UNIVERSITÀ DEGLI STUDI DI UDINE
DIPARTIMENTO DI SCIENZE ECONOMICHE E STATISTICHE

Credit ratings: a new objective method using the Rasch model

Enrico Gori, Gloria Gori

Gennaio 2017

n. 01/2017

Sezione
Amministrazione e Controllo

Credit ratings: a new objective method using the Rasch model

Enrico Gori – D.I.E.S. – University of Udine

Gloria Gori – Grenoble Graduate School of Business

Abstract

Key words: Rasch Model, Credit ratings, Credit rating agencies, Risk of default, S&P 500

Purpose: The purpose of this research 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.

Methodology: The credit ratings grades for the consumer discretionary, industrial and information technology sectors of the S&P were estimated using the Rasch model for period from 2004 to 2014. The Rasch model was applied by uploading the data in the softwareWinsteps.

Theoretical perspectives: This paper is therefore 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 in the paper but applying this data to the Rasch model has never been done yet in this field.

Conclusions: 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 and industrial sectors, where the measures estimated matched, except for a few discrepancies, with those of the Bloomberg default risk. On the other hand, it was not possible to construct a satisfactory estimate for the information technology industry due to the lack of indicators able to measure the samples at the extremes. This paper offers a new approach to credit rating that should be further explored in future researches.

Table of Contents

CHAPTER 1: INTRODUCTION

1.1. The project and its objectives

The goal of this paper is to understand if the Rasch model, a measurement tool widely used in psychology and education, can be applied to credit rating and can help to develop a rather simple and objective way to evaluate the creditworthiness of companies and their financial obligations. The idea is to compare results obtained by applying this model with those calculated by credit rating agencies (CRAs) whose complex methodologies will also be analysed. The results need not be the same but similarities would provide first empirical evidence that the Rasch model can be applied to credit rating or that it could be used as a tool to anticipate what credit rating agencies will publish.

For the purpose of this demonstration, the objectives of the paper will be the following:

• Understand which are the main variables used by credit rating agencies to conduct credit rating and what their methodology is.

• Collect historical data from the three sectors of the S&P 500 companies on which the analysis will be conducted over the period 2004-2014. The sectors under valuation will be industrial, information technology and consumer discretionary.

• Choose the appropriate variables to undertake the research and use the Rasch Model on the data collected to obtain credit rating based on an objective model.

• Understand if the results obtained are in line with the grade given by credit agencies throughout the years.

• Main research question and conclusion: Is it possible to use the Rasch model to provide an objective credit rating method and therefore use it to mimic and predict the grade of credit rating agencies?

1.2. The importance of the project and key definitions

A credit rating is defined as "an assessment of an entity's ability to pay its financial obligations"[1]. 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 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"[2].

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[3]. Usually, a higher value will correspond a lower risk to default. This are going to be discussed in the next Chapter. 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, which 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[4]. 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,

[1] U.S. SECURITIES AND EXCHANGE COMMISSION, https://www.sec.gov/investor/alerts/ib_creditratings.pdf, Investor Bulletin
[2] U.S. GOVERNMENT, Credit Rating Agency Reform Act 2006, page 2
[3] U.S. SECURITIES AND EXCHANGE COMMISSION, https://www.sec.gov/investor/alerts/ib_creditratings.pdf, Investor Bulletin
[4] THE GUARDIAN, http://www.theguardian.com/business/2012/feb/15/credit-ratings-agencies-moodys, 15 February, 2012

foreign regulatory schemes, and private financial contracts"[5]. 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[6]. 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[7]
- the increasing use of credit ratings in financial regulation and contracting[8]

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[9]. 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[10]. Following all these events, CRAs have been questioned on the quality of their opinions and whether

[5] U.S SECURITIES AND EXCHANGE COMMISSION, https://www.sec.gov/rules/concept/33-8236.htm, 28TH July 2003
[6] LAWRENCE, WHITE J. "*Markets: The Credit Rating Agencies*." Journal of Economic Perspectives, 24(2): 211-26, 2010
[7] U.S. SECURITIES AND EXCHANGE COMMISSION, "*Report on the role and function of Credit rating Agencies in the operation of the securities market*" SEC reports, January 2003
[8] GALIL, K. *"The Quality of Corporate Credit Rating: An Empirical Investigation"* EFMA 2003 Helsinki Meetings, 78, 2003
[9] THE GUARDIAN, http://www.theguardian.com/business/2012/feb/15/credit-ratings-agencies-moodys, 15 February, 2012
[10] THE GUARDIAN, http://www.theguardian.com/business/2012/feb/15/credit-ratings-agencies-moodys, 15 February, 2012

they should be more transparent in the processes adopted[11]. 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 project 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.

CHAPTER 2: LITERATURE REVIEW

This chapter aims to explore the relevant literature in support of this paper. In particular, the author will investigate the methodology adopted by the credit rating agencies, researches conducted in support of the topic and finally studies which have successfully applied the Rasch model. All these researches, we will be utilised to form expectations and hypothesis on the outcome of this study.

2.1. Credit rating methodology

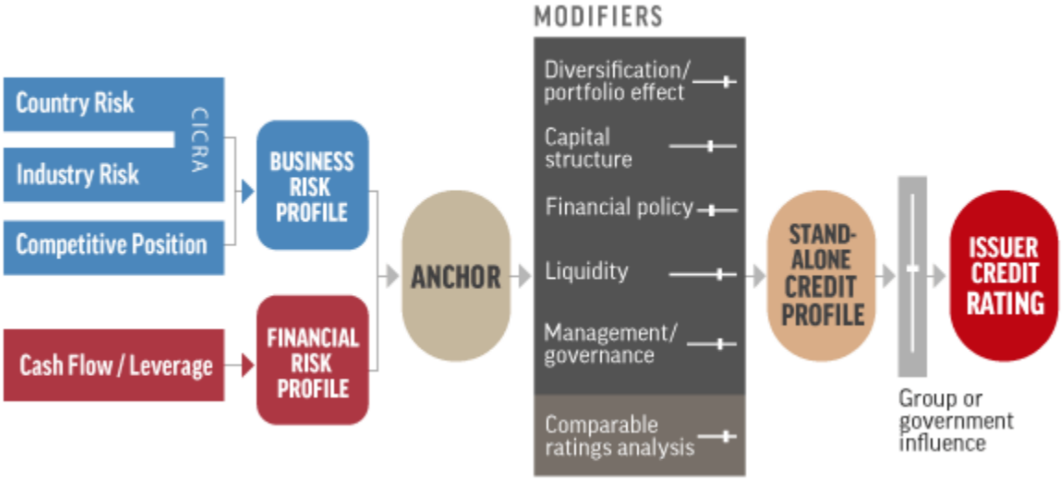
An initial fundamental research for the scope of this paper is to gain an understanding of the methodology used by CRAs when assessing corporate credit ratings. As the methodologies among the three main credit agencies are very similar, for simplicity, we will mainly focus on the methodology adopted by Standard’s and Poor.

2.1.1 Standard and Poor’s methodology

The corporate credit rating methodology of S&P is based on a common analysis and framework formed by several steps. The graphic below summarises the process for issuing a rating.

[11] U.S. SECURITIES AND EXCHANGE COMMISSION, “*Report on the role and function of Credit rating Agencies in the operation of the securities market”* SEC reports, January 2003

Figure 1- Standard & Poor's ratings issue process



Once a rating is requested by an issuer, 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 this 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[12]. On the other hand, the financial profile is considered to be 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

[12] STANDARD & POOR'S, www.standardandpoors.com/ratingsdirect , 19th November, 2013

operation to debt" and "debt to EBITDA". In addition to this, further supplementary ratios are considered in the analysis which usually are "cashflows from operation to debt", "free operating cashflows to debt", "discretionary cashflows to debt" and "EBITDA to interest"[13]. 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. 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 will required the rating to remain confidential[14].

2.1.2 Rating scale

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"[15]. "*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*"[16].

2.1.3 Additional matters

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

[13] STANDARD & POOR'S, www.standardandpoors.com/ratingsdirect, 19th November, 2013
[14] GALIL, K. *"The Quality of Corporate Credit Rating: An Empirical Investigation"* EFMA 2003 Helsinki Meetings, 78, 2003
[15] GALIL, K. *"The Quality of Corporate Credit Rating: An Empirical Investigation"* EFMA 2003 Helsinki Meetings, 78, 2003
[16] SANTOS, K., *"Corporate credit rating: a quick Guide"*, Rothschild, The treasurer handbook, 2015

available information[17]. 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.

2.2.Credit ratings researches

Credit rating and CRAs activities have been at the centre 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[18].Another important research is the one conducted by Beaver in 1966. Beaver tried to predict the failure of a companies' 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"[19]. 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[20]. In their research they discovered that market capitalisation 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:

[17] SANTOS, K., *"Corporate credit rating: a quick Guide"*, Rothschild, The treasurer handbook, 2015
[18] WU, C.Y., *"Using Non-Financial Information to Predict Bankruptcy: A Study of Public Companies in Taiwan",* International Journal of Management, Vol.21, No.2, 2004
[19] BEAVER, W. "*Financial Ratios as Predictors of Failure*", Journal of Accounting Research, 4, 71-111, 1966
[20] DOUMPOS M., NIKLIS D., ZOPOUNIDIS C., ANDRIOSOPOULOS K., *"Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms",* Journal of Banking and Finance, Vol. 50, Pages 599-607, 2015

1. the size of the company
2. a measure of the financial structure
3. a measure of performance
4. a measure of financial liquidity[21]

These studies revealed to be very effective as they were able to predict corporate failure in more than 90% of the cases[22]. 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%[23].Galil (2003) has analysed the methodology of Standard & Poor by using a sample of the S&P 500 corporate ratings and has 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[24]. An additional research is offered by Cardoso et.al (2013). 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"[25]. 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. A more recent investigation has been conducted by Lee 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

[21] OHLSON, J. *"Financial Ratios and the Probabilistic Prediction of Bankruptcy".* Journal of Accounting Research, 18(1), 109-131. doi:1. Retrieved from http://www.jstor.org/stable/2490395 doi:1, 1980
[22] WU, C.Y., *"Using Non-Financial Information to Predict Bankruptcy: A Study of Public Companies in Taiwan",* International Journal of Management, Vol.21, No.2, 2004
[23] WU, C.Y., *"Using Non-Financial Information to Predict Bankruptcy: A Study of Public Companies in Taiwan",* International Journal of Management, Vol.21, No.2, 2004
[24] KISGEN, D. J. *"Credit ratings and capital structure"*, The Journal of Finance, Volume 61, Issue 3 Pages 1035–1072, 2006
[25] CARDOSO V., GUIMARAES A., MACEDO H., LIMA J.C.O. *"Assessing corporate risk: a PD model based on corporate risk",* Proceeding in finance and Risk perspectives, 57-64, 2013

methods. In this study he showed that the support vector machine model outperform the other methods[26]. 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[27]. Figlewskia 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[28]. 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.[29] 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[30]. 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.

2.3 Influence of corporate governance on credit ratings

This research will analyse 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

[26] LEE Y.C., *"Application of support vector machines to corporate credit rating prediction",* Expert Systems with applications, Vol. 33, Issue 1, Pages 67-74, 2007

[27] KAMSTRA, M., KENNEDY, P., & SUAN, T.-K., *"Combining bond rating forecasts using logit",* The Financial Review, 37, 75–96, 2001

[28] FIGLEWSKI S., FRYDMAN H., LIANG W., *"Modelling the Effect of Macroeconomic Factors on Corporate Default and Credit Rating Transitions"* NYU Stern Finance Working Paper No. FIN-06-007, 2006

[29] BEAVER, W. H., MCNICHOLS, M. F., RHIE, J.W., *"Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy"*, Review of Accounting Studies, Vol.10, 93-122, 2005

[30] SHUMWAY, T., *"Forecasting bankruptcy more accurately: a simple hazard model",* The Journal of Business, Vol. 74 No. 1, pp. 101-24, 2001

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 prioritising their short term interests at the expenses of the benefits of shareholders, which will therefore expect lower future cash flows[31]. Therefore is a "firm's expect cash flows decline, the default risk of bondholders increases leading to lower credit ratings"[32]. 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[33]. For instance, shareholders could encourage managers in investing in riskier projects which could impact the volatility of the firm's future cashflows 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"[34].

Similar research has been conducted by Aman and Nguyen (2013) on the relation of corporate governance on 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[35]. Segupa (1998) proved that there is a

[31] JENSEN, M.C., MECKLING, W. *"Theory of the Firm: Managerial Behaviour, Agency Costs and Ownership Structure",* Journal of Financial Economics 3: 305-360, 1976
[32] SKAIFE, H. A., COLLINS, D.W., LAFOND, R., *"The Effects of Corporate Governance on Firms' Credit Ratings",* Journal of Accounting and Economics, pp. 203-243, 2006
[33] JENSEN, M.C., MECKLING, W. *"Theory of the Firm: Managerial Behaviour, Agency Costs and Ownership Structure",* Journal of Financial Economics 3: 305-360, 1976
[34] SKAIFE, H. A., COLLINS, D.W., LAFOND, R., *"The Effects of Corporate Governance on Firms' Credit Ratings",* Journal of Accounting and Economics, pp. 203-243, 2006
[35] AMAN, H., NGUYEN, P., *"Does good governance matter to debtholders? Evidence from the credit ratings of Japanese firms",* Research in International Business and Finance, Vol.29, Pages 14-34, 2013

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[36].Successively, in 2003, Bhojaraj and Sengupta conducted a studies aiming to analyse 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 can 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[37]. 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 will benefit of higher credit ratings.

2.4 Hypothesis development

In this section, the author will form hypothesis regarding the variables selected based on the literature analysed above.

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

[36] SENGUPTA, P., *"Corporate Disclosure Quality and the Cost of Debt",* The Accounting Review, 73(4), 459-474, 1998

[37] BHOJRAJ, S., & SENGUPTA, P., *"Effect of Corporate Governance on Bond Ratings and Yields: The Role of Institutional Investors and Outside Directors*", The Journal of Business, 76(3), 455-475, 2003

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[38]. 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[39].

The variables selected will be discussed in more details in Chapter 3.

2.4 The Rasch Model in the 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,

[38] LUNDQVIST D., STRAND, J., *"Bankruptcy Prediction with Financial Ratios- Examining Differences across Industries and Time"*, School of Economics and Management Department of Business Administration, 2013
[39]GUARDIAN, https://www.theguardian.com/business/2012/feb/15/credit-ratings-agencies-moodys, 15th February, 2012

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[40].

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, among which the Rasch model is included, in order to measure the bankruptcy risk of companies. Indeed in this study Raileanu 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."[41] 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"[42].

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. The rest of this paper is organised as follows: Chapter 3 will detail the research methodology including a discussion of the choice of methodology among the various different option available. This chapter also will go through the selection and collection of the variables with the respective explanations and challenges encountered and it will finally discuss in depth the model that will be used. Chapter 4 will then offer a section on data analysis while Chapter 5 will present the results with the respective findings. To conclude, Chapter 6 will discuss the

---

[40] SCHELLHORN, C., SHARMA,R., *"Using the Rasch model to rank firms by managerial ability"*, Managerial Finance, Vol. 39 Iss: 3, pp.306 – 319, 2013

[41] RĂILEANU S.M., *"Introducing an innovative mathematical method to predict the bankruptcy risk. Measures for the financial markets stability",* Department of Finance, Accounting and Economic Theory, Transylvania University of Brasov , B-dul Eroilor no.29 Brasov, ROMANIA, 2008

[42] LEHMANN, B., *"How good is "good"? - Managing Subjective Information in Credit Ratings",* Centre for Finance and Econometrics, University of Konstanz, Germany, 2004

limitations both methodological and theoretical of the research while Chapter 7 will suggest further area of studies.

CHAPTER 3: METHODOLOGY AND DATA COLLECTION

The research methodology used will ensue from those objectives and from the general philosophy of the research, as the methodology should not be an end in itself but on the contrary should follow from the philosophy stance of its author. The first step will therefore be to guide the readers through the general philosophy of the paper. The methodology will then outline the appropriate methods of research, which will help to achieve the aim and objectives of the research topic. Specifically, this chapter will aim to illustrate to the reader the empirical methodology, the approach, the tools (and more particularly the Rasch model), the data collected and respective challenges encountered while collecting the data.

The approach of this paper will be in accordance to the above philosophy of the author and with the objectives. Further details of the methodology will help better understand this approach but it can be said here that there is a clear willing of the author to always be objective in the research of data and the use of a new model. The strategy will be not to evaluate the credit agencies' approach but on the contrary to use their skills and knowledge of the appropriate variables to the purpose of a simpler and more universal (and therefore objective) model based on the Rasch model.

Most of the time has been spent looking for relevant data and more importantly the right variables that can be used to obtain satisfying results. Applying the data to the model is relatively straightforward (one of the main advantages of using this objective model) and therefore once the data is obtained and the variables chosen the results will be easily applied. However another difficulty will also be to compare the results obtained with the credit rating of agencies. The idea is that similar results to credit rating agencies could be good evidence of the success of the model, but also that if the results are different the model is not necessarily rejected.

Therefore, in terms of time, the author believes that the researches should be divided in two periods, the first focusing on relevant data research, and the second on the analysis of the data. Once again, the timing is closely linked to the philosophy of the author, as a lot of time should be spent in the research of objective variables, and on the justification of differences between credit rating agencies and the more universal goal of the Rasch model.

3.1 Credit agencies methodology

Understanding the methodology of credit rating agencies is a very difficult task as this is a very secretive subject and there is obviously no public information explaining precisely what it is that those agencies do exactly. However, getting a broad understanding of the method and especially of the variables used is critical for the purposes of this paper.

Standard & Poor's rating services website provides criteria for ratings that were a first step to our research and the same counts for Moody's and Fitch Ratings websites. Indeed these websites offer several sources explaining the general methodologies used according to the industry and sectors of the companies under analysis.

In addition to the credit agencies website, an analysis of relevant literature on credit rating has been conducted to better understand the variables needed. Indeed, credit agencies determine the ratings by analysing the probability distribution of the future cash flows to bondholders that are strictly interconnected with the cashflows that the firm will generate[43]. Therefore, if the future cashflows distribution decreases or the variance of the future cashflows increases, this will result in a higher probability of default of a company. So it is of relevant importance to find out all the variables that affect the cash flows of a company in order to make a deep and reliable analysis. The main research tools used by the author were ProQuest, Google Scholar and Science Direct which offered a wide range of studies and researches in support of the dataset selected.

3.2. Data collection

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.

3.2.1 Sample selection

In order to carry out our analysis, we have built a sample of 121 companies from S&P 500. 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. Among the remaining companies three different sectors were selected based on the number of companies per sector and the

[43] STANDARD & POOR'S, https://www.standardandpoors.com/en_US/web/guest/home, 2016

available data. This has been done to ensure that an analysis of the changing of rating over the entire period could be performed. The sectors selected are information technology, consumer discretionary and industrials.

The figure below shows the three main features[44]:

Figure 2- Sector characteristics

Sector	Reasons to Consider
Consumer Discretionary 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.	▪ 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 brands
Industrials The Industrials sector includes companies that manufacture and distribute capital goods in support of industries such as aerospace and defense, construction and engineering, electrical equipment and heavy machinery.	▪ Performance tends to be sensitive to economic cycles. ▪ Tends to perform better in the early-to-middle stages of the business cycle ▪ Offers potential exposure to growth associated with the global need for infrastructure replacement
Information Technology The Information Technology sector comprises companies that are engaged in the creation, storage, and exchange of digital information.	▪ Considered one of the more volatile sectors ▪ Largest sector in terms of market capitalization; deep and diverse set of companies and industries ▪ Offers potential exposure to growth associated with the rise of cloud computing, big data, and mobile computing

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 criticised to have wrongly evaluate the rating of several companies.

3.2.2 Data collection

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.

[44] FIDELITY, https://www.fidelity.com/sector-investing/compare-sectors, accessed: 15th August 2016

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[45]. 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 also 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 followed:

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 be expected to have a higher credit rating[46]. In order to summarise 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.

