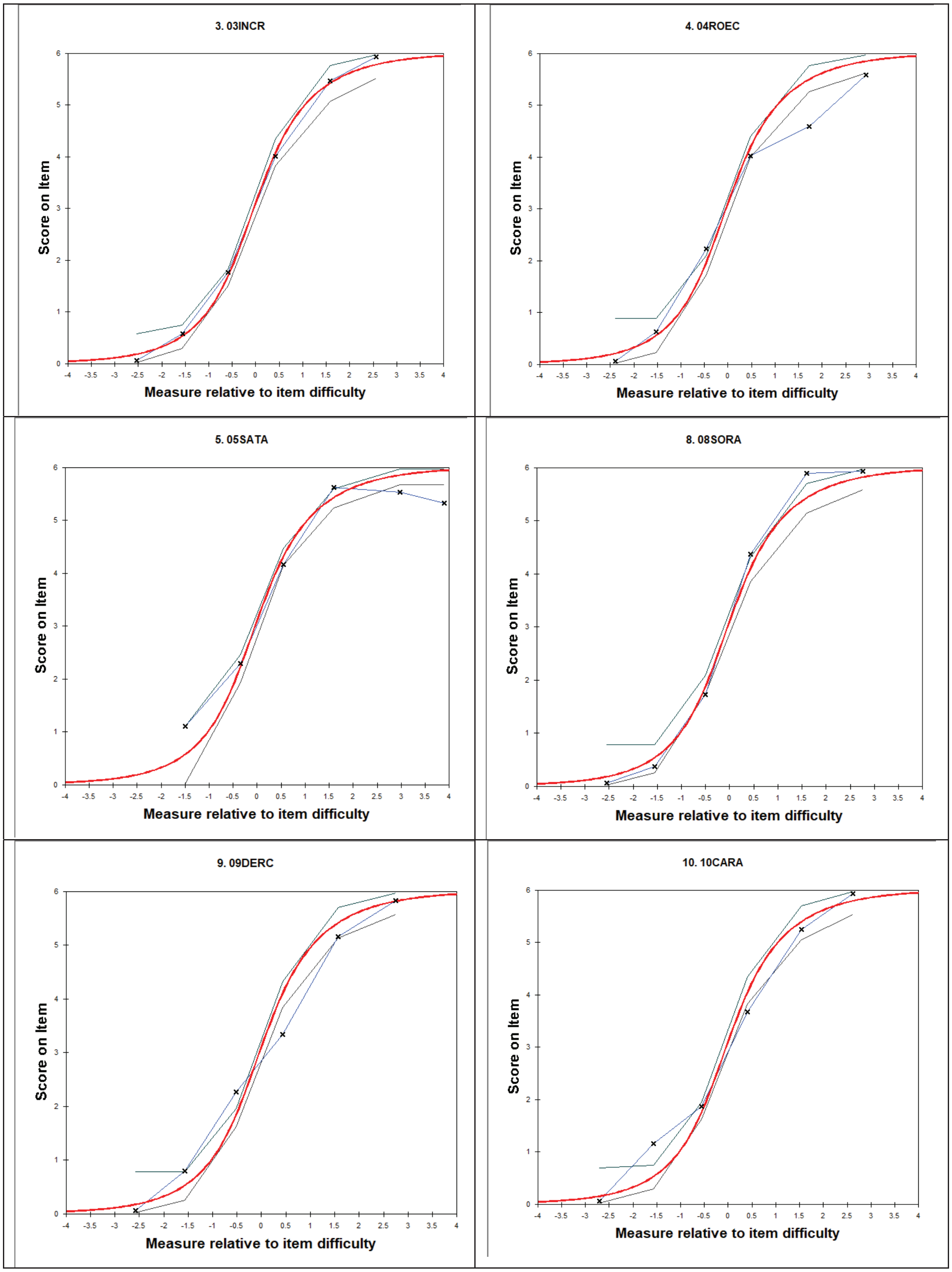
The final model with 7 categories provides a reliability of 0.98 for the items, and of 0.90 for the equities with a Cronbach Alpha of 0.90. We can observe that the difficulties of the items span from --0.58 to +0.26 **(**table 5**).** The easiest indicator (the one in which is easier to reach high values of the categories) is 05SATA which is Sales to Total Assets. While the hardest item is instead 03INC, which is Interest Coverage (with reversed order of the categories). All items present a fit in the desired range of 0.5-1.7, with the exception of 8SORA, the Solvency Ratio, with low fit as 0.38 and 0.41. Actually, this variable could be excluded from the model without losing much of information, but keeping it into the model do not even impact the goodness of the measure. The fit is shown also by the Item Characteristics Curves for the different items (figure 2): as we can see the fit to the model (red line) is quite good, also the one of 8SORA. In addition, from table 6 we can also see that the Andrich Thresholds are well ordered and all with good fit indices.