[45] U.S. SECURITY AND EXCHANGE COMMISSION, https://www.sec.gov/edgar/searchedgar/companysearch.html, EDGAR database research tool, 2016
[46] DOUMPOS M., NIKLIS D., ZOPOUNIDIS C., ANDRIOSOPOULOS K., *"Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms",* Journal of Banking & Finance, Vol. 50, Pages 599-607, 2015

2	Return on total asset	Earnings before interest and taxes/total asset	Return on total asset measures how productive the asset of a companies are 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"[47].
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 of time. 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

[47] ALTMAN, E.I. *"Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models"* Personal Homepage, 2000

			missing prices from the database were researched using Yahoo finance. The stock return is expected to be higher when investors take a greater risk and therefore it is expected to be negatively 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[48].

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

[48] ALTMAN, E.I. *"Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models"* Personal Homepage, 2000

related to credit scores[49]. 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. This matter has been discussed in more details in the section below "Limitations in collecting the data".

#	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"[50].

Bloomberg default risk

In order to assess the validity of the model, the result obtained will 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.

[49] AMAN, H., NGUYEN, P., *"Does good governance matter to debtholders? Evidence from the credit ratings of Japanese firms",* Research in International Business and Finance, Vol.29, Pages 14-34, 2013

[50] SKAIFE, H. A., COLLINS, D.W., LAFOND, R., *"The Effects of Corporate Governance on Firms' Credit Ratings",* Journal of Accounting and Economics, pp. 203-243, 2006

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"[51].

3.2.3 Limitations in the collection of the data

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.

3.3.The Rasch model

In 1960, George Rasch discovered that "he could obtain an invariance of test item characteristics over variations in persons only if the function through which persons and

[51] BLOOMBERG, http://www.bbhub.io/bat/sites/3/Paul-Laux-Lab-6.pdf, 2015

items interact has linear form"[52] (Rasch, 1960, p. 120). This is the measurement characteristic of specific objectivity "which 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"[53].

There are several Rasch models according to the nature of the variables. For two ordered categories the Dichotomous Rasch model is provided, while for higher ordered categories the Rating Scale model and the Partial Credit model[54] can be used. Below is a summary of the 3 main Rasch models:

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

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: $\ln\left(\frac{P(X_{ij}=k)}{P(X_{ij}=k-1)}\right)=\alpha_i-\beta_j-\tau_k$, $X_{ij}\in\{0,1,2\cdots K\}$,

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

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

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

[52] GORI, E., & MARIN, R. F., *"Rasch analysis of some MMPI-2 scales in a sample of university freshman",* International Conference for Academic Disciplines. Barcelona, 2015

[53] GORI, E., & MARIN, R. F., *"Rasch analysis of some MMPI-2 scales in a sample of university freshman",* International Conference for Academic Disciplines. Barcelona, 2015

[54] GORI, E., & MARIN, R. F., *"Rasch analysis of some MMPI-2 scales in a sample of university freshman",* International Conference for Academic Disciplines. Barcelona, 2015

In the model, the items are ranked in order of difficulty and there is a positive relationship between "the probability that a person will answer correctly to an item and the difference between a person's ability (Bn) and item (question) difficulty (Di)" [55].

$$P_n(x=1) = f(B_n - D_i)$$

Therefore there will be a higher probability to obtain a wrong answer from a person when the item is more difficult. As a consequence, the higher a person's ability, the more likely to have a correct answer to the item.

For instance, 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.

Therefore the Rasch models are defined measurement models which use dichotomous or ordinal data in order to construct a measure of the person under observation. As the Rasch models satisfy the fundamental measurement axioms, the main problem in the analysis will be to actually understand how good the data fits in the model.

In the final stage, all the responses of a person to each item will be summarised 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 Model 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

[55] RIDZAK, T. "*Are Some Banks More Lenient in the Implementation of Placement Classification Rules",* Zagreb: Croatian National Bank, 2011

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[56].

3.3.1 The Rasch analysis and model interpretation

The first step in applying the Rasch model will be to understand if the data is compatible with the model and satisfies its assumptions. We will look at the Person 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 don't agree with the latent variables and therefore the item will need to be removed from the analysis or 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. In case the Andrich Threshold will be disordered, the solution is usually to reduce the number of categories put into place.

Once all the issues will be resolved, we are going to apply the Rasch model in order to have an estimation of the expected response to each item for each person considered. In our case the items are going to be represented by the 16 variables and the persons by each company composing our sample. The model in its results will produce 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. 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 and therefore the predicable value of the variable will be reduced. Values less than 1.70 and greater than 0.5

[56] RASCH WEBSITE, http://www.rasch-analysis.com/rasch-analysis.htm, 2016

can be deemed to be acceptable and therefore a good fit but the best fit will be obtained with value close to 1[57]. This fit statistics will be divided in two categories, weighted called INFIT and unweighted, called OUTFIT.

A person which is under fitting the model indicates that it responds randomly to the items and a measure cannot be estimated. These items will therefore be removed from the model to increase the validity of the results obtained.

Finally it should be pointed out that in order to apply the Rasch model we will use a software called Winsteps. The process in order to upload the data on Winsteps will be analysed in the next paragraph.

---

[57] BOND, T. G., AND FOX, C. M., *"Applying the Rasch Model: Fundamental Measurement in the Human Sciences*". 3rd Edition, Routledge Taylor & Francis Group, Page 243, 2007

3.4.Organization of the data and construction of the Winsteps code for Rasch analysis

In order to apply the Rasch model to the data, we need to use a specialized software called "Winsteps". This section will walk the reader through the modification necessary to make the data compatible with the form required by Winsteps and to the upload process of the data into the system.

The first step to modify the data was to arrange in an Excel spreadsheet as illustrated in the table below.

Table 1- First step for the preparation of the data for the upload in Winsteps

	A	B	C	D	E	F	G	H	I	J	K
1	CODE	SECTOR	EQUITY	YEAR	EQUITY YEAR	14CEOP	15DEFA	16FREE	17STRT	01ROA_	02AROA
2	1	A	AN UN	M	14 AN UN	1	IG7	0	4	1	2
3	2	A	BBBY UW	M	14 BBBY UW	0	IG7	2	2	6	6
4	3	A	BBY US	M	14 BBY US	0	IG9	0	2	3	2
5	4	A	CCL UN	M	14 CCL UN	0	IG5	0	3	0	0
6	5	A	CBS UN	M	14 CBS UN	0	IG7	2	1	5	3
7	6	A	COH UN	M	14 COH UN	0	IG6	3	0	6	6
8	7	A	CMCSA UW	M	14 CMCSA UW	1	IG5	6	3	2	2
9	8	A	DRI UN	M	14 DRI UN	1	IG6	1	3	5	1
10	9	A	F UN	M	14 F UN	0	IG9	4	2	0	0
11	10	A	GPS UN	M	14 GPS UN	1	IG7	0	3	6	6
12	11	A	GPC UN	M	14 GPC UN	1	IG3	2	5	4	4
13	12	A	GT UW	M	14 GT UW	1	IG9	3	4	5	1
14	13	A	HRB UN	M	14 HRB UN	0	IG5	5	4	5	5
15	14	A	HOG UN	M	14 HOG UN	1	IG6	5	2	4	4
16	15	A	HAS UW	M	14 HAS UW	0	IG5	1	2	4	4
17	16	A	HD UN	M	14 HD UN	1	IG3	6	5	6	6
18	17	A	IPG UN	M	14 IPG UN	1	IG6	4	4	1	1
19	18	A	JCI UN	M	14 JCI UN	1	IG6	5	2	1	0
20	19	A	KSS UN	M	14 KSS UN	1	IG6	2	3	2	3
21	20	A	LB UN	M	14 LB UN	1	IG6	0	5	6	6
22	21	A	LEG UN	M	14 LEG UN	1	IG4	2	5	0	3
23	22	A	LOW UN	M	14 LOW UN	1	IG4	6	5	4	5

The first 9 columns identify the sample, the years and those variables which will then be used to test the reliability of our results. These first 9 columns have the following has been modify in the following way in order to be compatible with the Winsteps format:

1. CODE: this column contains the progressive number of observations. In this case, as our sample is composed of 121 companies, the number of observation was equal to 121.
2. SECTOR: for simplicity we have introduced the following keys for the sectors selected:
   - A= Consumer Discretionary
   - B=Industrials
   - C= Information Technology;
3. EQUITY: this column specify the name of the S&P 500 company selected.
4. YEAR: this indicate the year of the observations. Again for simplicity the following keys were adopted: A=2004, B=2005, C=2006, D= 2007, E=2008, F=2009, G=2010, H=2011, I= 2012, L=2013, M = 2014;

5. EQUITY YEAR: this column concatenate in the same cell the year of the observation and the name of the equity.
6. 14CEOP: as explained in Chapter 3, this is a dummy variable. This variable will be equal to one if the CEO is also the chairman of the board of directors, otherwise the variable will be zero.
7. 15DEFA: this is the Bloomberg default risk which is our proxy to synthetize the rating agency grade.
8. 16FREE: class of % of Free Float. The free float was divided in 7 classes delimited by the following seven percentiles:

$$\text{Minimum and Maximum} \begin{cases} 0 \quad \text{if} \quad 22.0 \le \%\text{FREE FLOAT} \le 88.3 \\ 1 \quad \text{if} \quad 88.3 < \%\text{FREE FLOAT} \le 95.3 \\ 2 \quad \text{if} \quad 95.3 < \%\text{FREE FLOAT} \le 98.5 \\ 3 \quad \text{if} \quad 98.5 < \%\text{FREE FLOAT} \le 99.2 \\ 4 \quad \text{if} \quad 99.2 < \%\text{FREE FLOAT} \le 99.5 \\ 5 \quad \text{if} \quad 99.5 < \%\text{FREE FLOAT} \le 99.7 \\ 6 \quad \text{if} \quad 99.7 < \%\text{FREE FLOAT} \le 100.0 \end{cases}$$

   The Free Float has been omitted by the analysis as it resulted to be incompatible and insignificant to the model.
9. 17STRT: class of the Stock Return. Also the stock return were divided in 7 classes delimited by the following 7 percentiles:

$$\text{Minimum and Maximum} \begin{cases} 0 \quad \text{if} \quad -0.81 \le \text{stock return} \le -0.23 \\ 1 \quad \text{if} \quad -0.23 < \text{stock return} \le -0.06 \\ 2 \quad \text{if} \quad -0.06 < \text{stock return} \le 0.05 \\ 3 \quad \text{if} \quad 0.05 < \text{stock return} \le 0.14 \\ 4 \quad \text{if} \quad 0.14 < \text{stock return} \le 0.26 \\ 5 \quad \text{if} \quad 0.26 < \text{stock return} \le 0.40 \\ 6 \quad \text{if} \quad 0.40 < \text{stock return} \le 4.20 \end{cases}$$

After that we have changed the format of the remaining 13 indicators which we will be used to construct the measure with Rasch models:

Table 2- Data formatting in Excel

J	K	L	M	N	O	P	Q	R	S	T	U	V
01ROA_	02AROA	03INCO	04ROEC	05SATA	06CURA	07QURA	08SORA	09DERC	10CARA	11WCTA	12RETT	13MVTL
1	2	5	4	6	1	0	0	5	5	1	4	1
6	6	2	6	6	4	1	5	3	4	5	6	4
3	2	2	5	6	3	1	3	5	2	4	2	2
0	0	5	0	0	0	0	3	1	2	0	4	3
5	3	4	6	1	2	3	3	5	5	2	0	2
6	6	0	6	5	5	4	6	1	0	5	0	6
2	2	5	2	0	0	1	2	4	5	0	1	2
5	1	6	5	5	0	1	4	4	4	0	1	3
0	0	6	0	2	0	0	0	6	6	0	0	0
6	6	2	6	6	4	2	5	4	3	5	3	4
4	4	1	4	6	3	1	3	4	1	4	4	4
5	1	6	6	4	3	2	4	5	6	3	1	0
5	5	3	5	2	3	4	4	3	2	4	3	4
4	4	0	5	2	3	4	2	5	6	3	6	3
4	4	5	5	4	5	5	3	5	5	5	6	3
6	6	3	6	6	2	0	4	6	6	2	5	5
1	1	4	4	1	1	2	0	6	4	1	0	0
1	0	6	1	5	1	1	1	4	4	1	2	2
2	3	5	2	5	4	0	3	3	5	4	6	2
6	6	5	6	6	4	3	3	6	6	4	0	4
0	3	4	1	5	3	2	1	4	4	3	5	4
4	5	4	5	6	1	0	3	5	5	1	2	4

The following keys were used to summarize this indicators:

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

In order to these variables to be compatibles to the requirements of Winsteps and the Rating scale Rasch model, we have divided the data in categories based on the percentiles. The percentiles were determined using the maximum and minimum value of the data. For the nature of the data, we have deemed to be more appropriate to divide the analysis in two groups:

1. Sector A and B: the analysis of this two sectors will be based on seven percentiles
2. Sectors C: the information technology sector analysis will be based on only four percentiles

This will be further explain in Chapter 4.

The table below summarizes the percentiles used in the analysis:

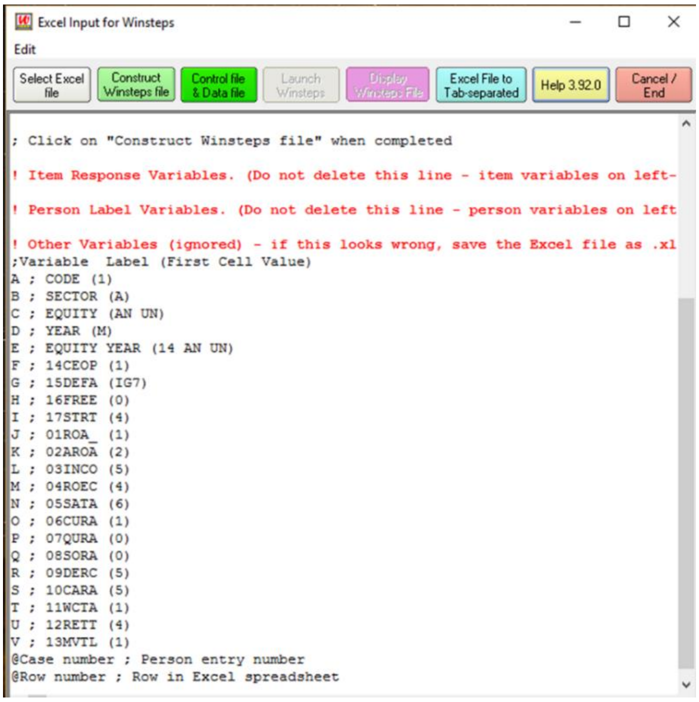
Table 3- Percentiles per sector

		CLASSIFICATION OF THE INDICATORS IN CATERGORIES FOR THE RASCH RATIG MODELS												
SECTORS A & B		01ROA_	02AROA	03INCO	04ROEC	05SATA	06CURA	07QURA	08SORA	09DERC	10CARA	11WCTA	12RETT	13MVTL
CATEGORIES	MIN	-0.85	-0.61	-85.00	-10.22	0.07	0.21	-0.39	-0.98	-259.25	0.00	-0.35	-2.95	0.02
0	0.14	0.03	0.05	0.00	0.08	0.46	1.00	0.70	0.09	0.51	0.01	0.00	0.12	0.88
1	0.29	0.05	0.08	0.03	0.12	0.59	1.20	0.92	0.13	0.80	0.17	0.05	0.25	1.31
2	0.43	0.07	0.10	0.06	0.16	0.75	1.42	1.09	0.17	1.11	0.25	0.11	0.33	1.91
3	0.57	0.08	0.12	0.10	0.19	0.93	1.75	1.30	0.22	1.47	0.32	0.18	0.41	2.57
4	0.71	0.10	0.15	0.14	0.23	1.12	2.17	1.69	0.30	1.95	0.40	0.26	0.51	3.83
5	0.86	0.14	0.19	0.21	0.31	1.51	2.93	2.40	0.45	3.21	0.56	0.40	0.69	6.78
6	MAX	0.46	0.61	8.95	70.48	3.58	13.52	12.40	173.40	990.31	2.86	3.66	3.29	61.34
SECTOR C		01ROA_	02AROA	03INCO	04ROEC	05SATA	06CURA	07QURA	08SORA	09DERC	10CARA	11WCTA	12RETT	13MVTL
CATEGORIES	MIN	-0.95	-0.71	-85.10	-10.32	-0.03	0.11	-0.49	-1.07	-259.34	-0.10	-0.45	-3.05	-0.08
0	0.25	0.05	0.07	0.02	0.12	0.57	1.15	0.87	0.12	0.73	0.15	0.04	0.23	1.22
1	0.5	0.07	0.11	0.08	0.17	0.85	1.57	1.17	0.20	1.30	0.28	0.14	0.36	2.22
2	0.75	0.11	0.15	0.15	0.24	1.19	2.31	1.83	0.33	2.20	0.43	0.28	0.54	4.29
3	MAX	0.46	0.61	8.95	70.48	3.58	13.52	12.40	173.40	990.31	2.86	3.66	3.29	61.34

Once the data has been transformed in the format required by Winsteps, we have then upload the data in the software. In order to achieve that, we have upload the excel spreadsheet constructed in one of the program of Winsteps, specialized in the application of the Rasch Model[58].

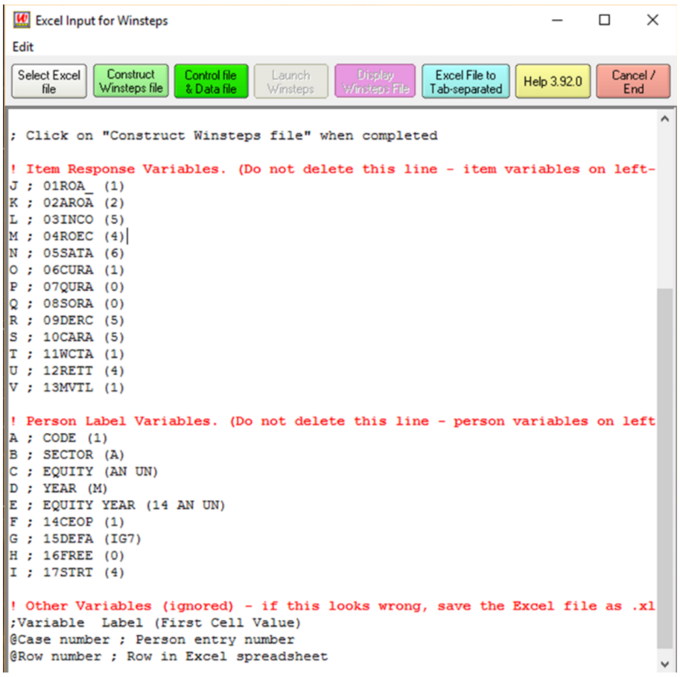
The following figures illustrate how the upload of the data in the program works:

1. We have then choose the option "Select Excel file" and imported our document in the program. Once imported the variables appears in the following format in the programme:



[58] WINSTEPS WEBSITE, http://www.winsteps.com/index.htm, 2016

2. We enter in the programme the labels of the items and the persons with their respective meaning.



4. At this point the programme code for the analysis is built and we have checked using the figure below that all the information has been properly processed:

```
RASCH7 - Blocco note
File   Modifica   Formato   Visualizza   ?
&INST
Title= "RASCH GLORIA7.xlsx"
; Excel file created or last modified: 28/07/2016 11.30.38
; Foglio1
;     Excel Cases processed = 1320
; Excel Variables processed = 22
ITEM1 = 1 ; Starting column of item responses
NI = 13 ; Number of items
NAME1 = 15 ; Starting column for person label in data record
NAMLEN = 41 ; Length of person label
XWIDE = 1 ; Matches the widest data value observed
; GROUPS = 0 ; Partial Credit model: in case items have different
CODES = "0123456 " ; matches the data
TOTALSCORE = Yes ; Include extreme responses in reported scores
; Person Label variables: columns in label: columns in line
@CODE = 1E4 ; $C15W4
@SECTOR = 6E6 ; $C20W1
@EQUITY = 8E15 ; $C22W8
@YEAR = 17E17 ; $C31W1
@EQUITY-YEAR = 19E29 ; $C33W11
@14CEOP = 31E31 ; $C45W1
@15DEFA = 33E36 ; $C47W4
@16FREE = 38E38 ; $C52W1
@17STRT = 40E40 ; $C54W1
&END ; Item labels follow: columns in label
01ROA_ ; Item 1 : 1-1
02AROA ; Item 2 : 2-2
03INCO ; Item 3 : 3-3
04ROEC ; Item 4 : 4-4
05SATA ; Item 5 : 5-5
```

Indeed we can observe that NI is equal to 13 which indicates that there are 13 items (our selected variables) and that the "CODE="0123456 explains that the programme has found seven categories plus " " which represents the missing data. We will transform this command in CODE=0123456 in order tell to the program to exclude the missing data from the analysis. For the other instructions is possible to look at the help routine of the program on the Winsteps website.