Table 5. Fit indices and measures of the items

ITEM STATISTICS: MISFIT ORDER

ENTRY NUMBER	TOTAL SCORE	TOTAL COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD	PTMEASUR-AL CORR.	PTMEASUR-AL EXP.	EXACT MATCH OBS%	EXACT MATCH EXP%	ITEM
4	1480	484	-.10	.03	1.51	7.2	1.66	7.9	A .58	.70	17.6	29.4	04ROEC
5	1883	484	-.58	.04	1.62	8.2	1.66	7.5	B .55	.66	19.0	32.2	05SATA
11	1259	484	.15	.03	1.47	6.6	1.56	6.8	C .60	.72	24.6	30.3	11WCTA
9	1317	484	.08	.03	1.34	5.0	1.38	4.9	D .61	.72	30.2	29.5	09DERC
3	1168	484	.26	.03	.98	-.3	1.21	2.8	E .73	.72	43.4	30.4	03INCR
10	1204	484	.22	.03	1.07	1.1	1.13	1.7	e .67	.72	27.7	30.3	10CARA
2	1540	484	-.17	.03	.59	-7.8	.57	-7.2	d .81	.70	39.5	30.0	02AROA
1	1406	484	-.02	.03	.50	-9.9	.49	-9.1	c .84	.71	40.5	29.5	01ROA_
13	1177	438	.09	.04	.50	-9.5	.50	-8.3	b .84	.72	40.4	29.7	13MVTL
8	1334	484	.06	.03	.38	-9.9	.41	-9.9	a .86	.71	42.1	29.4	08SORA
MEAN	1376.8	479.4	.00	.03	1.00	-1.0	1.06	-.3			32.5	30.1	
P.SD	206.6	13.8	.23	.00	.45	7.2	.49	7.1			9.4	.8	




3. 03INCR
Score on Item
Measure relative to item difficulty
4. 04ROEC
Score on Item
Measure relative to item difficulty
5. 05SATA
Score on Item
Measure relative to item difficulty
8. 08SORA
Score on Item
Measure relative to item difficulty
9. 09DERC
Score on Item
Measure relative to item difficulty
10. 10CARA
Score on Item
Measure relative to item difficulty

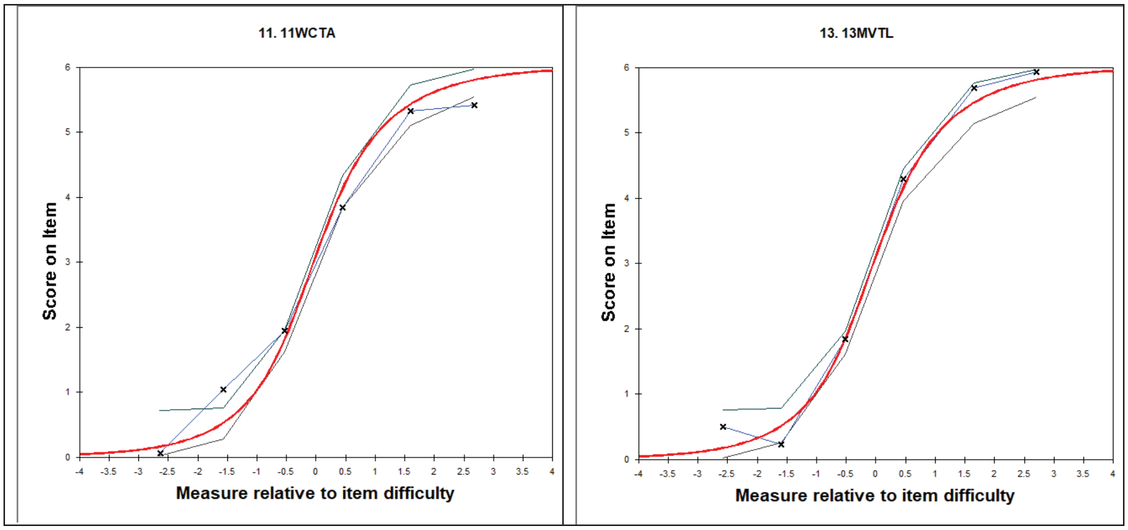


Figure 2. Item Characteristics Curve

Table 6. Andrich Thresholds

SUMMARY OF CATEGORY STRUCTURE. Model="R"

CATEGORY LABEL	SCORE	OBSERVED COUNT	%	OBSVD AVRGE	SAMPLE EXPECT	INFIT MNSQ	OUTFIT MNSQ	ANDRICH THRESHOLD	CATEGORY MEASURE	
0	0	763	16	-.94	-.93	.99	1.00	NONE	(-2.24)	0
1	1	768	16	-.63	-.63	.86	.85	-.78	-1.03	1
2	2	676	14	-.38	-.37	.93	1.00	-.37	-.45	2
3	3	614	13	-.08	-.11	.85	.86	-.14	-.04	3
4	4	666	14	.18	.18	.96	1.06	-.05	.38	4
5	5	700	15	.62	.57	.88	.99	.31	1.04	5
6	6	607	13	1.21	1.27	1.38	1.55	1.03	(2.41)	6
MISSING		46	1	-.04						

OBSERVED AVERAGE is mean of measures in category. It is not a parameter estimate.

From figure 3 (the so-called construct-key map: see Winsteps for details) we may answers to the question "what is the average score that we expect to observe for persons of a particular measure?" This score information is expressed in terms of expected scores (with ":" at the half-point thresholds). For example an equity with measure as low as -2.5, tends to score 1 on the easiest item 05SATA, while an equity with measure as high as 2.5 tends to score the maximum on all items.

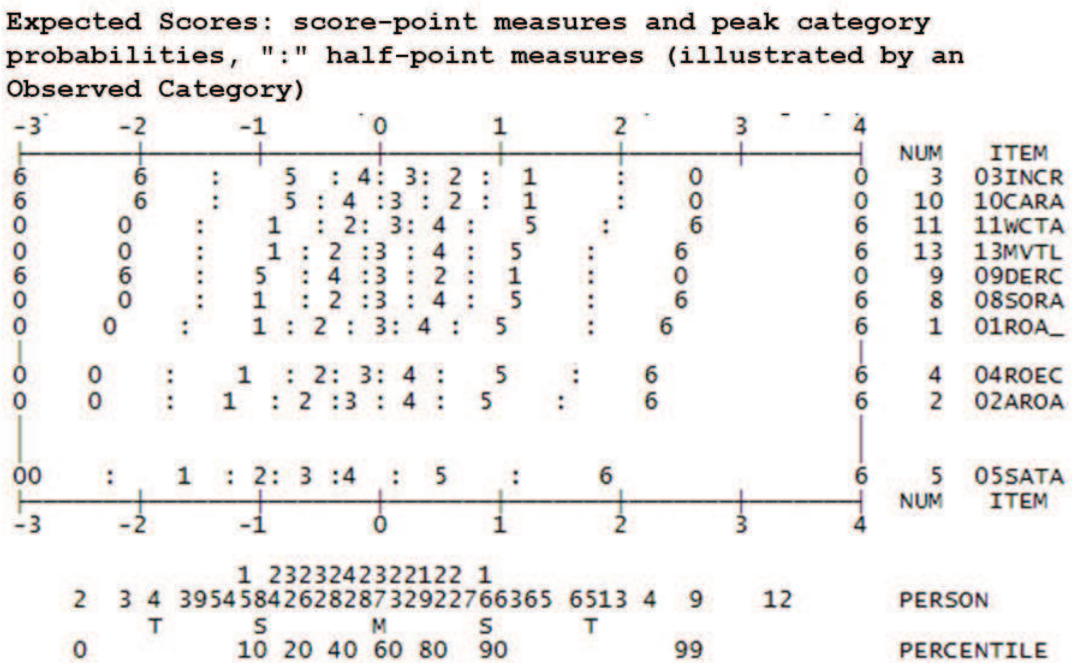


Figure 3. Construct key map

For what concerns the eventual presence of DIF (Differential Item Functioning of the model (Lord, 1980); Holland and Wainer, 1993), we investigated the stability of the difficulties of the items in the period 2004-2014. To this end we can look at figure 5 which shows the level of difficulty of the items for the different years, from 2004 (=A) to 2014 (=M). Although we may observe some deviation from the mean (first figure), in the second one, the t-value of the difference of each year with respect to the mean lies in the interval -2.58, +2.58 in the majority of the cases. Therefore, we can conclude that the results obtained are satisfactory and that the data has a good fit with the Rasch model.