Now the Rasch model is ready to be applied. In the next chapter we are going to analyze the preliminary results obtained.

CHAPTER 4: THE DATA ANALYSIS USING THE RASCH MODEL

In this chapter we are going to apply the Rasch model to the data selected. Particularly, the first part of the analysis will focus on the determination of a number of categories that we will need to use in the model together with the illustration of the preliminary models resulted to the first considerations. Finally, we are going to apply the Rating Scale Rasch model and determine the final models.

4.1.The preliminary Rasch analysis and the choice of the optimal categorization

In order to apply the Rasch models, the data must be transformed into an ordinal scale. As already explained in the previous chapter, this is done by using the percentiles. However, the main issue will be to determine how many categories need to be used. To this end, we followed what was suggested by the literature on the argument:

"Typical decimal data is over-precise. Its numerical precision is greater than its substantive precision. Example: I can measure and report my weight to the nearest gram, but my "true" weight has a precision of about 500 grams.

A solution to this is to discover the precision in the data empirically and therefore the following steps need to be taken:

1. Dichotomize the data for each item around the median decimal value into 0 = below median, 1= above median

2. Analyze those data.

3. If the analysis makes sense, then dichotomize each subset of the data again, so that it is now scored 0,1, 2,3

4. Analyze those data.

5. If the analysis makes sense, then dichotomize each subset of the data again, so that it is now scored 0,1, 2,3, 4,5, 6,7

6. Analyze those data.

7. If .... (and so on)."[59]

In this study, we have performed 9 different analysis using respectively 2 to10 percentiles in the following way: as the literature suggested above, 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 of this type:

---

[59] WINSTEPS WEBSITE, http://www.winsteps.com/index.htm, 2016

$$P(X_{ni}=1)=\frac{\exp(\beta_n-\delta_i)}{1+\exp(\beta_n-\delta_i)}, \qquad P(X_{ni}=0)=\frac{1}{1+\exp(\beta_n-\delta_i)},$$

Where β_n are the "ability" parameters that in this case may be interpreted as a sort of rating of the equity n (it measures its goodness i.e. reliability 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.

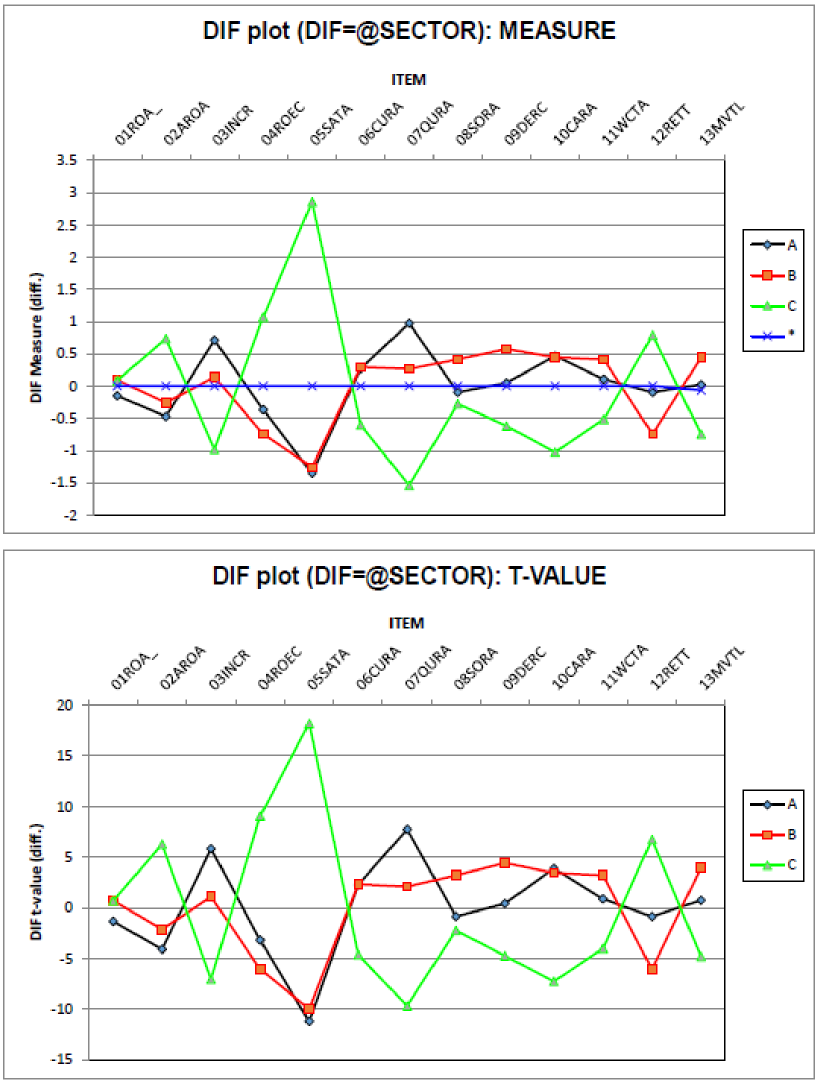
A first run of Winsteps on the overall dataset provided the results showed in Appendix 1. Here, we can see that the reliability of the items was zero, meaning that the item difficulties has no variation. It is possible to get more insight into the meaning of the reliability index for Rasch models looking at http://www.rasch.org/rmt/rmt94n.htm, but as a rule of thumb, the measure will be more significant when it assumes a value close to 1. This has been explained as well in the previous chapter. In addition, in Appendix 1, we can see that all difficulties ("MEASURE" column) are almost the same and this is the reason why the item reliability is zero. In order to understand what can have produced such result, we have performed a data check. By looking in more details, we have noticed that items 3, 9 and 10, which correspond respectively to Interest Coverage reversed, Debt equity ratio and Cap Ratio present "reverse polarity", which means that these variables are negatively correlated with the estimated measure and therefore they don't follow the same ascending rating score as the other variables (Please refer to Appendix 1 to view these results). In order to resolve this issue, we have reversed these variables and modified the coding in Winsteps and rerun the program. After applying again the model, we have noticed that the reverse polarity problem was resolved but the reliability of the model was still equal to zero. This means that for the model all the items measures are all equal to each other. This case can be observed in two different scenarios:

1. The items have actually the same meaning, which would result in an unexpected result
2. The presence of a strong differential item functioning. This scenario can occur for instance when the difficulties parameters of the items are very different for some subset of data. In this situation, applying the model to the all dataset would determine a regression towards the mean, which is set at zero[60].

[60] BOND, T. G., AND FOX, C. M., *"Applying the Rasch Model: Fundamental Measurement in the Human Sciences*". 3rd Edition, Routledge Taylor & Francis Group, p. 243, 2007

Considering the second case the most plausible option, we have looked at the presence of a strong differential item function among the three sectors under analysis (Consumer discretionary, industrials and Information Technology) and we have actually observed that it was the case.

Figure 3- Differential item functioning analysis



Indeed, by looking at Figure 3, we can observe that the items show the same average value, while the difficulties of the items for each sector are quite different from the mean value obtained with the overall data. This is especially the case for Sector C, which shows in several cases opposite results compared to the other two sectors. Therefore, followed this first outcome, we have decided to split the study among the three different sectors. This had to be expected as every sector has different characteristics and therefore different variables will have a different weight or importance among different industries. However, this will imply that the measures obtained will be not comparable among different sectors but this is usually what happens using the rating measures. The preliminary results of the analysis by sector will be discussed in the next section.

4.2.Preliminary sectors analysis

In this section, we have applied the Rasch model to each sector in order to overcome the problem of strong differential item functioning encountered in the previous analysis. A strong increase in the reliability index was noticed and the results per sectors are set out below.

4.2.1 Sector A (Consumer Discretionary)

The Rasch model was applied to Sector A. The reliability obtained from the model is 0.96 for the items (the variables) and 0.76 for the persons (the equity), while the difficulties of the items range between -1.40 and 1.00. The results are presented in Appendix 2. Here, 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[61].

In addition, the principal component analysis (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 due to two items with a correlation of 0.77, above the advice limit of 0.70, which imply a violation of Local Independence hypothesis of the Rasch Model. These are items, 6 and 11, respectively "Current ratio" and "Working capital/Total asset" (Table 4).

---

[61] BOND, T. G., AND FOX, C. M., *"Applying the Rasch Model: Fundamental Measurement in the Human Sciences*". 3rd Edition, Routledge Taylor & Francis Group, p. 243, 2007

Table 4- Correlation between items

LARGEST STANDARDIZED RESIDUAL CORRELATIONS
USED TO IDENTIFY DEPENDENT ITEM

CORREL-ATION	ENTRY NUMBER	ITEM	ENTRY NUMBER	ITEM
.77	6	06CURA	11	11WCTA
.45	1	01ROA_	2	02AROA
.36	9	09DERC	10	10CARA
.28	1	01ROA_	8	08SORA
.25	6	06CURA	7	07QURA
-.38	4	04ROEC	9	09DERC
-.31	2	02AROA	9	09DERC
-.29	6	06CURA	8	08SORA
-.29	5	05SATA	7	07QURA
-.29	8	08SORA	11	11WCTA
-.27	4	04ROEC	10	10CARA
-.27	1	01ROA_	9	09DERC
-.26	1	01ROA_	10	10CARA
-.26	7	07QURA	8	08SORA
-.25	2	02AROA	6	06CURA
-.25	1	01ROA_	11	11WCTA
-.24	1	01ROA_	6	06CURA
-.24	2	02AROA	10	10CARA
-.24	11	11WCTA	13	13MVTL
-.23	5	05SATA	9	09DERC

In order to avoid this high correlation, we have omitted item 6, which reduced the unexplained variance to 2.3. We then started to exclude from the analysis the indicator with INFIT or OUTFIT indices outside the range 0.5-1.7 (Appendix 2).We ended up excluding from the analysis the indicators 6, 7 and 12. The omission of items 7 and 12 was judgmental. Indeed, the items were in the suggested range but, in order to have a more accurate analysis, when possible we have tried to maintain the range between 0.7 and 1.2. At this point, we have rerun the programme. 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. From Appendix 5 (and specifically Appendix 5.A), 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 was 1.

4.2.2 Sector B (Industrials)

The Rasch model was applied to Sector B. The reliability of the items is 0.95 and the one of the equity 0.76, while the difficulties of the items range between -1.30 and 0.59. Only item 4 shows very poor fit with INFIT and OUTFIT of 1.8-2.6, which is outside the suggested range of 0.5-1.7 (Appendix 3). Again, from the PCA analysis of standardized residuals, we have observed a level of unexplained variance of 2.79 in the first contrast, a bit higher than the level 2 suggested for unidimensionality. However, by omitting items 6, with the highest correlation, this reduced sensibly (Table 5).

Table 5- Correlation of the items

LARGEST STANDARDIZED RESIDUAL CORRELATIONS
USED TO IDENTIFY DEPENDENT ITEM

CORREL-ATION	ENTRY NUMBER	ITEM	ENTRY NUMBER	ITEM
.62	6	06CURA	11	11WCTA
.51	6	06CURA	7	07QURA
.43	1	01ROA_	2	02AROA
.34	7	07QURA	11	11WCTA
.33	8	08SORA	13	13MVTL
.26	9	09DERC	10	10CARA
-.37	4	04ROEC	9	09DERC
-.35	2	02AROA	6	06CURA
-.34	1	01ROA_	6	06CURA
-.32	1	01ROA_	7	07QURA
-.31	3	03INCR	6	06CURA
-.30	4	04ROEC	6	06CURA
-.28	2	02AROA	7	07QURA
-.26	11	11WCTA	12	12RETT
-.25	4	04ROEC	8	08SORA
-.25	4	04ROEC	13	13MVTL
-.25	3	03INCR	7	07QURA
-.24	4	04ROEC	7	07QURA
-.24	1	01ROA_	11	11WCTA
-.24	5	05SATA	13	13MVTL

After analysis of the data we have further excluded items with poor fit and we ended up excluding the following variables: 4, 6, 7 and 12. After rerunning the program, we have obtained a reliability of .96 for items and of 0.69 for equities while the difficulties of the items range between -1.71 to 0.57 (Appendix 3), which are acceptable fit indices. In Appendix 5 the unexplained variance in the first contrast is 1.93 and all the correlations between equities measures determined on the base of the tentatively different item clusters was 1.

4.2.3 Sector C (Information Technology)

The Rasch model was finally applied to Sector C and from Appendix 4 we can observe that the reliability of items and companies were respectively 0.99 and 0.72 while the difficulties of the items range from -1.64 to 3.26. However, some items highly misfit. The PCA analysis of standardized residuals shows a level of 3.23 for the unexplained variance in the first contrast, which is reduced to 2.78 (Appendix 5) after the exclusion of item 6 which is highly correlated with item 11 for this sector.

Table 6- Correlation of the items

LARGEST STANDARDIZED RESIDUAL CORRELATIONS
USED TO IDENTIFY DEPENDENT ITEM

CORREL-ATION	ENTRY NUMBER	ITEM	ENTRY NUMBER	ITEM
.75	6	06CURA	11	11WCTA
.50	6	06CURA	7	07QURA
.47	7	07QURA	11	11WCTA
.47	1	01ROA_	2	02AROA
.40	9	09DERC	13	13MVTL
.37	9	09DERC	10	10CARA
.37	8	08SORA	9	09DERC
-.45	4	04ROEC	9	09DERC
-.43	5	05SATA	13	13MVTL
-.40	4	04ROEC	7	07QURA
-.39	2	02AROA	9	09DERC
-.37	2	02AROA	7	07QURA
-.35	4	04ROEC	11	11WCTA
-.35	5	05SATA	9	09DERC
-.32	4	04ROEC	6	06CURA
-.32	1	01ROA_	7	07QURA
-.32	1	01ROA_	9	09DERC
-.31	2	02AROA	6	06CURA
-.30	2	02AROA	10	10CARA
-.30	2	02AROA	11	11WCTA

After deleting some missfitting equities (equities numbers 2, 4, 5, 6 and 12), we obtained the following results: A reliability of the items equal to 0.94 and 0.44 the one of the equities which is not very satisfying. We have therefore increased the number of categories, hoping that this change would make the index improve. However, the item difficulties range from -1.13 to 1.18 which is a good fit index (Appendix 4).

From Appendix 5, it is possible to observe that the unexplained variance in the first contrast is 1.92 and all the correlations between equity measures based on the tentatively different item clusters was 1.

Therefore, we may say that this first run of the Rasch model for all sectors was quite successful and we may go on to analyze data with a greater number of categories as suggested by the literature. This will be presented in the next section.

4.3.The Rasch Rating scale model

In this second part of the analysis we have transformed the data Y in X and we have expressed it in an ordinal scale with m levels. In addition, we have used m classes defined by m percentiles and the Minimum and Maximum percentiles. The model applied was therefore the Rasch rating Scale model of the following kind:

$$P(X_{ni} = x) = \frac{\exp\sum_{k=0}^{x}[\beta_n - (\delta_i + \tau_k)]}{\sum_{j=0}^{m}\exp\sum_{k=0}^{j}[\beta_n - (\delta_i + \tau_k)]},\ x = 0,1,2,\cdots,m,$$

Where β_n are again the "ability" parameters, δ_i are the "average difficulty" parameters, and τ_k is the difficulty to reach the level (category) k.

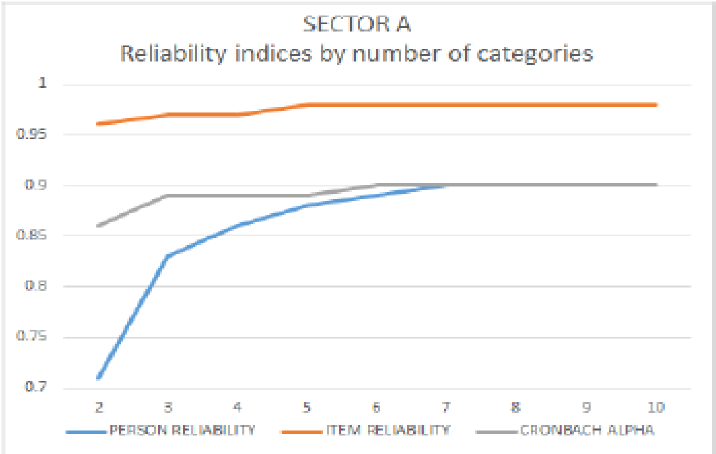
In order to decide which categorization was the most adequate for each sector, we need to consider three main indicators:

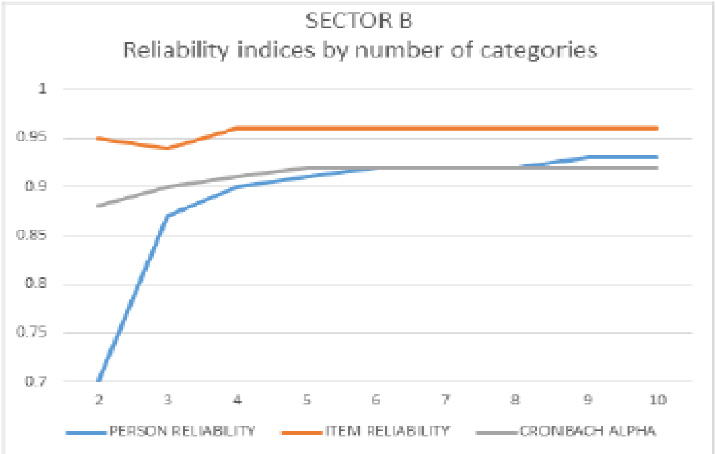
- The Reliability indices
- The fit of the model, determined by the measures of INFIT and OUTFIT
- The Andrich Thresholds: this is a parameter which shows if a Rasch rating is disordered.

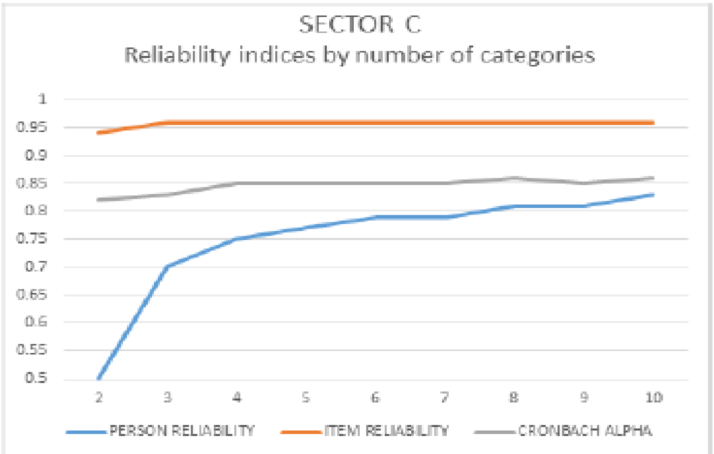
We have summarized these three indicators in the following tables and figures.

Figure 4 illustrates that with the increase of the number of categories, the person's reliability grows sensibly reaching levels of 0.85-0.90 in all sectors. 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 for Sector A and B that the reliability remains constant after reaching 7 categories, while for Sector C this remains constant when the number of categories is 4.

Figure 4- Reliability index per sector







From Table 7 we can also see that INFIT and OUFIT indices lie between the limit of 0.5 and 1.7 for almost every sector with the exception of sector A were we observe INFIT and OUTFIT 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, which would damage the validity of the measure obtained with the model.

Table 7- INFIT and OUTFIT indices

Infit and Outfit indices for the different models

	NUMBER OF CATEGORIES								
SECTOR A	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	1.79	1.59	1.74	1.7	1.69	1.66	1.66	1.61	1.61
MIN OUTFIT	0.49	0.44	0.44	0.42	0.42	0.41	0.41	0.4	0.4

	NUMBER OF CATEGORIES								
SECTOR B	2	3	4	5	6	7	8	9	10
MAX INFIT	1.37	1.55	1.55	1.49	1.76	1.54	1.59	1.59	1.57
MIN INFIT	0.68	0.69	0.62	0.6	0.44	0.55	0.55	0.53	0.54
MAX OUTFIT	1.51	1.62	1.62	1.52	1.61	1.61	1.63	1.65	1.62
MIN OUTFIT	0.61	0.62	0.64	0.62	0.59	0.57	0.59	0.56	0.57

	NUMBER OF CATEGORIES								
SECTOR C	2	3	4	5	6	7	8	9	10
MAX INFIT	1.36	1.36	1.37	1.4	1.41	1.39	1.41	1.4	1.41
MIN INFIT	0.62	0.59	0.6	0.59	0.56	0.54	0.56	0.58	0.59
MAX OUTFIT	1.4	1.32	1.28	1.4	1.39	1.35	1.37	1.37	1.37
MIN OUTFIT	0.53	0.54	0.53	0.55	0.51	0.49	0.51	0.52	0.55

Finally, from Table 8, 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, 8 and 7 respectively for Sector A, B and C.

Table 8- Andrich Thresholds per sector

ANDRICH THRESHOLDS FOR THE RATING SCALE MODELS

SECTOR	CATEGORIES							
A	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

SECTOR	CATEGORIES							
B	3	4	5	6	7	8	9	10
0	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
1	-1.44	-1.63	-1.68	-1.55	-1.42	-1.3	-1.22	-1.17
2	1.44	-0.24	-0.78	-0.94	-1.02	-1.1	-1.03	-1.04
3		1.87	0.37	-0.28	-0.55	-0.59	-0.68	-0.74
4			2.09	0.74	0.08	-0.29	-0.47	-0.52
5				2.03	0.89	0.34	-0.07	-0.25
6					2.03	0.9	0.53	0.12
7						2.05	0.9	0.57
8							2.03	0.99
9								2.03

SECTOR	CATEGORIES							
C	3	4	5	6	7	8	9	10
0	NONE	NONE	NONE	NONE	NONE	NONE	NONE	NONE
1	-0.59	-0.55	-0.37	-0.31	-0.21	-0.25	-0.20	-0.22
2	0.59	-0.15	-0.43	-0.50	-0.48	-0.27	-0.18	-0.09
3		0.70	0.11	-0.04	-0.21	-0.40	-0.47	-0.50
4			0.69	0.12	0.08	-0.06	-0.14	-0.27
5				0.73	0.13	0.07	0.05	-0.06
6					0.70	0.21	0.00	0.06
7						0.70	0.30	0.04
8							0.65	0.17
9								0.87

To sum up, we have seen that the reliability of the model reached is maximum results when the categories are 7 for sector A and B and 4 for C. After that the reliability is constant. Also the fit parameter and the Andrich threshold present good results for this number of categories. Therefore, considering these results, we have deemed that the optimal results is obtained when we limit the categories to 7 for sector A and B, while for sector C we must limit our choice to 4. The final models will be presented and analyzed in the next section.

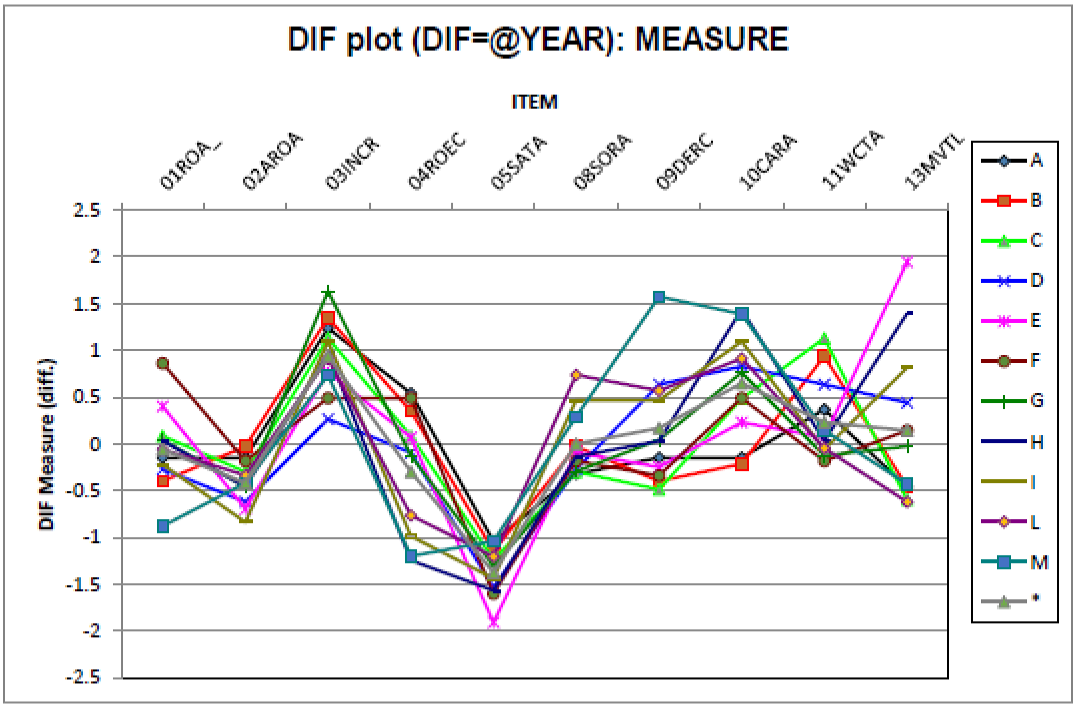
4.4.The final models

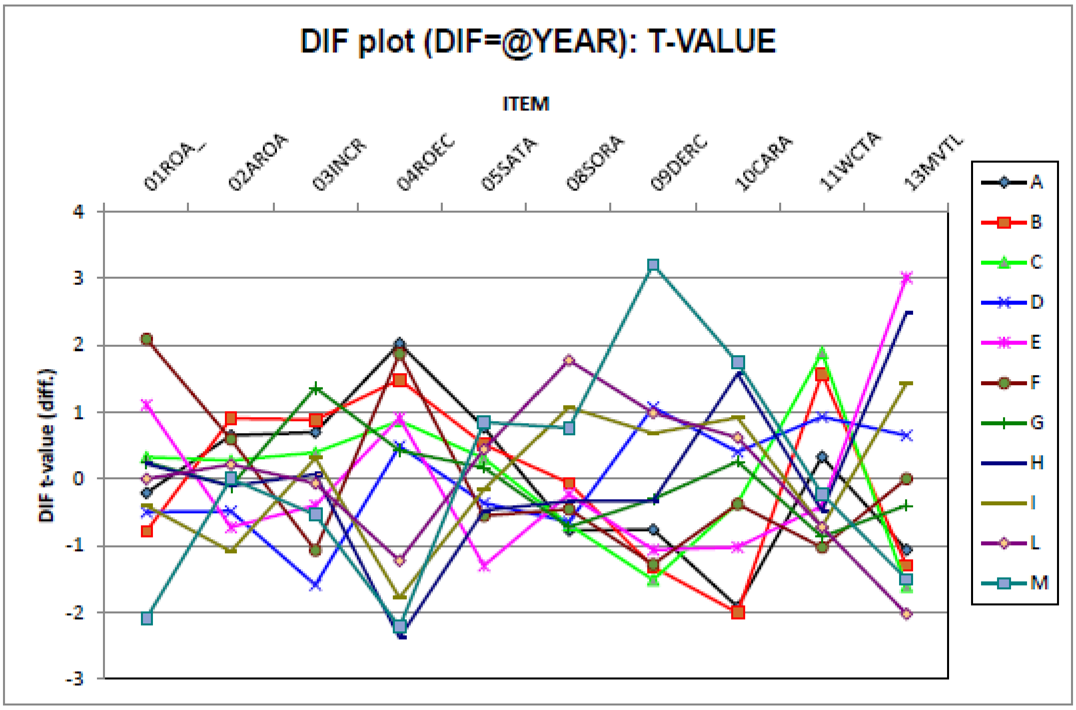
In this section, we are going to illustrate the results obtained from the final models chosen from the previous analysis.

4.4.2 Sector A (Consumer Discretionary)

In Appendix 6, we can see that this model with 7 categories provides a reliability of 0.98 for the items and of 0.88 for the equities with a Cronbach Alpha of 0.88. In addition, we can observe that the difficulties of the items span from -0.58 to +0.26. 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 (not reversed because although the indicator was entered in the data set as reversed, in Winsteps we had to reverse the order of the categories). The most missfitting item was 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. Anyway if we eliminate it from the model, all items present a fit in the desired range of 0.5-1.7. In particular, from Appendix 6.A, which shows the Item Characteristics Curves for the different items, we can see that the fit is quite good, also the one of 8SORA. In addition, from Appendix 6.B we can also see that the Andrich Thresholds are well ordered and all with good fit indices. Very interesting is Appendix 6.C, which shows the item-map of the results. Here, the equities are on the left with their measures and item are on the right with their difficulty parameters. For instance, we can notice that reaching a level of 6 in the 05sata (Sales to Total assets), corresponds to a level of 2 in the estimated scale of the measure of equity and such level corresponds to two standard deviation from the mean of the equities. For what concerns the stability and validity of the model, 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):

Figure 5- Level of items' difficulties per year





Although we may observe some deviation from the mean (first figure), in the second one, the t-value of the difference of each year in respect to the mean lies in the interval -2.58, +2.58 in the majority of the cases.

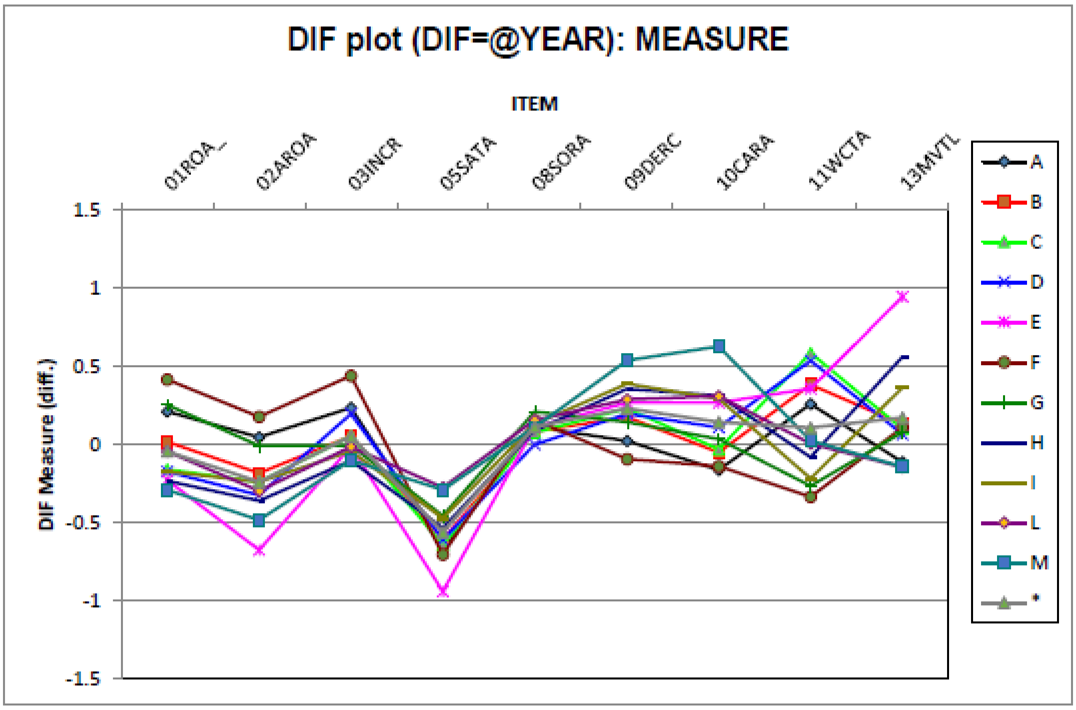
Therefore we can conclude that the result obtained for Sector A are satisfying and that the Rasch model has a good fit with the data.

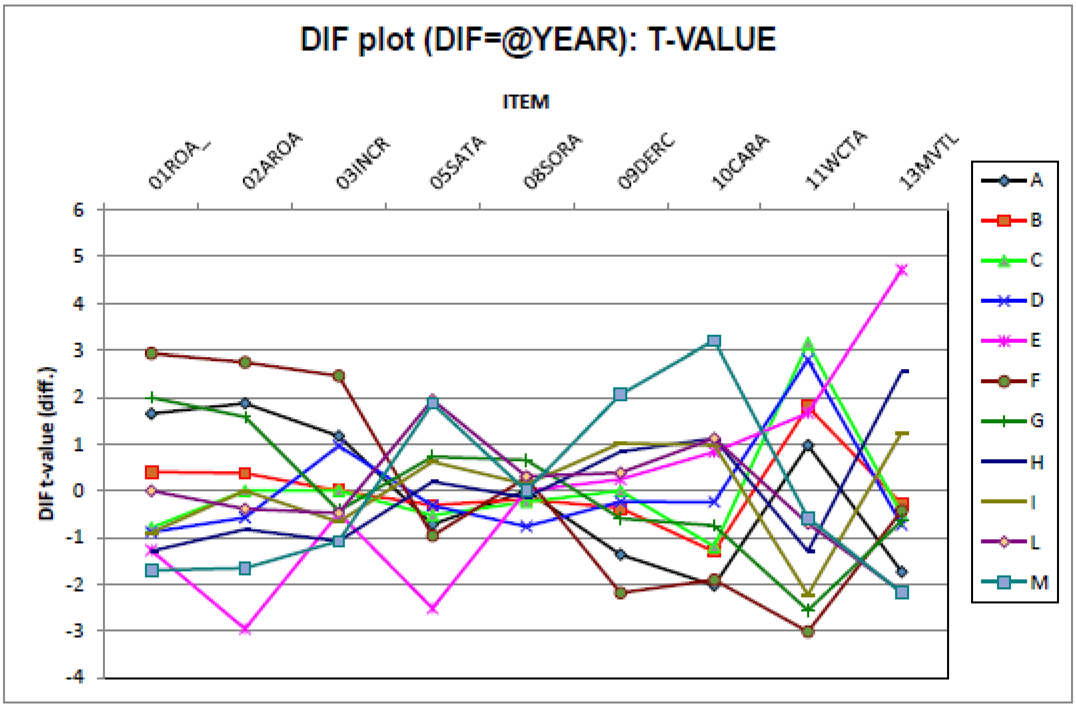
4.4.3 Sector B (Industrials)

In Appendix 7 we can see that this model with 7 categories provides a reliability of 0.96 for the items and of 0.92 for the equities, with a Cronbach Alpha of 0.92. Regarding the the difficulties of the items, those span from -0.56 to +0.23, with the easiest indicator again 05SATA, “Sales to Total Assets”. The hardest item is instead 09Debtequity, “Debt equity ratio” (reserved in order to resolve the issue of reverse polarity). The most missfitting item is 11WCTA, i.e. “Working cap to total asset”, with INFIT and OUTFIT of 1.54 and 1.63, which is still in the desired range 0.5-1.7. Appendix 7.A, showing the Item Characteristics Curves for the different items, presents quite good fits, with the exception of 03INCR which however presents INFIT and OUFIT in the range of acceptability. From Appendix 7.B we may see that the Andrich Thresholds are well ordered and all with good fit indices, while Appendix 7.C shows the item-map. For instance in this appendix, we can observe that reaching a level 5 in the indicator 08SORA corresponds to a level of 2 on the scale of the measure for equity and such level corresponds to two standard deviation from the mean of the equities.

For what it concerns the stability and validity of the model we may look at Figure 6 which shows the level of difficulty of the items for the different years, from 2004 (=A) to 2014 (=M):

Figure 6- Level of items' difficulties per year





Although we may observe some deviation from the mean, in the second table the majority of the cases lie in the interval (-2.58,+2.58).

To conclude, also for Sector B, the results obtained are satisfactory with the model showing a good fit with the data.

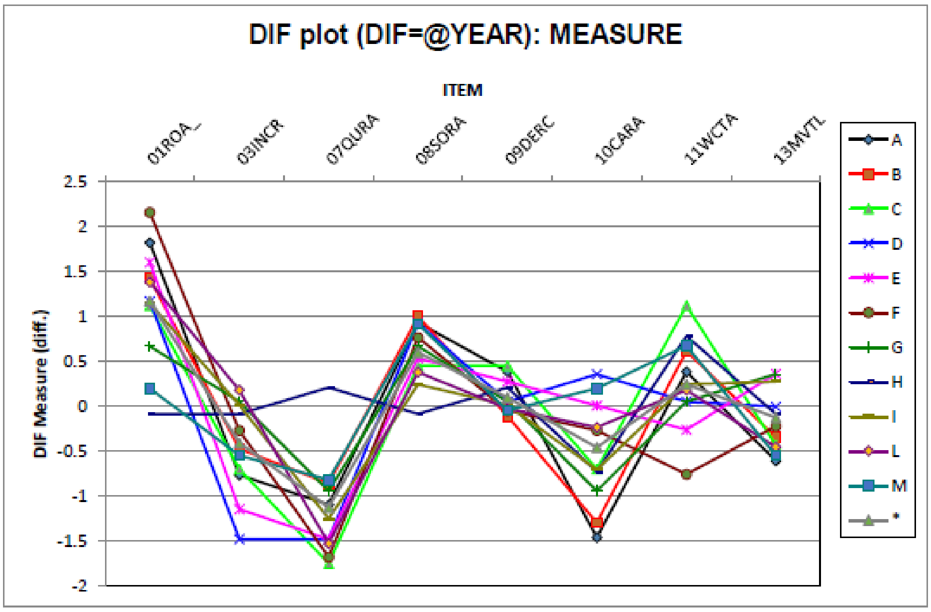
4.4.4 Sector C (Information Technology)

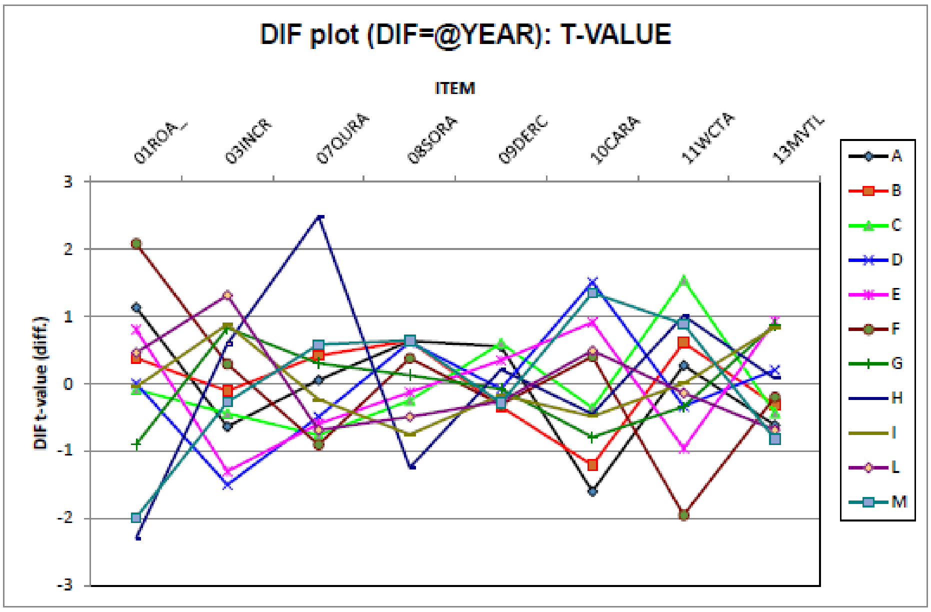
Finally the Rasch model was applied to Sector C. In Appendix 8 we can see that this model with 4 categories provides a reliability of 0.95 for the items and of 0.75 for the equities, with a Cronbach Alpha of 0.85. In addition, the difficulties of the items span from -0.64 to +0.64, with the easiest indicator being 07QURA, i.e. Quick ratio and the hardest item is instead 01ROA_, i.e. Return on Asset. The most missfitting item is 03INCR, i.e. Interest Coverage, with INFIT and OUTFIT of 1.37 and 1.26, which is still in the desired range 0.5-1.7. The lower reliability of this scale depends largely from the fact that there are equities that are at the "extremes", which means that for these equities a measure cannot be found due to the lack of indicators in the upper side of the scale as we may see from the item-map in Appendix 8.C. Indeed, we can observe that the items selected are "not difficult enough" to give a measure to the persons with value 3. This lack of indicators also determines a larger level of the standard error of measurements.