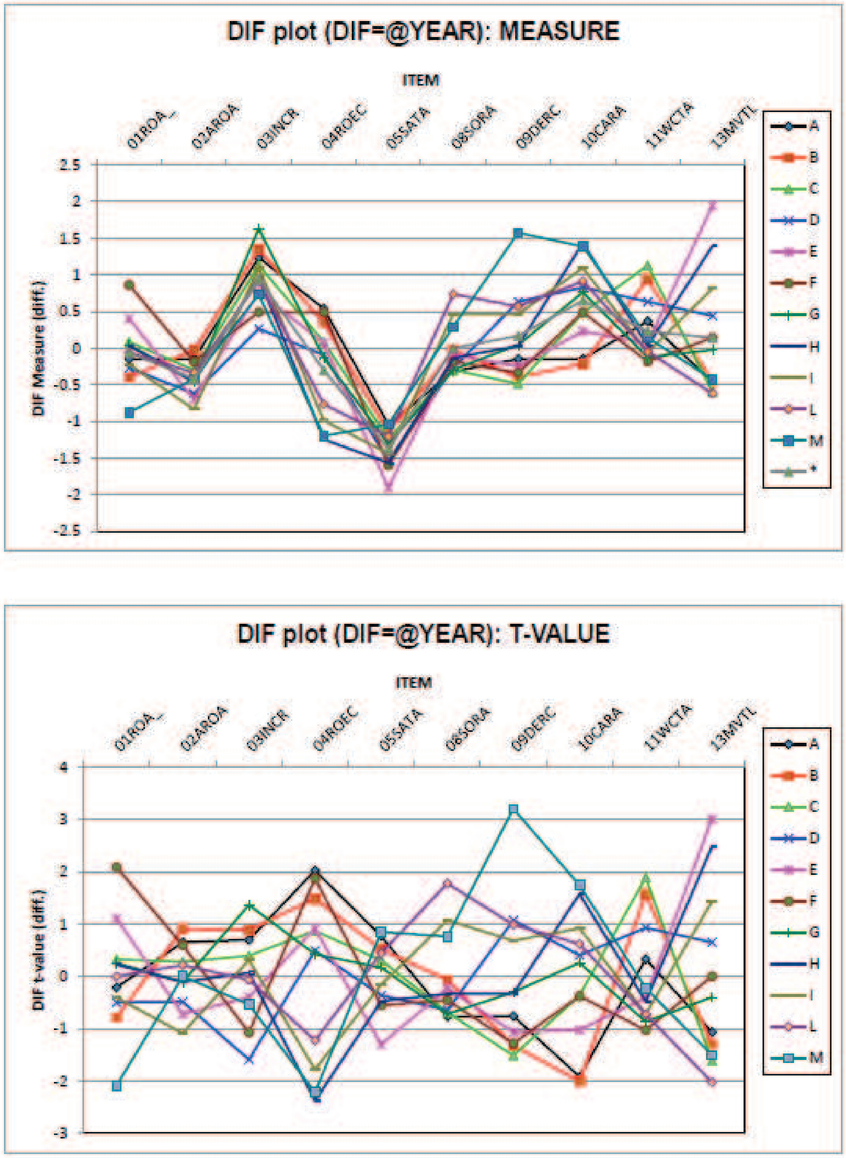


Figure 5. Differential Item Functioning: stability in the period 2004-2014

If the first validation of the measure obtained relies on the fit of the data to the model, a second important step deals with how this measure relates to important aspects of the study. In particular, we are going to investigate how the measure obtained by Rasch models (Rasch Ratings) mimics the rating of credit rating agencies, and how do they relate to other variables of interest, such as CEO power and stock return. To this end, we are going to compare the Rasch Ratings with the Bloomberg default risk, which is the proxy that represents the CRAs credit ratings. In doing this, we will answer the main research question, which is to determine if the Rasch model can be used to provide an objective credit rating method and therefore use it to mimic and predict the grade of credit rating agencies. The comparison can be seen in figure 6, which shows the average Rasch Rating with respect to the Bloomberg rating of the equities. This has been constructed by performing the following steps:

- Group the equities with the same Bloomberg default risk
- Compute the conditional expected value of the Rasch ratings in respect to the Bloomberg ratings +/- 2 S.E.

We can observe that the Rasch Rating of +0.5 corresponds to a Bloomberg rating of IG3/IG4, while a Rasch Rating of -1.2 corresponds to a Bloomberg rating of HY3. As we may see from figure 6, the average Rasch Rating grows with the Bloomberg rating. This is the expected results as it is the confirmation that the Rasch Ratings constructed are valid. Moreover, from table 7, we may see, from the analysis of variance table, that the relation with the Bloomberg rating is statistically significant.

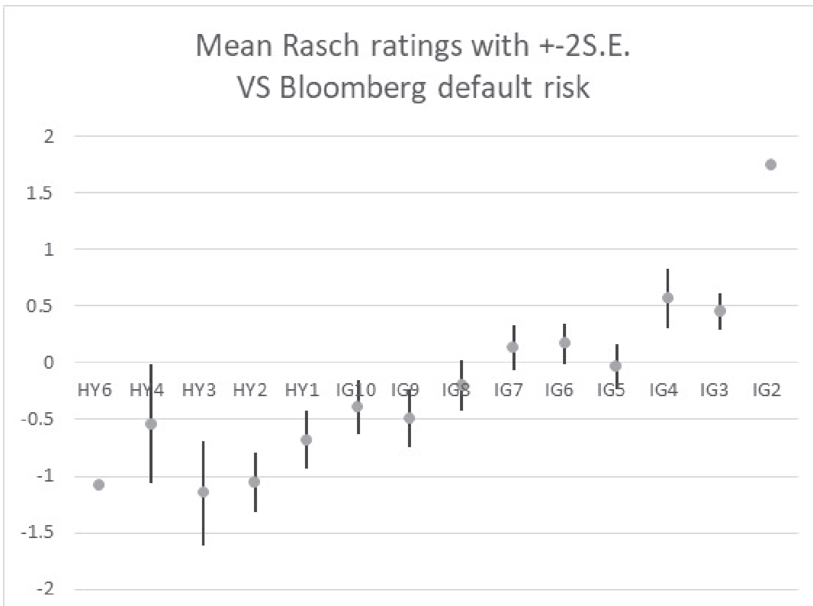


Figure 6. Relationship between Rasch ratings and Bloomberg default risk

Table 7. Analysis of variance of the Rasch Rating conditioned by Bloomberg default risk (@15DEFA)

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@15DEFA	85.07	15.00	5.67	8.46	.0000
Error	313.90	468.00	.67		
Total	398.97	483.00	.83		

To further confirm the validity of the Rasch Rating, we have inserted the Bloomberg default risk (14RATI) as a variable of the Rasch model in order to understand if this variable fits the model. The indices of fit of this item are acceptable (INFIT = 1.46, OUTFIT=1.58), meaning that the Bloomberg rating try to measure the same dimension that we are measuring with the Rasch Rating based on the chosen variables. In addition, Figure 7 shows the figure of the Item Characteristic Curve for the Bloomberg default risk, which lies in the interval of confidence, except for high values of the Rasch Rating. The reason for this may be the following.

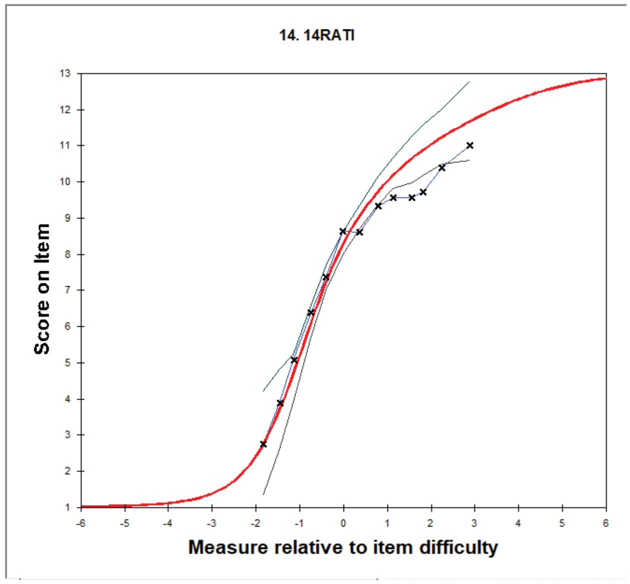


Figure 7. Item Characteristic Curve for Bloomberg default risk

By adding the Bloomberg rating in the model, it was also possible to calculate the most unexpected response of the model compared to the Bloomberg rating. This are reported in Table 8. As we may see from the first row of the table for the equity BBBY UW, in 2008, the Bloomberg rating assigns a level of 5 while, according to the Rasch Rating estimated, this level should be expected 9.82 with a residual of -4.82. This means that this equity in this year has been underestimated by Bloomberg rating. Please note that the Bloomberg ratings has been coded in Winsteps using an ascending scale, with 1 corresponding to HY4 and IG1 equal to 14. We can notice that over the 10 years period, the number of discrepancies with the Bloomberg rating is quite low (in 2008 only four equities presents unexpected responses, three in 2009 etc.), which again confirms the validity of the model. On the other end the analysis of the most unexpected response shows the way to judge the ratings assigned by credit rating agencies: an unexpected response with respect what could be expected on the base of the objective indicators used and the objective measure produce by the Rasch model, may be suspicious and susceptible of attention.

Table 8. Most unexpected response for Bloomberg default risk (variable 14RATI)