Again, Appendix 8.A shows the Item Characteristics Curves for the different items which indicate a quite a good fit of the items to the model. In Appendix 8.B, we may see that the Andrich Thresholds are well ordered and all with good fit indices. Appendix 8.C shows the item-map. Here we can observe that reaching a level 3 in the indicator 01ROA (Return on Asset) corresponds to almost a level of 3 on the scale of the measure for equity and such level corresponds to two standard deviation from the mean of the equities.

For what it concerns the stability and validity of the model we may look at Figure 7 which shows the level of difficulty of the items for the different years, from 2004 (=A) to 2014 (=M).

Figure 7- Level of items' difficulties per year





All the observations lie in the interval (-2.58,+2.58).

We may conclude that the models built have good properties and the measures obtained are valid and represent an important dimension of the data that we can define "Rasch Ratings" of the equities. Sector C presents less significant results due to a lack of parameters able to measures the equities at the extremes. The use of more significant variables in the information technology industry could provide a more complete analysis. In the next chapter we will investigate the validity of the result obtained by comparing the Rasch rating to the Bloomberg ratings and other variables of interest.

CHAPTER 5: DISCUSSION AND CONTRIBUTIONS

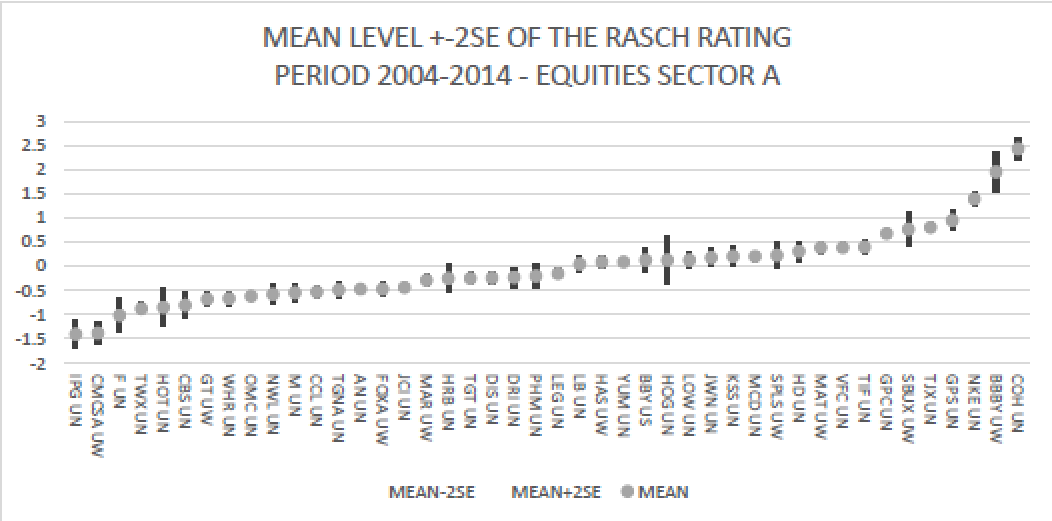
In this chapter we are going to analyze the Rasch ratings obtained with the preceding measurement models and to see how they relate with important aspects of the study. In particular, we are going to answer to the main objective of this paper, which is the possibility to use the ratings obtained to mimic the rating of credit rating agencies. In addition, we are going to understand the implications and contributions of these results by, for instance, analyzing the Rasch ratings obtained in relation to other variables of interest, such as CEO power and stock return.

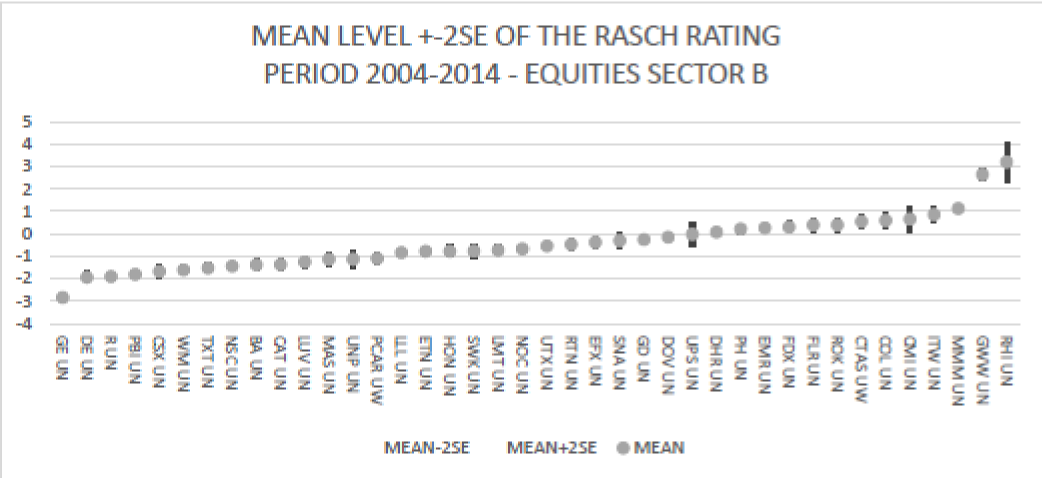
5.1.Comparing the Rasch ratings to the Bloomberg default risk

In this section, we are going to compare the Rasch ratings obtained 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.

In order to answer the research question, as a first step, we have synthetized in Figure 8 the measures obtained with the Rasch model in a scale, showing for each sector the equities with the higher and lower grades. As we can observe, the table shows for every equity the average value of the Rasch rating during the period of observation 2004-2014. In sector A, Coach Inc. (COH UN) is the equity with the highest average rating (+2.5) during the 10 years period and the Interpublic Group of Companies (IPG UN) the one with the lowest (-1.5). In sector B, Robert Half International Inc. (RHI UN) is at the top (+3) and General Electric Company (GE UN) at the bottom (-3). Finally in sector C, Qualcomm Inc. (QCOM UW) has the highest value with +3.5 and Xerox Corporation (XRX UN) the lowest with 1.

Figure 8- Estimated average scale over 2004-2014





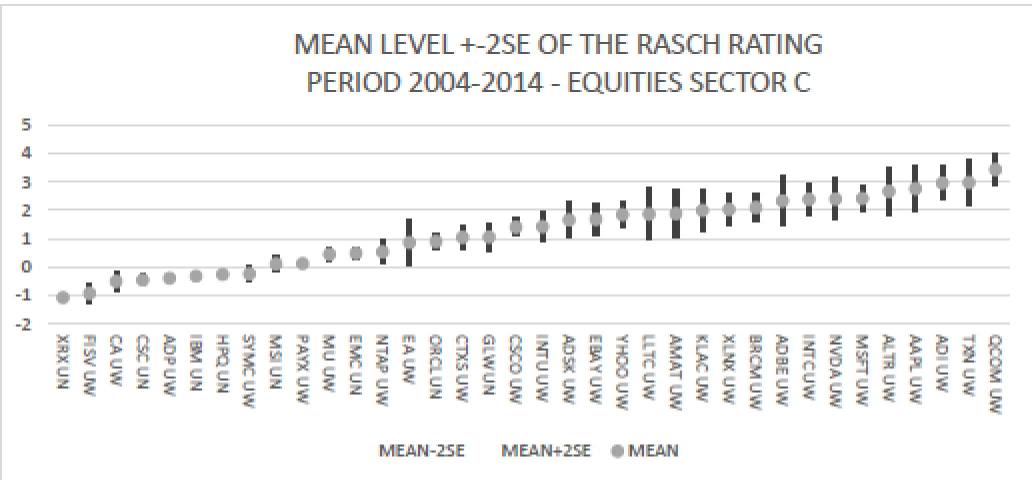
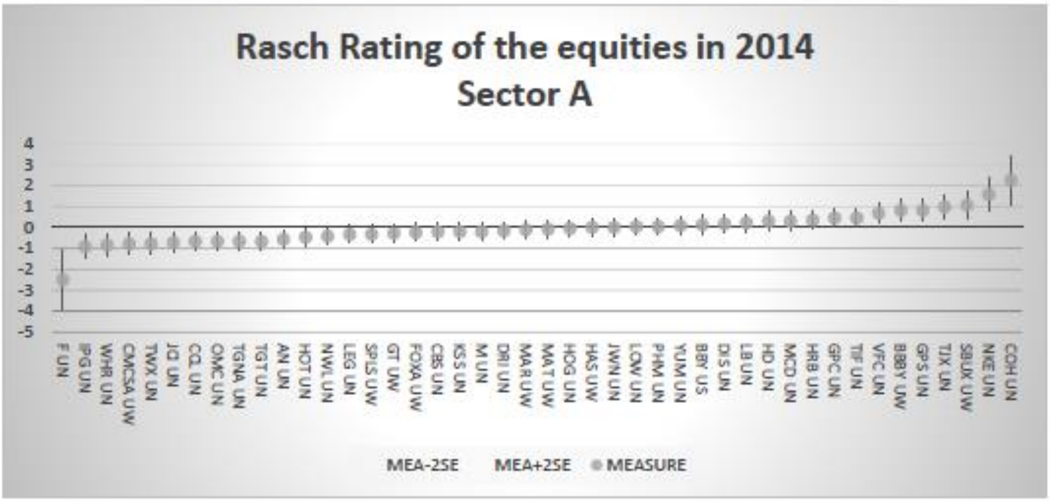
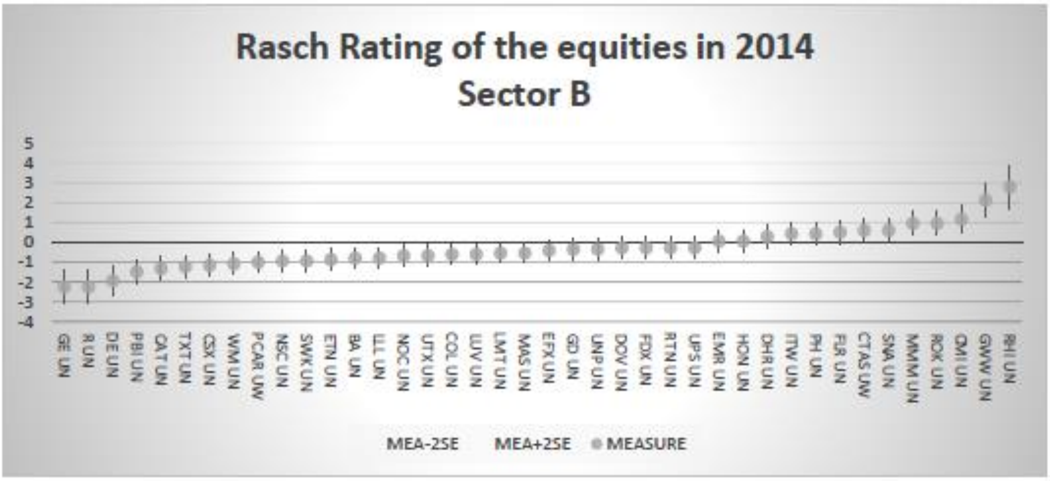
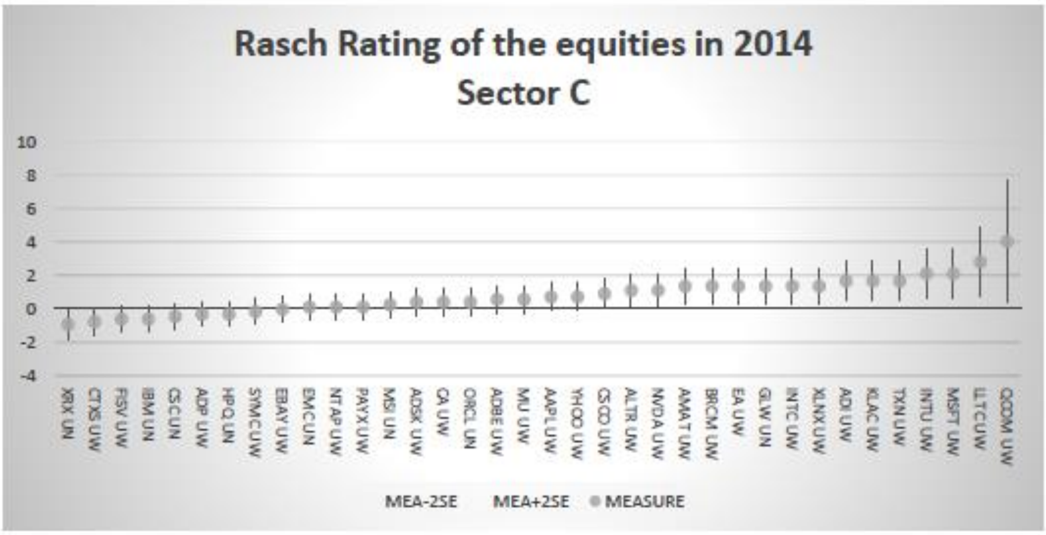


Fig. 8 shows instead the Rasch ratings for the equities in the year 2014. It has to point out that negative values doesn’t correspond to a “negative” meaning or result. The negative values are obtained simply because the zero in this scales is set as the average of the difficulties of the item parameters.

Figure 9- Estimated scale for year 2014



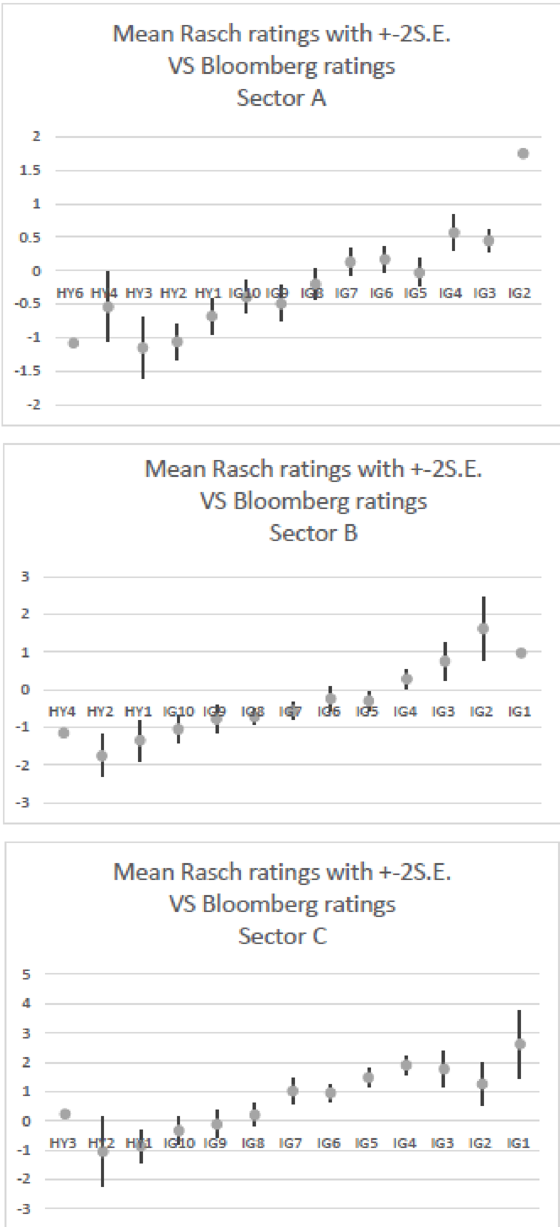




Now that the measures have been summarized in the figures above, in order to give a meaning to these results, we have compared them to the Bloomberg rating, our proxy for the credit rating agency measures as explained in Chapter 3. The comparison can be seen in Figure 10, which shows the average Rasch rating in respect to the Bloomberg rating of the equities. This has been constructed by performing the following steps:

- Group the equities with the same Bloomberg grade
- Compute the conditional expected value of the Rasch ratings in respect to the Bloomberg ratings

Figure 10- Relationship between Rasch ratings and Bloomberg default risk



Means without interval correspond to single observations

We can observe that for sector A, 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. For sector B a Rasch rating of +1.5 corresponds to a Bloomberg rating of IG2, while -1.8 to HY2. In sector C +2.5 corresponds to IG1 and -1 to HY2. In the figure, dots without error bars correspond to a single observation. As we may see from Figure 10, the average Rasch rating grows with the Bloomberg rating. The comparison between the two ratings has also been illustrated in Appendix 9. This is the expected results as it is the confirmation that the Rasch ratings constructed are valid. Moreover, from Table 9, we may see, from the analysis of variance table, that the relation with the Bloomberg rating is statistically significant for all the sectors.

Table 9- Analysis of variance per sector

SECTOR A

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		
Fixed-Effects Chi-squared: inestimable					

SECTOR B

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@15DEFA	165.73	15.00	11.05	8.54	.0000
Error	548.32	424.00	1.29		
Total	714.05	439.00	1.63		
Fixed-Effects Chi-squared: inestimable					

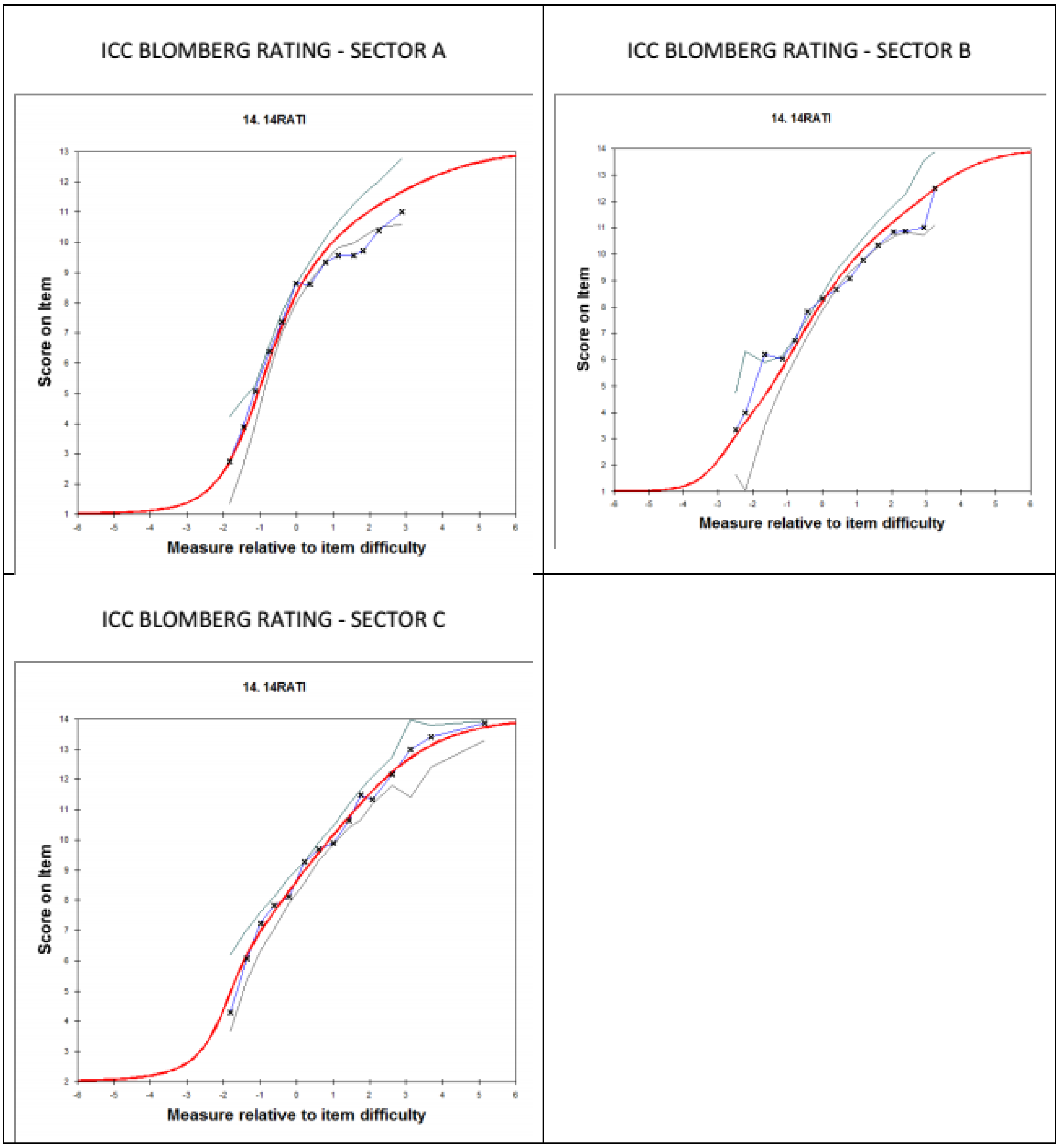
SECTOR C

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@15DEFA	172.40	15.00	11.49	6.15	.0000
Error	709.87	380.00	1.87		
Total	882.27	395.00	2.23		
Fixed-Effects Chi-squared: inestimable					

To further confirm the validity of the model, we have also insert the Bloomberg rating (14RATI) as a variable of the model in order to understand if this variable fit with the ratings.

The results are presented for each sector in Appendix 9.The indices of fit of this item are quite good, for sector A and C meaning that the Bloomberg rating try to measure the same dimension that we are measuring with the Rasch Rating. For sector B, instead, the fit is little worse, although acceptable. For sector A and B the Bloomberg rating has the lowest difficulty, meaning that the other items add value to the measure. Instead for sector C the Bloomberg rating is located in the middle. From Appendix 9 we can also see that the Andrich thresholds which are ordered for each sectors and the average comparison of estimated ratings with the Bloomberg ratings. In addition, Figure 11 shows the figure of the Item Characteristic Curve for the Bloomberg rating, which lies in the interval of confidence (expect for a slightly deviation in Sector A), showing a good fit of the Bloomberg Ratings (14RATI) with the model.

Figure 11- Item Characteristic Curve for the Bloomberg rating



By adding the Bloomberg rating in the model, it was also possible to see the most unexpected response of the model compared to the Bloomberg rating. This are reported in Table 10. 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 9.82 with a residual of -4.82. This means that this equity in this year has been underestimated by Bloomberg rating with respect to his reliability. 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 (e.g. for Sector A in 2008 only four equities presents unexpected responses, three in 2009 etc.), which again confirms the validity of the model. In order to explain the reasons of these discrepancies, further researches and analysis should be performed, but this is outside the scope of this paper.

Table 10- Discrepancies between Rasch ratings and Bloomberg ratings

MOST UNEXPECTED RESPONSES IN BLOOMBERG RATING
SECTOR A

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

MOST UNEXPECTED RESPONSES IN BLOOMBERG RATING
SECTOR B

DATA	OBSERVED	EXPECTED	RESIDUAL	ST. RES.	MEASDIFF	ITEM	PERSON	ITEM	PERSON
10	5	9.91	-4.91	-4.05	.99	14	778	14RATI	778 B FLR UN E 08 FLR UN
11	4	8.95	-4.95	-3.70	.40	14	770	14RATI	770 B CMI UN E 08 CMI UN
9	6	10.09	-4.09	-3.45	1.12	14	792	14RATI	792 B RHI UN E 08 RHI UN
9	6	10.04	-4.04	-3.38	1.08	14	658	14RATI	658 B FLR UN F 09 FLR UN
8	7	10.61	-3.61	-3.27	1.51	14	432	14RATI	432 B RHI UN H 11 RHI UN
10	5	9.22	-4.22	-3.23	.56	14	793	14RATI	793 B ROK UN E 08 ROK UN
10	5	9.22	-4.22	-3.23	.56	14	789	14RATI	789 B PH UN E 08 PH UN
10	5	9.11	-4.11	-3.11	.50	14	657	14RATI	657 B FDX UN F 09 FDX UN
11	4	8.33	-4.33	-3.09	.07	14	777	14RATI	777 B FDX UN E 08 FDX UN
4	11	6.35	4.65	3.09	-.85	14	203	14RATI	203 B WM UN L 13 WM UN
9	6	9.78	-3.78	-3.07	.90	14	417	14RATI	417 B FDX UN H 11 FDX UN
10	5	9.00	-4.00	-3.00	.43	14	796	14RATI	796 B SNA UN E 08 SNA UN
14	1	5.26	-4.26	-2.95	-1.34	14	799	14RATI	799 B TXT UN E 08 TXT UN
9	6	9.67	-3.67	-2.94	.83	14	433	14RATI	433 B ROK UN H 11 ROK UN
6	9	12.00	-3.00	-2.92	2.78	14	912	14RATI	912 B RHI UN D 07 RHI UN
10	5	8.89	-3.89	-2.89	.37	14	650	14RATI	650 B CMI UN F 09 CMI UN
3	12	8.02	3.98	2.79	-.08	14	921	14RATI	921 B UPS UN D 07 UPS UN
3	12	8.03	3.97	2.79	-.08	14	83	14RATI	83 B WM UN M 14 WM UN
5	10	5.87	4.13	2.77	-1.06	14	1280	14RATI	1280 B UNP UN A 04 UNP UN

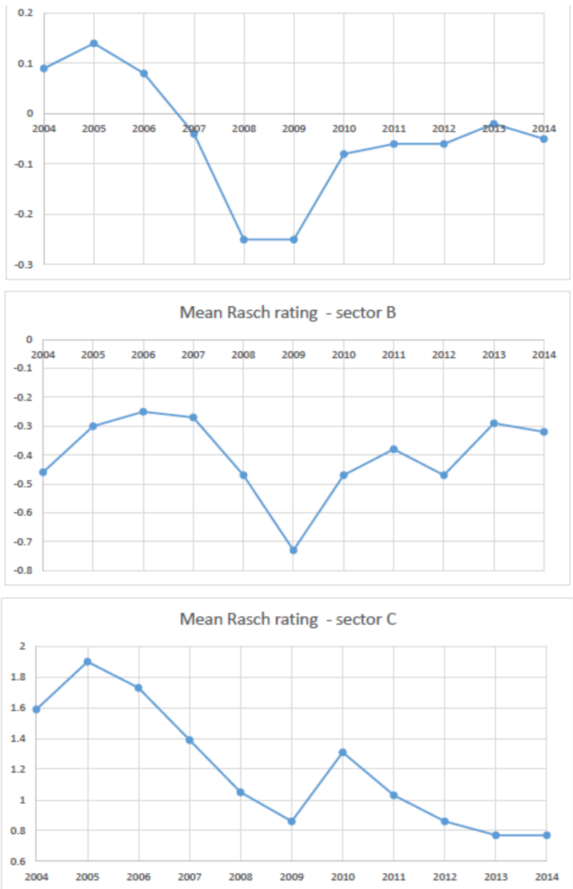
MOST UNEXPECTED RESPONSES IN BLOOMBERG RATING
SECTOR C

DATA	OBSERVED	EXPECTED	RESIDUAL	ST. RES.	MEASDIFF	ITEM	PERSON	ITEM	PERSON
3	12	7.68	4.32	3.33	-.58	14	948	14RATI	948 C FISV UW D 07 FISV UW
13	2	6.54	-4.54	-3.12	-1.21	14	817	14RATI	817 C MU UW E 08 MU UW
2	13	9.20	3.80	3.07	.36	14	1188	14RATI	1188 C FISV UW B 05 FISV UW
2	13	9.31	3.69	2.99	.43	14	108	14RATI	108 C FISV UW M 14 FISV UW
2	13	9.32	3.68	2.99	.43	14	331	14RATI	331 C ADP UW I 12 ADP UW
2	13	9.80	3.20	2.64	.76	14	228	14RATI	228 C FISV UW L 13 FISV UW
3	12	9.00	3.00	2.40	.23	14	571	14RATI	571 C ADP UW G 10 ADP UW
3	12	9.00	3.00	2.40	.23	14	451	14RATI	451 C ADP UW H 11 ADP UW
1	14	11.30	2.70	2.35	1.83	14	350	14RATI	350 C PAYX UW I 12 PAYX UW
1	14	11.30	2.70	2.35	1.83	14	230	14RATI	230 C PAYX UW L 13 PAYX UW
1	14	11.30	2.70	2.35	1.83	14	110	14RATI	110 C PAYX UW M 14 PAYX UW
2	13	10.20	2.80	2.34	1.03	14	1051	14RATI	1051 C ADP UW C 06 ADP UW
2	13	10.20	2.80	2.34	1.03	14	1171	14RATI	1171 C ADP UW B 05 ADP UW
3	12	9.11	2.89	2.32	.30	14	348	14RATI	348 C FISV UW I 12 FISV UW

5.2.Historical analysis of the results

As a further step in our analysis of the results, we have performed a historical analysis of the Rasch ratings estimated. The results are showed in Figure 12 where we can observe the average value of the Rasch ratings for the three sectors in the period 2004-2014. As we can see, for sector A and C, a worsening of the market conditions is observed since 2006, while for sector

Figure 12- Historical average performance of Rasch Ratings



B the worsening is visible only from 2008. 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.

5.3. Analysis of the Rasch model in relation to CEO power

In this paragraph, we are going to analyze the results obtained in relation to the CEO power. Appendix 10.A, B and C show that 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 for sector A and C 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 is again confirm the validity of our model as we were expecting to obtain the following results. Indeed, as we have pointed out in the literature in Chapter 2, there are a lot of studies that have demonstrated that good corporate governance is associated with higher credit ratings and more specifically, CEO power is negatively related to the credit ratings[62]. No statistical significant difference is instead observed for sector B. An analysis of additional corporate governance variables would probably give a more complete results, but this is out of the scope of this paper.

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 by the Bloomberg rating. Now that the validity of the model has been confirmed, in the next section, 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.

5.4. Explaining the sign of the stock return

In this section 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. For

[62] SKAIFE, H. A., COLLINS, D.W., LAFOND, R., *"The Effects of Corporate Governance on Firms' Credit Ratings",* Journal of Accounting and Economics, pp. 203-243, 2006

this purpose, the observations have been regrouped within years[63] defined by the following Bernoulli equation:

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

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

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

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. In this thesis, 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[64]. 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

[63] WONG, G. Y., MASON, W. M. *"The Hierarchical Logistic Regression Model for Multilevel Analysis."* Journal of the American Statistical Association 80, 513-24, 1985 and
BRYK, A.S., RAUDENBUSH, S.W., *"Hierarchical Linear Models Applications and Data Analysis Methods"* 2nd Edition, Sage Publishing, 2002

[64] GRILICHES, Z., RINGSTAD, V., *"Error in the variables bias in nonlinear context"*, Econometrica, 38:368-370, 1970

of additive measurement error. The method is especially helpful for complex models with a simple measurement error structure. The R package simex[65], 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_ε^2 (estimated by the Rasch model) and the bias of the estimator when ignoring the measurement error. In particular, we can define the function

$$\sigma_\varepsilon^2 \rightarrow \tilde{\beta}\left(\sigma_\varepsilon^2\right) := G\left(\sigma_\varepsilon^2\right)$$

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 $G\left(\sigma_\varepsilon^2\right) = \beta_n$ the result of the naive estimator. The idea of the SIMEX method is to approximate the function $G\left(\sigma_\varepsilon^2\right)$ by a parametric approach $G\left(\sigma_\varepsilon^2, \Gamma\right)$, for example with a quadratic approximation $G\left(\sigma_\varepsilon^2, \Gamma\right) = \gamma_0 + \gamma_1 \cdot \sigma_\varepsilon^2 + \gamma_2 \cdot \left(\sigma_\varepsilon^2\right)^2$. To estimate Γ the method adds in the simulation step to a given data set additional measurement error with variance $\lambda\sigma_\varepsilon^2$ to the contaminated variable. The resulting measurement error variance is then $(1+\lambda)\sigma_\varepsilon^2$. The naive estimator for this increased measurement error is calculated and repeated R times. The average over R converges to $G\left((1+\lambda)\sigma_\varepsilon^2\right)$. Repeating this simulation for a fixed grid of λ, leads to an estimator for $\hat{\Gamma}$ of the parameters $G\left(\sigma_\varepsilon^2, \Gamma\right)$, for example by least squares. In the extrapolation step the approximated function $G\left(\sigma_\varepsilon^2, \hat{\Gamma}\right)$ is extrapolated back to the case of no measurement error and so the SIMEX estimator is defined by $\beta_{simex} = G\left(0, \hat{\Gamma}\right)$, 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 for the sectors A, B and C 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).

[65] LEDERER, W., KÜCHENHOFF, H, *"Simex: SIMEX- and MCSIMEX-Algorithm for Measurement Error Models. R Package Version 1.5"*, 2013 and
CHESHER, A., *"The effect of measurement error"*, Biometrika, Vol. 78 (3): 451–462, 1991

Table 11- – Logistic regression models for the sign of the stock return

Naive – Sector A

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 –Sector A

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			

Naive – Sector B

Variables	Estimates	S.E.	T-test	Pvalue
Intercept	0.9416	0.3163	2.9770	0.0029
Aij	0.8571	0.1703	5.0320	0.0000
Bij	0.5402	0.3527	1.5320	0.1256
σ_u	0.8042			

SIMEX –Sector B

Variables	Estimates	S.E.	T-test	Pvalue
Intercept	0.9462	0.3236	2.9240	0.0037
Aij	0.8432	0.1699	4.9630	0.0000
Bij	1.0222	0.5584	1.8300	0.0680
σ_u	0.8270			

Naive – Sector C

Variables	Estimates	S.E.	T-test	Pvalue
Intercept	0.6572	0.4299	1.5290	0.1263
Aij	0.5716	0.1493	3.8290	0.0001
Bij	0.1327	0.1815	0.7310	0.4647
σ_u	1.1820			

SIMEX –Sector C

Variables	Estimates	S.E.	T-test	Pvalue
Intercept	0.6709	0.4405	1.5230	0.1287
Aij	0.5439	0.1526	3.5640	0.0004
Bij	0.2908	0.2976	0.9770	0.3292
σ_u	1.2147			

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, with the exception of the Rasch rating for the sector C. 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. This is represented by the difference between two Rasch rantings in two consecutive years and has a variance equal to the sum of the error variance in the two years.

Table 12 contains, only for the sectors A and B, the probabilities that the sign of the stock return will be positive, given different levels of the independent variable Aij and Bij posed 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. As we may see from the table, 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 have remarkable value 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. The non-significant level of the Rasch rating for sector C suggests again that for this sector it is necessary to look for more reliable scale, maybe adding items (indicators) that are specific of this sector.

Table 12- Probability of positive stock return at time T, given (x,y) (*)

Calculated with the coefficients of models of Table 11, setting the random component equal to zero

((*) a probability of 0.50 means equal probability of positive or negative stock return)

SECTOR A		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

SECTOR B		B = RASCH RATING (T)-(T-1)				
		-0.66	-0.20	0.00	0.25	0.63
A = BLOOMBERG RATING (T)-(T-1)	-4	0.04	0.07	0.08	0.10	0.14
	-1	0.36	0.47	0.53	0.59	0.68
	0	0.57	0.68	0.72	0.77	0.83
	1	0.75	0.83	0.86	0.89	0.92
	2	0.88	0.92	0.93	0.95	0.96

CORR(A,B) = 0.151

5.5.Final results discussion

In this section we are going to compare the results of the model with our initial hypothesis and expectations. In addition, we are going to analyze the theoretical and managerial implication arising from the results estimated.

5.4.1 Results discussion

This study aimed to understand 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 estimated results were in line with the initial hypothesis and expectations.

Leverage has revealed to be negatively related to the credit rating grades as the model showed that it is more difficult to obtain a higher measure in the financial ratios related to this category. Indeed for Sector A, the model has showed that it is very difficult (lower probability) to obtain a high measure in the reverse of debt to equity ratio. Particularly a value of 0.6 debt to equity ratio corresponds to a measure of 2.5 which has been achieved only by two companies (COH UN and BBBY UN) as showed in Figure 8 of Chapter 5. This correspond to Bloomberg rating of IG2. Similar results can be observed in Sector B, where it is difficult to obtain a high measure in the "solvency" and "debt to equity" ratios. Indeed a value of 0.5 in these ratios correspond to a measure of 2 and 1.8 respectively. For sector B this corresponds to a Bloomberg rating of IG2 which has been achieved only by RHI UN and GWW UN.

Profitability ratios also revealed to be positively related to the ratings (in line with our hypothesis) even if, especially for sector A, the model showed that it was easier to achieve a higher measure in these kind of ratios. Particularly, for sector A, a value of 0.6 in "Sales to total asset" and in "Interest coverage" corresponds respectively to a measure of 1 and 3, which is a Bloomberg rating of IG3 and IG2 for the Bloomberg scale. Similar results were obtained for sector B, where to achieve a value of 0.5 in the "sales to total asset" and "return on Asset", correspond to a grade of IG3.

Finally, liquidity ratios were confirmed to be positively related to credit ratings. For instance, a result of 0.6 in "Working capital to total assets" in sector A corresponds to a higher measure and particularly to 2.6 which is equal to a Bloomberg rating of IG2. Similar results have been obtained in sector B, where a result of 0.5 in the quick ratio corresponds to a measure of 1.2, which is an IG3/IG4 in the Bloomberg rating.

For sector C, the hypothesis could not be confirmed due to the lack of indicators able to measures companies at the extremes.

In addition, the estimated model was also tested in relation to a corporate governance variable, CEO power. Again, our hypothesis has been confirmed, with the results showing a negative relationship between the ratings and the CEO power. This has been demonstrated by several studies including "The effects of corporate governance of on firm credit ratings" (Skaife et al. 2006), discussed in Chapter 2.

Finally, we have also observed that the estimated results are in line with our hypothesis in a historical and economic perspective. Indeed, previously in this Chapter, we have compared the measures obtained on a yearly basis and noticed a drastic decrease in the measures in the year of the financial crisis, which is expected considering the extent of the crisis.

5.4.2 Theoretical and managerial implications

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, as it has been explained in paragraph 5.4, 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) 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[66]. 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

[66] SECURITY AND EXCHANGE COMMISSION, https://www.sec.gov/rules/concept/33-8236.htm, 6TH October, 2003

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. Indeed, as it will be explained in the next Chapter, we should not forget the ethical implications surrounding these results, as, if demonstrated erroneous, could cause damage to their users and companies to which they relate.

CHAPTER 6: RELIABILITY, VALIDITY AND LIMITATIONS

In this Chapter, we are going to analyse the reliability and the validity of the model applied together with the limitations of the study both from a theoretical and methodological perspective. In addition, we are going to talk about possible concerns of ethical issues arising from the research.

6.1.Reliability and validity of the model

Reliability and validity are two fundamental criteria used in order to evaluate a research. According to Bryman and Bell (2015), reliability "is the degree of the consistency of the application of the observation schedule over time"[67] that is the possibility to reapply the model several times and obtain each time the same outcome. Therefore, if the results of the model are not impacted by different conditions every time it is applied, then the model will be reliable. On the other hand, validity "relates to the question of whether or not a measure is measuring what is supposed to measure"[68].

6.1.1 Reliability

In order to confirm the reliability of the model we have made sure that the data obtained and applied to the model was reliable by extracting it from reliable sources. Indeed, the financial ratios and stock return data used were downloaded from the Bloomberg terminal database, which is a well-known database provided by the financial data vendor Bloomberg L.P. However, the data collected presented some problems, as some data, especially for 2004, was missing or presented a default number. This missing or inaccurate data was easily spotted and

[67] BRYMAN, A., BELL, E., *"Business research methods",* 4th Edition, Oxford University Press, Chapter 12, p. 288-289, 2015

[68] BRYMAN, A., BELL, E., *"Business research methods",* 4th Edition, Oxford University Press, Chapter 12, p. 288-289, 2015

updated with the right amount using the 10-k provided by EDGAR, a database including the submission of companies who are required by law to file forms with the SEC (U.S. Security and Exchange Commission). In addition, for some stock price data, we have used Yahoo finance website, which is another reliable resource to find financial information. The CEO power data was again obtained from the 10-k found in the EDGAR database. Finally, we have also performed random checks of the data to further ensure that the data obtained was accurate and that no mistake in the extraction was made.

All these checks provided us with assurance over the reliability of the model and they guarantee that a future reapplication of the model will provide the same outcomes.