DATA	OBSERVED	EXPECTED	RESIDUAL	ST. RES.	MEASDIFF	ITEM	PERSON	ITEM	PERSON
10	5	9.82	-4.82	-4.10	.85	14	722	14RATI	722 A BBBY UW E 08 BBBY UW
10	5	9.74	-4.74	-3.96	.79	14	730	14RATI	730 A GPS UN E 08 GPS UN
9	6	10.22	-4.22	-3.87	1.16	14	726	14RATI	726 A COH UN E 08 COH UN
14	1	7.26	-6.26	-3.61	-.39	14	734	14RATI	734 A HOG UN E 08 HOG UN
9	6	9.93	-3.93	-3.41	.93	14	610	14RATI	610 A GPS UN F 09 GPS UN
8	7	10.37	-3.37	-3.19	1.29	14	606	14RATI	606 A COH UN F 09 COH UN
7	8	10.89	-2.89	-3.08	1.82	14	362	14RATI	362 A BBBY UW H 11 BBBY UW
8	7	10.29	-3.29	-3.07	1.22	14	490	14RATI	490 A GPS UN G 10 GPS UN
8	7	10.26	-3.26	-3.01	1.19	14	602	14RATI	602 A BBBY UW F 09 BBBY UW
7	8	10.70	-2.70	-2.76	1.61	14	242	14RATI	242 A BBBY UW I 12 BBBY UW
11	4	8.21	-4.21	-2.73	-.04	14	1231	14RATI	1231 A PHM UN A 04 PHM UN

As a further step of validation, we have performed a historical analysis of the Rasch Ratings estimated. The results are showed in Figure 8 where we can observe the average value of the Rasch Ratings for the period 2004-2014. As we can see, a worsening of the market conditions is observed since 2006. This again confirmed the validity of the model as, in line with our expectations, we would expect the rating to decrease during the financial crisis.

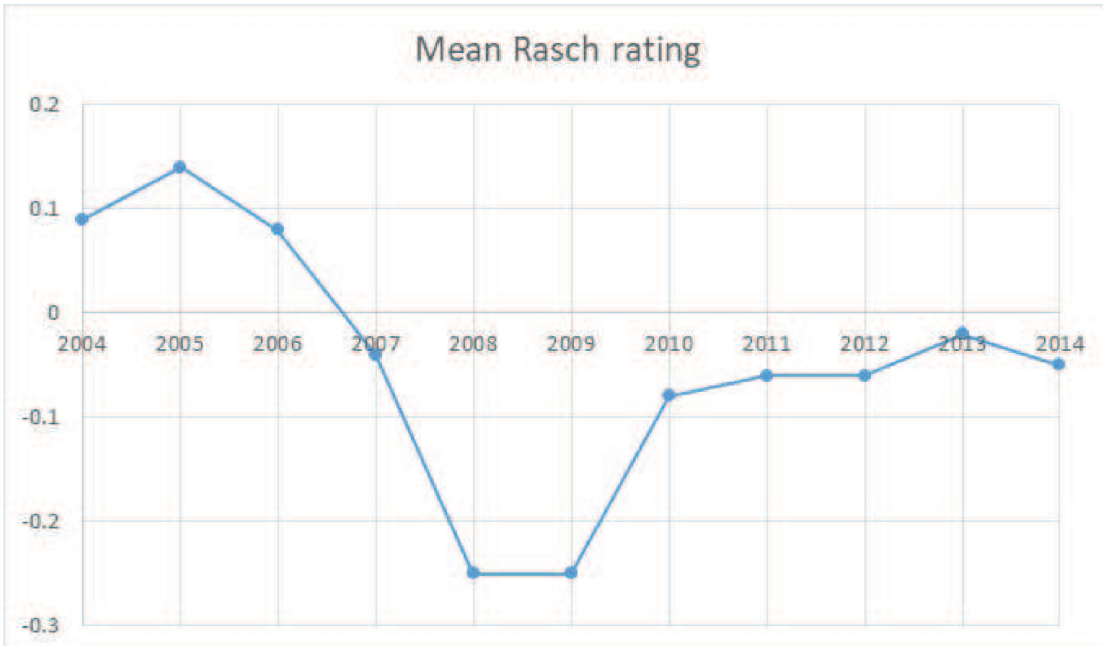


Figure 8. Historical average performance of Rasch Ratings

The results obtained are now analyzed in relation to the CEO power. From table 9, we may se the average value of the Rasch Ratings with respect to the variable CEOP together with the analysis of the variance. From these results we can observe that the average Rasch Rating is greater for CEOP=0 (when the CEO is not also the Chairman of the board of directors) than when the CEOP=1 and the analysis of variance confirms that this difference is statistically significant. Therefore, this mean that the fact that the CEO is the Chairman of the board of directors will influence somehow the credit ratings. This was expected from what is pointed out in literature (Skaife et al., 2006), and again confirms the validity of the model. In conclusion, the model has proven to produce satisfactory results. The analysis above has confirmed that the Rasch model could be used as an objective tool to mimic the grade given, for example, by the Bloomberg default risk. Now that the validity of the model has been confirmed, in the next paragraph, we will try to look at the implications of the model and particularly how the Rasch model can be use in the prediction of the sign of the stock return.