6.1.2 Validity

One first step to ensure the validity of the model was to use variables suggested by previous studies and literature. Indeed all the financial ratios together with the other parameters selected have been previously used in other researches with the same or similar objective (e.g. mimic or predict credit ratings, measure the risk of default or bankruptcy). A second step to test the validity of the model was with the results obtained. Indeed, our results, except for few discrepancies, were highly correlated with the one of the Bloomberg ratings, our proxy for the credit rating agency scores. This is strong evidence of the validity of the model as it shows that the model measured the ratings as it was determined by the objectives of this paper. In addition, as the model proved to work over a period more than 10 years, this can be considered an additional support to the validity of the study. However, it could be interesting, in order to further confirm the validity of the model, to apply it to another period or sample, but this is out of the scope of this paper.

6.2.Limitations of the model

This section will describe the theoretical and methodological limitations encountered in this research. In addition, we are going to illustrate also the possible concerns and ethical issues of this study.

6.2.1 Methodological limitations

One of the main methodological limitation encountered was the limited number of resources available. More access could have allowed to extract more proper and complete data. This problem was encountered mainly for the credit ratings from the credit rating agencies and for corporate governance variables, among which only CEO power was possible to obtain. In regards to the credit rating agencies, it was only possible to find the current rating (2016) and not the historical ones. Indeed, access to historical credit ratings was restricted on the credit agencies' websites. The use of the credit ratings from the main three agencies (Moody's, Standard & Poor and Fitch) would have increased the reliability and validity of the model. In order to extract corporate governance variables, we would have needed the access to databases like Bordex. Another solution would have been to inspect the financial statements of each companies in order to find variables such as "percentage of institutional investors" but this would have not guaranteed that data would have been found for each company and in addition it would have been extremely time consuming compared to the time allowed for the completion of this study. The limitation of the resource has surely constituted an impediment to this research as for instance qualitative variables would have increased the precision of the model. Indeed, corporate governance is a variable largely used both in the literature but also from the credit rating agency themselves and summarising it with only the parameter "CEO power" has surely produced a less complete result.

It should also be noted that the model was applied to three different sectors using the same variables. This failed to incorporate in the research an industry element.This was particularly noticeable in sector C, were satisfactory results couldn't be achieved due to the lack of significant indicators. The use of more industry characteristic variables (e.g. R&D for Information technology) would have made the analysis more complete and precise as the model would have captured these features in the industry selected. To obtain the best results, we should have probably conducted a research for each company or industry subsector (as every subsector has different characteristics) but this would have been complicated due both to the resources available and the time allowed.

Finally, another way to ensure a higher reliability of the results would have been to apply the model to defaulted companies or companies with a very low rating. Indeed among the sample there were no companies with a ratings equal to the status of distress. A more complete sample of companies covering all the categories of grades would have proven if the Rasch model could also predict the rating of a company on the verge of default.

6.2.2 Theoretical limitations

The main theoretical limitation to this study was obviously the secrecy of the methodology used by the credit rating agencies. Indeed, even if the agencies websites provide several articles regarding the methodology used, the full methodology constitutes private information that cannot be disclosed. Moreover the credit ratings agencies have fully access to both public and private information, which ensures a more complete and in depth analysis of the companies ratings compared to the ratings obtained with the Rasch model. This limitation has then led to another limitation which is the inability of the author to analyse the discrepancies obtained by comparing our ratings with those of the Bloomberg default risk. Indeed, it would have been interesting to understand if the ratings obtained could have been considered "better" or more representative than those estimated by the agencies. Indeed in order to do that, we would have needed to have access to the full analysis made by the agencies, task that is impossible to perform considering the privacy issues mentioned above.

Finally, the Rasch model is a model using ordinal data, which was applied to continuous data, such as the financial ratios. This is the case also for all the kind of ratings which summarise different kind of data (including financial ratios) in an ordinal scale (e.g. A, B, C). In our case, the division in categories of the variables could result in a limitation of the ability of the model to capture some differences among the companies, e.g companies at the extreme of percentiles limits.

6.2.3 Possible concerns and ethical issues

The main concern was to what extent the variables chosen will give a clear and realistic representation of the companies chosen. As explained above, the variables were selected based on previous research and what suggested on the CRAs website, but there is still the risk is that the model results lead to an erroneous evaluation of a company. This could rise some ethical issues, in the case the valuation would be used and relied upon by third parties. Indeed, if a valuation would be wrong, this could cause financial and reputational consequences on the company. This concern is very important for the author of this paper and it is also linked to the ethical issues around the ratings given by the main rating agencies. Indeed, as it has been explained before, several investors have been damaged as they relied on the CRAs ratings, which then they have been proved to be wrong. It is therefore important to note that the results obtained, even if considered conclusive, should be taken with caution as they could have serious impacts.

CHAPTER 7: CONCLUSION AND POSSIBLE FUTURE RESEARCHES

This study has demonstrated that the Rach model can be successfully applied to estimate a company credit rating. Even if the application of the model in this field it is just at the beginning and additional exploration and research is needed, the satisfactory results obtained suggest that this model could be considered a significant addition to the existing literature. Taking this into account, 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 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.

Bibliography

AGARWAL V., TAFFLER R., "Comparing the performance of market-based and accounting-based bankruptcy prediction models", Journal of Banking & Finance, Vol.32, Issue 8, Pages 1541-1551, 2008

ALTMAN, E. I. *"Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy",* The Journal of Finance, 23, pp. 589-609, 1968

ALTMAN, E.I. *"Predicting Financial Distress of Companies: Revisiting the Z-score and Zeta Models"* Personal Homepage, 2000

AMAN, H., NGUYEN, P., *"Does good governance matter to debtholders? Evidence from the credit ratings of Japanese firms",* Research in International Business and Finance, Vol.29, Pages 14-34, 2013

BEAVER, W. "*Financial Ratios as Predictors of Failure*", Journal of Accounting Research, 4, 71-111. doi:1. Retrieved from http://www.jstor.org/stable/2490171 doi:1, 1966

BEAVER, W. H., MCNICHOLS, M. F., RHIE, J.W., *"Have Financial Statements Become Less Informative? Evidence from the Ability of Financial Ratios to Predict Bankruptcy"*, Review of Accounting Studies, Vol.10, 93-122, 2005

BERTRAND, M., AND SCHOAR, A., *"Managing with Style: The Effects of Managers on Firm Policies*", The Quarterly Journal of Economics, 118 (4): 1169-1208, 2003

BHOJRAJ, S., & SENGUPTA, P., *"Effect of Corporate Governance on Bond Ratings and Yields: The Role of Institutional Investors and Outside Directors*", The Journal of Business, 76(3), 455-475, 2003

BOND, T. G., AND FOX, C. M., *"Applying the Rasch Model: Fundamental Measurement in the Human Sciences*". 3rd Edition, Routledge Taylor & Francis Group, 2007

BRYK, A.S., RAUDENBUSH, S.W., *"Hierarchical Linear Models Applications and Data Analysis Methods"* 2nd Edition, Sage Publishing, 2002

BRYMAN, A., BELL, E., *"Business research methods",* 4th Edition, Oxford University Press, Chapter 12, p. 288-289, 2015

CARDOSO V., GUIMARAES A., MACEDO H., LIMA J.C.O. *"Assessing corporate risk: a PD model based on corporate risk",* Proceeding in finance and Risk perspectives, 57-64, 2013

CHENG, M., NEAMTIU, M., "*An empirical analysis of changes in credit rating properties:*

Timeliness, accuracy and volatility", Journal of Accounting and Economics, Vol.47, Pages 108-130, 2009

CHENG, S., *"Board size and the variability of corporate performance",* Journal of Financial Economics, Vol.87, Issue 1, Pages 157-176, 2008

CHESHER, A., *"The effect of measurement error". Biometrika, Vol. 78 (3): 451–462, 1991*

COMPANY PARTNERS, https://www.companypartners.com/content/resource/understanding-financial-ratios, 2016

DOUMPOS M., NIKLIS D., ZOPOUNIDIS C., ANDRIOSOPOULOS K., *"Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms",* Journal of Banking & Finance, Vol. 50, Pages 599-607, 2015

DR. OTHMAR M. LEHNER, DR. HARRISON, R. *"ACRN Proceedings in Finance and Risk Series '13: Proceedings of the 13th FRAP"*, Conference in Cambridge, Volume 2 of ACRN Finance, Risk and Accounting Perspectives, 2014

ELTON, E.J., GRUBER, M.J., AGRAWAL, D., MANN, C., *"Factors affecting the valuation of corporate bonds"*, Journal of Banking & Finance, Vol.28, Issue 11, Pages, 2747-2767, 2004

FIDELITY, https://www.fidelity.com/sector-investing/compare-sectors, accessed: 15th August 2016

FIGLEWSKI S., FRYDMAN H., LIANG W., *"Modelling the Effect of Macroeconomic Factors on Corporate Default and Credit Rating Transitions"* NYU Stern Finance Working Paper No. FIN-06-007, 2006

FROST, C. A., "*Credit Rating Agencies in Capital Markets: A Review of Research Evidence on Selected Criticisms of the Agencies",* Journal of Accounting, Auditing, and Finance, Forthcoming, 2006

GALIL, K. *"The Quality of Corporate Credit Rating: An Empirical Investigation"* EFMA 2003 Helsinki Meetings, 78, 2003

GOLDSTEIN, H., *"Consequences of Using the Rasch Model for Educational Assessment",* British Educational Research Journal, 5: 211–220, 1979

GOLIA, S. M. C., *"Measuring the quality of work: The case of the Italian social cooperatives"*, Quality and Quantity Journal Impact Factor & Information, Pages 1659-1685, 2015

GOODMAN, M., *"Pharmaceutical Industry Financial Performance",* Nature Review Drug Discovery, 8(12): 927-28, 2009

GORI, E., & MARIN, R. F., *"Rasch analysis of some MMPI-2 scales in a sample of university freshman",* International Conference for Academic Disciplines. Barcelona, 2015

GRABLE, J., LYTTON, R.H., *"Financial risk tolerance revisited: the development of a risk assessment instrument"*, Financial Services Review 8, Pages 163-181, 1999

GRILICHES, Z., RINGSTAD, V., *"Error in the variables bias in nonlinear context"*, Econometrica, 38:368-370, 1970

HWANG, R.C., CHUNG, H., CHU, C., *"Predicting issuer credit ratings using a semiparametric method",* Journal of Empirical Finance 17 (1), 120–137, 2010

JENSEN, M.C., MECKLING, W. *"Theory of the Firm: Managerial Behaviour, Agency Costs and Ownership Structure",* Journal of Financial Economics 3: 305-360, 1976

KAMSTRA, M., KENNEDY, P., & SUAN, T.-K., *"Combining bond rating forecasts using logit",* The Financial Review, 37, 75–96, 2001

KISGEN, D. J. *"Credit ratings and capital structure"*, The Journal of Finance, Volume 61, Issue 3, Pages 1035–1072, 2006

KLOCK, M. S., MANSI, S.A., MAXWELL, W.F*., "Does Corporate Governance Matter to Bondholders?",* Journal of Financial and Quantitative Analysis, 40, pp 693-719, 2005

LARS NORDEN, M. W., *"Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements",* Journal of Banking &Finance, Vol.28, pp. 2813-2843, 2004

LEDERER, W., KÜCHENHOFF, H, *"Simex: SIMEX- and MCSIMEX-Algorithm for Measurement Error Models. R Package Version 1.5"*, 2013

LEE Y.C., *"Application of support vector machines to corporate credit rating prediction",* Expert Systems with applications, Vol. 33, Issue 1, Pages 67-74, 2007

LEHMANN, B., *"How good is "good"? - Managing Subjective Information in Credit Ratings",* Centre for Finance and Econometrics, University of Konstanz, Germany, 2004

LEWELLEN, J., *"Predicting Returns with Financial Ratios*", Journal of Financial Economics. 74: 209–235, 2004

LUNDQVIST D., STRAND, J., *"Bankruptcy Prediction with Financial Ratios- Examining Differences across Industries and Time"*, School of Economics and Management Department of Business Administration, 2013

MOODY'S WEBSITE, https://www.moodys.com/, 2015, September 2

OHLSON, J. *"Financial Ratios and the Probabilistic Prediction of Bankruptcy".* Journal of Accounting Research, 18(1), 109-131, 1980

PALLANT, J.F., TENNANT, A., *"An introduction to the Rasch measurement model: An example using the Hospital Anxiety and Depression Scale (HADS)",* British Journal of Clinical Psychology, 46, 2007

RĂILEANU S.M., *“Introducing an innovative mathematical method to predict the bankruptcy risk. Measures for the financial markets stability”,* Department of Finance, Accounting and Economic Theory, Transylvania University of Brasov, B-dul Eroilor no.29 Brasov, ROMANIA, 2008

RASCH, G., *“Probabilistic Models for Some Intelligence and Attainment Tests”,* Copenhagen: Denmark, Paedagogiske Institut, 1960

RASCH WEBSITE, http://www.rasch-analysis.com/rasch-analysis.htm, 2016

RIDZAK, T. “*Are Some Banks More Lenient in the Implementation of Placement Classification Rules”,* Zagreb: Croatian National Bank, 2011

SALINI, S. A. *“The Rasch Model to Measure Service Quality*”, UNIMI, Economics Working Paper, No.27, p.18, 2003

SANTOS, K., *“Corporate credit rating: a quick Guide”*, Rothschild, The treasurer handbook, 2015

SCHELLHORN, C., SHARMA, R., JAMBILINGAM, T., *“Using a Rasch Model to Rank Big Pharmaceutical Firms by Financial Performance”,* Journal of Commercial Biotechnology, 22(1), Pages 49-60, 2016

SCHELLHORN, C., SHARMA, R., *"Using the Rasch model to rank firms by managerial ability"*, Managerial Finance, Vol. 39 Iss: 3, pp.306 – 319, 2013

SCHUERMANN, T., HANSON, S., *“Estimating Probabilities of Default”,* Federal Reserve bank of New York, Staff report N. 190, July 2004

SENGUPTA, P., *“Corporate Disclosure Quality and the Cost of Debt”,* The Accounting Review, 73(4), 459-474, 1998

SHUMWAY, T., *“Forecasting bankruptcy more accurately: a simple hazard model”,* The Journal of Business, Vol. 74 No. 1, pp. 101-24, 2001

SKAIFE, H. A., COLLINS, D.W., LAFOND, R., *“The Effects of Corporate Governance on Firms' Credit Ratings”,* Journal of Accounting and Economics, pp. 203-243, 2006

STANDARD & POOR’S, *“Corporate ratings criteria”,* Standard & Poor’s, a division of The McGraw-Hill Companies, 2013

STANDARD & POOR’S, https://www.standardandpoors.com/en_US/web/guest/home, 2016

STANDARD & POOR’S, www.standardandpoors.com/ratingsdirect, 19th November, 2013

STEFANSKI, L. A., COOK, J. R., *“Simulation Extrapolation: The Measurement Error Jack knife”* Journal of the American Statistical Association, 90: 1247–1256, 1995

TECHNICAL COMMITTEE OF THE INTERNATIONAL ORGANIZATION OF SECURITIES COMMISSIONS, *"the role of credit rating agencies in structured finance markets"*, Consultation report, March 2008

THE GUARDIAN, http://www.theguardian.com/business/2012/feb/15/credit-ratings-agencies-moodys, 15th February, 2012

TICKELL, S., *"PharmaFutures: Pathways to Value: Pharma in a Changing World",* Oxford, UK: Meteos Ltd, 2013

U.S. GOVERNMENT, Credit Rating Agency Reform Act 2006, page 2

U.S SECURITIES AND EXCHANGE COMMISSION, https://www.sec.gov/rules/concept/33-8236.htm, 28th July 2003

U.S. SECURITIES AND EXCHANGE COMMISSION, "*Report on the role and function of Credit rating Agencies in the operation of the securities market"* SEC reports, January 2003

U.S. SECURITY AND EXCHANGE COMMISSION, https://www.sec.gov/edgar/searchedgar/companysearch.html, EDGAR database research tool, 2016

U.S. SECURITY AND EXCHANGE COMMISSION, https://www.sec.gov/rules/concept/33-8236.htm, 6th October, 2003

U.S. SECURITIES AND EXCHANGE COMMISSION, https://www.sec.gov/investor/alerts/ib_creditratings.pdf, Investor Bulletin

VASSALOU, M., XING, Y., *"Equity Returns Following Changes in Default Risk: New Insights into the Informational Content of Credit Ratings*", EFA 2003 Annual Conference Paper No. 326, 2003

WHITE, L. J. "*Markets: The Credit Rating Agencies*." Journal of Economic Perspectives, 24(2): 211-26, 2010

WINSTEPS WEBSITE, http://www.winsteps.com/index.htm, 2016

WONG, G. Y., MASON, W. M. *"The Hierarchical Logistic Regression Model for Multilevel Analysis."* Journal of the American Statistical Association 80, 513-24, 1985

WRIGHT, B. D., *"Solving Measurement Problems with the Rasch Model",* Journal of Educational Measuramnet, Vol. 14, No. 2, Applications of Latent Trait Models, pp. 97-116.

WRIGHT, B.D., PERKINS, K., DORSEY, J.K., *"Rasch Measurement Instead of Regression",* Multiple Linear Regression Viewpoints, 26(2), Pages 36-41, 2000

WU, C.Y., *"Using Non-Financial Information to Predict Bankruptcy: A Study of Public Companies in Taiwan",* International Journal of Management, Vol.21, No.2, 2004

YAHOO FINANCE, https://uk.finance.yahoo.com/, Yahoo finance research tool, 2016

ZHENG, Y., *"The development of the risky financial behaviour scale: A measure of financial risk tolerance",* Electronic Theses and Papers. Paper 734, 2013

Appendix

In the appendix we are going to present all those useful tables and figures which will help the reader to understand the analysis and the results obtained in this paper.