Table 9. Analysis of variance of Rasch Rating with respect to CEO power

Subtotal specification is: PSUBTOTAL=@14CEOP

ALL PERSON SCORES ARE NON-EXTREME

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
484	-.04	.04	.91	.91	-.16	2.94	.90	*
176	.05	.07	.98	.99	-.12	3.06	.90	0
308	-.10	.05	.86	.86	-.20	2.84	.89	1

SUBTOTAL RELIABILITY: .33
UMEAN=0 USCALE=1

PERSON CODE	CODE	MEAN DIFFERENCE MEASURE	S.E.	t	Welch-2sided d.f.	Prob.
0	1	.15	.09	1.73	324	.085

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@14CEOP	2.65	1.00	2.65	3.22	.0695
Error	396.32	482.00	.82		
Total	398.97	483.00	.83		
Fixed-Effects Chi-squared: 2.9887 with 1 d.f., prob. .0838					

Using the Rasch Rating to Predict the Sign of the Stock Return

In this paragraph, we try to look at one implication of model and particular, if the results obtained can contribute in explain the sign of the stock return. In order to understand the role of the estimated Rasch Rating in explaining the sign (+/-) of the stock return in a given year T we applied a multilevel (mixed) logistic regression model (Wong and Mason, 1985), where the observations have been regrouped within years:

$$Y_{ij} \approx Bernoulli(\pi_{ij})$$

$$\ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + \beta_1 \cdot x_{1ij} + \beta_1 + \beta_2 \cdot x_{2ij} + \cdots + \beta_k \cdot x_{kij} + u_i$$

$$u_i \approx N(0, \sigma_u^2$$

where $Y_{ij} = 1$, if the sign of the stock return for equity *j* in year *i*, is positive, $Y_{ij} = 0$, if is negative (no zero stock returns were observed), X_{rij} is the $r-th$ explanatory variable, u_i is the effect of the $i-th$ year. We have tried several explanatory variables for the models, but finally the only one that result statistically different from zero in explaining the probability of the sign of the stock return were the following:

$A_{ij} =$ Bloomberg rating at time *i* – Bloomberg rating at time *i*-1

$B_{ij} =$ Rasch Rating at time *i* – Rasch Rating at time *i*-1

The most common methods for estimating multilevel logistic models are based on likelihood. We estimated the model using the R routine glmer, which is based on adaptive Gauss-Hermite approximations to the likelihood. However, being the Rasch ratings, constituting variable B, estimated, they are, by definition, affected by error, and a straightforward estimation of the model would lead to inconsistent estimates of the coefficients (Griliches and Ringstad, 1970). Among many other methods, the simulation and extrapolation method (SIMEX) by Cook and Stefanski (1994) has become a useful tool for correcting estimates in the presences of additive measurement error. The method is especially helpful for complex models with a simple measurement error structure. The R package simex (Lederer and Kuchenhoff, 2013), provides functions to use the SIMEX method for various kinds of regression objects and to produce graphics and summary statistics for corrected objects. The SIMEX method uses the relationship between the variance of the measurement error, σ^2 (estimated by the Rasch model) and the bias of the estimator when ignoring the measurement error. In particular, we can define the function

$$\sigma_s^2 \to \tilde{\beta}(\sigma_s^2) := G\sigma_s^2$$

where $\tilde{\beta}$ is the limit to which the "naive estimator" converges as the sample size tends to infinity. A consistent estimator of β, when there is no measurement error, is called the "naive estimator. It is easily seen, that $G(0) = \beta$ is the true parameter, and $G(\sigma_s^2) = \beta_n$ the result of the naive estimator. The idea of the SIMEX method is to approximate the function $G(\sigma_s^2)$ by a parametric approach $G(\sigma_s^2, \Gamma)$, for example with a quadratic approximation $G(\sigma_z^2, \Gamma) = \gamma_0 + \gamma_1 + \sigma_z^2 + \gamma_2(\sigma_z^2)^2$. To estimate Γ the method adds in the simulation step to a given data set additional measurement error with variance $\lambda\sigma_z^2$ to the contaminated variable. The resulting measurement error variance is then $(1+\lambda)\sigma_z^2$. The naive estimator for this increased measurement error is calculated and repeated R times. The average over R converges to $G((1+\lambda)\sigma_z^2)$. Repeating this simulation for a fixed grid of λ, leads to an estimator for $\hat{\Gamma}$ of the parameters $G(\sigma_z^2\Gamma)$, for example by least squares. In the extrapolation step the approximated function $G(\sigma_z^2\hat{\Gamma})$ is extrapolated back to the case of no measurement error and so the SIMEX estimator is defined by $\beta_{simax} = G(0, \hat{\Gamma})$, which corresponds to $\lambda = -1$. The naïve estimator was obtained applying the proc glmer. The results of the estimate of the multilevel logistic regression model are reported in the following tables: for the purpose of comparison, we have reported both the results of the naïve model (on the left) and the ones of the SIMEX corrected model (on the right). As we may see from the results of the estimate, the Bloomberg rating and the Rasch rating are significant and positive in explaining the sign of the stock return. It is interesting to note also that the coefficients of the Rasch rating in the naïve models are almost 50% of the level of the coefficient in the models estimated with the SIMEX correction, which takes into account the error of measurement of the independent variable Bij. Table 11 contains the probabilities that the sign of the stock return will be positive, given different levels of the independent variable Aij and Bij, equal respectively to the 0.05, 0.25, 0.75, 0.95 percentiles of the observed level of these variables in the dataset. Obviously, a level of the probability of zero means that positive and negative signs are equally likely. The effect of the year is set to zero, which is the mean level of the estimated model.

Table 10. Logistic regression models for the sign of the stock return

Naive model

Variables	Estimates	S.E.	T-test	Pvalue
Intercept	0.9030	0.3076	2.9350	0.0033
Aij	1.0957	0.1569	6.9810	0.0000
Bij	1.2779	0.4012	3.1860	0.0014
σ_u	0.7798			

SIMEX model

Variables	Estimates	S.E.	T-test	Pvalue
Intercept	0.9420	0.3135	3.0050	0.0028
Aij	1.0290	0.1591	6.4680	0.0000
Bij	2.3800	0.6072	3.9200	0.0001
σ_u	0.7892			

As we may see from table 11, as the difference in Bloomberg rating grows, the probability of the positive stock return tends to one as we were expecting. It is interesting to note that the knowledge of the difference in the Rasch rating may change remarkably this probability, meaning that this information may be important in modifying the opinion regarding the sign of the stock return. It is also interesting to observe that the two indicators have a low correlation: this means that is possible to find equities whose Blomberg rating is equal to zero, but whose Rasch rating may growth (decrease) leading to a remarkable change of opinion.

Table 11. Probability of positive stock return at time T, given different levels of variation of Rasch rating (B) and Bloomberg rating (A), setting the random component equal to zero

		B = RASCH RATING (T)-(T-1)				
		-0.70	-0.21	0.00	0.17	0.57
A = BLOOMBERG RATING (T)-(T-1)	-4	0.01	0.02	0.04	0.06	0.14
	-1	0.15	0.36	0.48	0.58	0.78
	0	0.33	0.61	0.72	0.79	0.91
	1	0.58	0.81	0.88	0.91	0.96
	2	0.79	0.92	0.95	0.97	0.99

CORR(A,B) = 0.305

Conclusions

This study has demonstrated that the Rasch model can be used as an additional tool to predict the credit ratings of a company, contributing to the literature of the credit ratings prediction models. More specifically, we have showed how purely financial ratios analysis can be used in the construction of prediction models, confirming what has been demonstrated by several studies among which the Z-score model of Altman. Another theoretical implication of the model is its contribution to the prediction of the sign of the stock return. Indeed, we have found positive relationship between the Rasch ratings and the change in the stock return sign. This additional research could be an additional support to the existing literature around the stock return. Regarding the theoretical implications of the Rasch model, we have showed how this model can be applied successfully to finance. Indeed, the use of Rasch model in this field is just at its beginning. Few researches were conducted, first by Ridzak (2011), which ranks banks by their strictness in classifying risk and then by Schellhorn et al. (2013 and 2011) which have applied the Rasch model to rank firm based on managerial abilities. Therefore, this paper can be considered as an encouragement to continue the application of Rasch models in finance related disciplines. On a managerial side, the Rasch model could have a practical use by agencies and investors. For instance, the Rasch model could be included among the methods to estimate corporate credit ratings by a NRSROs ("nationally recognised statistical rating organizations"), which are the only agencies from which the issue of ratings are permitted and recognised by the U.S. Security Exchange Commission (Security and Exchange Commission, 2003). Indeed, as showed in this study, the Rasch model is an independent tool, which is free of subjective decisions. Therefore, the use of this model in practice could resolve the various issues of independence and conflict of interests surrounding the credit rating agencies and their credit scores. In addition, the use of an objective tool, as the Rasch model, could contribute to reinstate the credibility of the agencies, which have been weakened after the moral hazard created by the financial crisis. However, it has to be noted that these practical applications will be possible only if the outcome of the model in this field can be proven to be very successful and reliable by additional future researches. Considering this, it would be interesting to extend the research of the model in this field. Adding to the model more qualitative variables (e.g. corporate governance parameters) and sector characteristic indicators (e.g. financial ratios proper of an industry or also market variables such as sector competition) could produce a more accurate and complete result. In addition, obtaining the ratings from the three main credit rating agencies would give an additional element of comparison to assess the validity of the results. Finally, it would be advisable to extend the application of the model to additional sectors and periods and particularly to companies, which are in distress or bankrupt.

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