Appendix 1- Preliminary application of the model

This table shows the preliminary results obtained after applying the Rasch model to the overall data. On the top of the table, they are presented respectively the reliability of the persons and of the items (zero in this case), while in the column

TABLE 26.1 RASCH GLORIA2.xlsx ZOU576WS.TXT Jul 23 2016 13:57
INPUT: 1320 PERSON 13 ITEM REPORTED: 1320 PERSON 13 ITEM 2 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 1.08 REL.: .54 ... ITEM: REAL SEP.: .00 REL.: .00

ITEM STATISTICS: CORRELATION 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
3	660	1320	.00	.06	1.61	9.9	1.78	9.9	-.24	.39	35.5	66.6	03INCR
9	660	1320	.00	.06	1.57	9.9	1.65	9.9	-.18	.39	36.0	66.6	09DERC
10	660	1320	.00	.06	1.46	9.9	1.51	9.9	-.07	.39	41.9	66.6	10CARA
5	660	1320	.00	.06	.98	-1.2	.96	-1.6	.42	.39	65.5	66.6	05SATA
12	660	1320	.00	.06	.96	-2.0	.95	-1.8	.43	.39	68.5	66.6	12RETT
7	660	1320	.00	.06	.93	-3.5	.92	-3.0	.46	.39	71.1	66.6	07QURA
4	660	1320	.00	.06	.90	-5.1	.86	-5.3	.50	.39	70.8	66.6	04ROEC
13	610	1219	-.02	.06	.86	-6.9	.85	-5.4	.53	.39	75.2	66.7	13MVTL
8	660	1320	.00	.06	.79	-9.9	.77	-9.3	.60	.39	78.4	66.6	08SORA
6	660	1320	.00	.06	.79	-9.9	.75	-9.9	.60	.39	76.9	66.6	06CURA
11	660	1320	.00	.06	.77	-9.9	.73	-9.9	.62	.39	78.1	66.6	11WCTA
2	660	1320	.00	.06	.69	-9.9	.64	-9.9	.70	.39	83.9	66.6	02AROA
1	660	1320	.00	.06	.68	-9.9	.64	-9.9	.71	.39	84.9	66.6	01ROA_
MEAN	656.2	1312.2	.00	.06	1.00	-3.0	1.00	-2.8			66.7	66.6	
P.SD	13.3	26.9	.01	.00	.32	7.7	.37	7.6			16.7	.0	

TABLE 26.3 RASCH GLORIA2.xlsx ZOU576WS.TXT Jul 23 2016 13:57
INPUT: 1320 PERSON 13 ITEM REPORTED: 1320 PERSON 13 ITEM 2 CATS WINSTEPS 3.92.0

ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES: CORRELATION ORDER

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
3	0	0	660	50	.23	.85	.03	1.6	1.7	.24	03INCR
	1	1	660	50	-.22*	.94	.04	1.7	1.8	-.24	
9	0	0	660	50	.17	.88	.03	1.5	1.6	.18	09DERC
	1	1	660	50	-.17*	.94	.04	1.6	1.7	-.18	
10	0	0	660	50	.07	.88	.03	1.4	1.5	.07	10CARA
	1	1	660	50	-.06*	.96	.04	1.5	1.6	-.07	
5	0	0	660	50	-.38	.83	.03	1.0	.9	-.42	05SATA
	1	1	660	50	.39	.85	.03	1.0	1.0	.42	
12	0	0	660	50	-.40	.88	.03	1.0	1.0	-.43	12RETT
	1	1	660	50	.40	.79	.03	.9	.9	.43	
7	0	0	660	50	-.42	.85	.03	.9	1.0	-.46	07QURA
	1	1	660	50	.43	.79	.03	.9	.9	.46	
4	0	0	660	50	-.46	.79	.03	.9	.8	-.50	04ROEC
	1	1	660	50	.46	.82	.03	.9	.9	.50	
13	0	0	609	50	-.51	.81	.03	.9	.9	-.53	13MVTL
	1	1	610	50	.46	.75	.03	.8	.8	.53	
	MISSING	***	101	8#	.27	.99	.10			.08	
8	0	0	660	50	-.55	.76	.03	.8	.8	-.60	08SORA
	1	1	660	50	.55	.73	.03	.8	.7	.60	
6	0	0	660	50	-.55	.75	.03	.8	.8	-.60	06CURA
	1	1	660	50	.56	.73	.03	.8	.7	.60	
11	0	0	660	50	-.57	.74	.03	.8	.7	-.62	11WCTA
	1	1	660	50	.57	.72	.03	.8	.7	.62	
2	0	0	660	50	-.65	.66	.03	.7	.6	-.70	02AROA
	1	1	660	50	.65	.66	.03	.7	.6	.70	
1	0	0	660	50	-.65	.67	.03	.7	.6	-.71	01ROA_
	1	1	660	50	.66	.64	.03	.7	.6	.71	

* Average ability does not ascend with category score
\# Missing % includes all categories. Scored % only of scored categories

"MEASURE", it is possible to see the items difficulties, which are equal to zero, meaning that for the model all the measures are the same. In addition, in the second table, we can see from column "PTMA CORR." that 03INCR, 09DERC and 10CARA presents "reserve polarity as they have a negative sign in the score value 1 instead than in 0.

Appendix 2- Preliminary analysis- Sector A

In this table we have presented the preliminary results after applying the Rasch model to Sector A. Particularly, the first table (Appendix i) shows the outcome of the first model application while the second table (Appendix ii) shows how the results improved after eliminating the missfitting items. The fit of the item to the model can be observed in the columns "INFIT" and "OUTFIT".

Appendix i

TABLE 13.1 RASCH GLORIA2.xlsx ZOU411WS.TXT Jul 23 2016 14: 4
INPUT: 1320 PERSON 13 ITEM REPORTED: 484 PERSON 13 ITEM 2 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 1.76 REL.: .76 ... ITEM: REAL SEP.: 4.37 REL.: .95

ITEM STATISTICS: MEASURE 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
7	154	484	1.00	.13	1.32	4.3	1.49	3.3	.50	.61	70.2	79.8	07QURA
3	171	484	.73	.12	.95	-.8	1.09	.8	.63	.62	80.4	78.5	03INCR
10	188	484	.48	.12	1.10	1.6	1.09	.8	.59	.62	73.4	77.3	10CARA
6	202	484	.27	.12	.92	-1.3	.76	-2.6	.66	.62	76.9	76.6	06CURA
11	214	484	.10	.12	.86	-2.6	.70	-3.5	.69	.62	79.2	76.0	11WCTA
9	218	484	.05	.12	1.18	3.0	1.12	1.3	.56	.62	70.0	75.8	09DERC
13	194	438	.02	.13	.71	-5.3	.56	-5.1	.74	.63	83.8	75.8	13MVTL
8	229	484	-.11	.12	.67	-6.8	.55	-5.9	.75	.62	84.1	75.3	08SORA
12	229	484	-.11	.12	1.30	5.0	1.57	5.3	.50	.62	67.0	75.3	12RETT
1	233	484	-.16	.12	.64	-7.4	.51	-6.5	.76	.62	86.1	75.0	01ROA_
4	249	484	-.38	.12	1.36	6.0	1.18	6.4	.46	.62	67.2	75.1	04ROEC
2	257	484	-.49	.12	.70	-6.1	.56	-5.3	.73	.62	85.2	75.0	02AROA
5	321	484	-1.40	.12	1.30	4.7	1.38	2.4	.48	.59	69.1	77.2	05SATA
MEAN	219.9	480.5	.00	.12	1.00	-.4	1.01	-.7			76.4	76.4	
P.SD	40.7	12.3	.57	.00	.26	4.7	.42	4.2			6.9	1.4	

TABLE 13.3 RASCH GLORIA2.xlsx ZOU411WS.TXT Jul 23 2016 14: 4
INPUT: 1320 PERSON 13 ITEM REPORTED: 484 PERSON 13 ITEM 2 CATS WINSTEPS 3.92.0

ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES: MEASURE ORDER

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
7	0	0	330	68	-.89	1.66	.09	1.3	1.4	-.50	07QURA
	1	1	154	32	1.19	1.72	.14	1.4	1.5	.50	
3	1	0	313	65	-1.13	1.45	.08	.9	.9	-.63	03INCR
	0	1	171	35	1.42	1.62	.12	1.0	1.2	.63	
10	1	0	296	61	-1.14	1.48	.09	1.0	.9	-.59	10CARA
	0	1	188	39	1.21	1.70	.12	1.2	1.2	.59	
6	0	0	282	58	-1.31	1.41	.08	.9	.8	-.66	06CURA
	1	1	202	42	1.29	1.51	.11	.9	.7	.66	
11	0	0	270	56	-1.41	1.35	.08	.8	.7	-.69	11WCTA
	1	1	214	44	1.27	1.49	.10	.9	.7	.69	
9	1	0	266	55	-1.22	1.50	.09	1.1	1.0	-.56	09DERC
	0	1	218	45	.98	1.72	.12	1.2	1.2	.56	
13	0	0	244	56	-1.59	1.26	.08	.7	.6	-.74	13MVTL
	1	1	194	44	1.33	1.42	.10	.7	.6	.74	
	MISSING	***	46	10#	.45	1.47	.22			.11	
8	0	0	255	53	-1.60	1.23	.08	.7	.6	-.75	08SORA
	1	1	229	47	1.30	1.36	.09	.7	.5	.75	
12	0	0	255	53	-1.14	1.73	.11	1.5	2.1	-.50	12RETT
	1	1	229	47	.79	1.63	.11	1.1	1.1	.50	
1	0	0	251	52	-1.64	1.18	.07	.6	.5	-.76	01ROA_
	1	1	233	48	1.30	1.36	.09	.6	.5	.76	
4	0	0	235	49	-1.15	1.67	.11	1.4	1.9	-.46	04ROEC
	1	1	249	51	.65	1.76	.11	1.3	1.5	.46	
2	0	0	227	47	-1.73	1.18	.08	.7	.5	-.73	02AROA
	1	1	257	53	1.10	1.44	.09	.7	.6	.73	
5	0	0	163	34	-1.53	1.52	.12	1.3	1.4	-.48	05SATA
	1	1	321	66	.43	1.79	.10	1.3	1.4	.48	

Missing % includes all categories. Scored % only of scored categories

Appendix ii

TABLE 13.1 RASCH GLORIA2.xlsx ZOU404WS.TXT Jul 23 2016 16:50
INPUT: 1320 PERSON 13 ITEM REPORTED: 484 PERSON 10 ITEM 2 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 1.54 REL.: .70 ... ITEM: REAL SEP.: 4.35 REL.: .95

ITEM STATISTICS: MEASURE 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
3	171	484	.94	.13	1.01	.2	1.18	1.3	.67	.68	82.5	79.7	03INCR
10	188	484	.65	.13	1.16	2.3	1.14	1.2	.63	.68	75.1	78.2	10CARA
11	214	484	.23	.12	1.13	2.1	1.11	1.1	.63	.67	70.6	76.4	11WCTA
9	218	484	.17	.12	1.37	5.4	1.45	4.3	.55	.67	62.9	76.1	09DERC
13	194	438	.14	.13	.71	-5.1	.56	-5.2	.77	.67	85.4	75.8	13MVTL
8	229	484	.00	.12	.63	-7.2	.55	-6.1	.78	.66	89.6	75.4	08SORA
1	233	484	-.06	.12	.61	-7.6	.49	-7.0	.78	.66	89.1	75.4	01ROA_
4	249	484	-.30	.12	1.39	6.1	1.16	7.3	.51	.65	64.7	75.0	04ROEC
2	257	484	-.42	.12	.66	-6.8	.55	-6.0	.76	.65	85.5	74.8	02AROA
5	321	484	-1.37	.13	1.25	4.2	1.34	2.3	.51	.60	69.3	75.3	05SATA
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	

TABLE 13.3 RASCH GLORIA2.xlsx ZOU404WS.TXT Jul 23 2016 16:50
INPUT: 1320 PERSON 13 ITEM REPORTED: 484 PERSON 10 ITEM 2 CATS WINSTEPS 3.92.0

ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES: MEASURE ORDER

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
3	1	0	313	65	-1.10	1.44	.08	.9	1.0	-.67	03INCR
	0	1	171	35	1.78	1.73	.13	1.1	1.3	.67	
10	1	0	296	61	-1.12	1.47	.09	1.0	1.0	-.63	10CARA
	0	1	188	39	1.56	1.81	.13	1.3	1.2	.63	
11	0	0	270	56	-1.25	1.47	.09	1.1	1.2	-.63	11WCTA
	1	1	214	44	1.39	1.76	.12	1.1	1.1	.63	
9	1	0	266	55	-1.12	1.56	.10	1.4	1.4	-.55	09DERC
	0	1	218	45	1.18	1.90	.13	1.4	1.5	.55	
13	0	0	244	56	-1.58	1.21	.08	.7	.6	-.77	13MVTL
	1	1	194	44	1.66	1.52	.11	.7	.5	.77	
	MISSING	***	46	10#	.52	1.57	.23			.09	
8	0	0	255	53	-1.61	1.16	.07	.6	.6	-.78	08SORA
	1	1	229	47	1.62	1.44	.10	.6	.5	.78	
1	0	0	251	52	-1.65	1.11	.07	.6	.5	-.78	01ROA_
	1	1	233	48	1.60	1.45	.09	.6	.5	.78	
4	0	0	235	49	-1.16	1.65	.11	1.5	2.1	-.51	04ROEC
	1	1	249	51	.94	1.90	.12	1.3	1.5	.51	
2	0	0	227	47	-1.75	1.08	.07	.6	.5	-.76	02AROA
	1	1	257	53	1.39	1.55	.10	.7	.6	.76	
5	0	0	163	34	-1.58	1.46	.11	1.3	1.4	-.51	05SATA
	1	1	321	66	.68	1.92	.11	1.2	1.3	.51	

Missing % includes all categories. Scored % only of scored categories

Appendix 3- Preliminary analysis- Sector B

In this table we have presented the preliminary results after applying the Rasch model to Sector B. Particularly, the first table (Appendix iii) shows the outcome of the first model application while the second table (Appendix iv) shows how the results improved after eliminating the missfitting items. The fit of the item to the model can be observed in the columns "INFIT" and "OUTFIT".

Appendix iii

```
TABLE 13.1 RASCH GLORIA2.xlsx                        ZOU371WS.TXT   Jul 23 2016 14:13
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  13 ITEM  2 CATS WINSTEPS 3.92.0

 PERSON: REAL SEP.: 1.73  REL.: .75 ... ITEM: REAL SEP.: 4.20  REL.: .95

        ITEM STATISTICS:  MEASURE 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
9	152	440	.59	.13	.99	-.1	1.04	.4	.63	.62	77.0	77.5	09DERC
13	157	434	.45	.13	.72	-4.8	.64	-3.6	.72	.63	85.9	77.1	13MVTL
10	160	440	.45	.13	1.00	.1	1.02	.2	.62	.63	77.3	76.9	10CARA
8	162	440	.42	.13	.67	-5.8	.63	-3.9	.73	.63	88.5	76.8	08SORA
11	162	440	.42	.13	1.03	.4	.89	-1.0	.63	.63	75.1	76.8	11WCTA
6	169	440	.30	.13	1.05	.8	.93	-.7	.62	.63	74.3	76.4	06CURA
7	171	440	.27	.13	1.16	2.5	1.28	2.6	.57	.63	70.6	76.3	07QURA
3	179	440	.14	.13	.98	-.2	1.00	.1	.63	.63	77.3	75.8	03INCR
1	182	440	.09	.13	.71	-5.3	.56	-5.4	.74	.63	84.5	75.8	01ROA_
2	205	440	-.28	.13	.80	-3.6	.68	-3.8	.71	.63	81.3	75.3	02AROA
4	237	440	-.78	.13	1.70	9.9	2.28	9.2	.37	.63	55.1	75.1	04ROEC
12	237	440	-.78	.13	1.01	.1	1.48	4.1	.60	.63	77.0	75.1	12RETT
5	270	440	-1.30	.13	1.06	1.0	1.16	1.2	.59	.62	77.3	75.7	05SATA
MEAN	187.9	439.5	.00	.13	.99	-.4	1.05	.0			77.0	76.2	
P.SD	36.1	1.6	.57	.00	.25	3.9	.44	3.7			7.9	.8	

```
TABLE 13.3 RASCH GLORIA2.xlsx                        ZOU371WS.TXT   Jul 23 2016 14:13
INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  13 ITEM  2 CATS WINSTEPS 3.92.0

        ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES:  MEASURE ORDER
```

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
9	1	0	288	65	-1.36	1.54	.09	1.0	1.0	-.63	09DERC
	0	1	152	35	1.30	1.64	.13	1.0	1.1	.63	
13	0	0	277	64	-1.55	1.42	.09	.8	.8	-.72	13MVTL
	1	1	157	36	1.49	1.37	.11	.7	.6	.72	
	MISSING	***	6	1#	.42	1.27	.57			.05	
10	1	0	280	64	-1.39	1.53	.09	1.0	.9	-.62	10CARA
	0	1	160	36	1.23	1.66	.13	1.0	1.1	.62	
8	0	0	278	63	-1.57	1.34	.08	.7	.6	-.73	08SORA
	1	1	162	37	1.50	1.42	.11	.7	.7	.73	
11	0	0	278	63	-1.41	1.54	.09	1.0	.9	-.63	11WCTA
	1	1	162	37	1.22	1.63	.13	1.1	.9	.63	
6	0	0	271	62	-1.43	1.54	.09	1.0	.9	-.62	06CURA
	1	1	169	38	1.15	1.65	.13	1.1	.9	.62	
7	0	0	269	61	-1.36	1.60	.10	1.2	1.2	-.57	07QURA
	1	1	171	39	1.01	1.74	.13	1.2	1.3	.57	
3	1	0	261	59	-1.50	1.49	.09	1.0	.9	-.63	03INCR
	0	1	179	41	1.11	1.66	.12	1.0	1.1	.63	
1	0	0	258	59	-1.69	1.34	.08	.7	.6	-.74	01ROA_
	1	1	182	41	1.33	1.40	.10	.7	.5	.74	
2	0	0	235	53	-1.77	1.35	.09	.8	.7	-.71	02AROA
	1	1	205	47	1.09	1.52	.11	.8	.7	.71	
4	0	0	203	46	-1.24	1.85	.13	1.8	2.6	-.37	04ROEC
	1	1	237	54	.25	1.90	.12	1.6	1.8	.37	
12	0	0	203	46	-1.76	1.63	.11	1.1	1.9	-.60	12RETT
	1	1	237	54	.69	1.59	.10	.9	.9	.60	
5	0	0	170	39	-1.94	1.54	.12	1.2	1.3	-.59	05SATA
	1	1	270	61	.51	1.68	.10	1.0	1.0	.59	

Missing % includes all categories. Scored % only of scored categories

Appendix iv

```
TABLE 13.1 RASCH GLORIA2.xlsx                        ZOU763WS.TXT  Jul 28 2016 15: 5
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  9 ITEM  2 CATS WINSTEPS 3.92.0
--------------------------------------------------------------------------------
 PERSON: REAL SEP.: 1.44  REL.: .67 ... ITEM: REAL SEP.: 4.44  REL.: .95

        ITEM STATISTICS:  MEASURE 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
9	152	440	.57	.14	1.12	1.6	1.15	1.1	.67	.70	76.4	77.8	09DERC
13	157	434	.41	.14	.73	-4.2	.66	-3.2	.77	.70	85.4	77.3	13MVTL
10	160	440	.41	.14	1.02	.3	.92	-.6	.70	.70	74.1	77.1	10CARA
8	162	440	.37	.14	.68	-5.1	.59	-4.2	.78	.70	88.2	76.9	08SORA
11	162	440	.37	.14	1.44	5.5	1.71	5.1	.58	.70	68.4	76.9	11WCTA
3	179	440	.04	.14	1.06	.9	1.15	1.5	.68	.70	74.8	75.9	03INCR
1	182	440	-.02	.14	.78	-3.5	.65	-4.0	.77	.70	80.5	75.8	01ROA_
2	205	440	-.45	.14	.92	-1.2	.86	-1.5	.73	.70	78.3	75.2	02AROA
5	270	440	-1.71	.14	1.20	2.8	1.58	3.1	.62	.69	78.3	77.6	05SATA
MEAN	181.0	439.3	.00	.14	.99	-.3	1.03	-.3			78.3	76.7	
P.SD	35.1	1.9	.67	.00	.23	3.3	.38	3.1			5.6	.8	

```
TABLE 13.3 RASCH GLORIA2.xlsx                        ZOU763WS.TXT  Jul 28 2016 15: 5
INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  9 ITEM  2 CATS WINSTEPS 3.92.0
--------------------------------------------------------------------------------

        ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES:  MEASURE ORDER
```

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
9	1	0	288	65	-1.65	1.66	.10	1.2	1.2	-.67	09DERC
	0	1	152	35	1.50	1.68	.14	1.1	1.1	.67	
13	0	0	277	64	-1.87	1.45	.09	.8	.8	-.77	13MVTL
	1	1	157	36	1.72	1.41	.11	.7	.6	.77	
	MISSING	***	6	1#	.15	2.08	.93			.04	
10	1	0	280	64	-1.75	1.57	.09	1.0	.9	-.70	10CARA
	0	1	160	36	1.51	1.65	.13	1.0	.9	.70	
8	0	0	278	63	-1.90	1.39	.08	.7	.6	-.78	08SORA
	1	1	162	37	1.73	1.42	.11	.7	.6	.78	
11	0	0	278	63	-1.56	1.77	.11	1.4	1.6	-.58	11WCTA
	1	1	162	37	1.14	1.91	.15	1.5	1.7	.58	
3	1	0	261	59	-1.83	1.53	.09	1.0	1.0	-.68	03INCR
	0	1	179	41	1.29	1.78	.13	1.1	1.3	.68	
1	0	0	258	59	-2.01	1.39	.09	.8	.7	-.77	01ROA_
	1	1	182	41	1.48	1.50	.11	.7	.6	.77	
2	0	0	235	53	-2.09	1.40	.09	.9	.8	-.73	02AROA
	1	1	205	47	1.18	1.68	.12	.9	.9	.73	
5	0	0	170	39	-2.32	1.57	.12	1.4	1.8	-.62	05SATA
	1	1	270	61	.54	1.86	.11	1.0	1.1	.62	

Missing % includes all categories. Scored % only of scored categories

Appendix 4- Preliminary analysis- Sector C

In this table we have presented the preliminary results after applying the Rasch model to Sector C. Particularly, the first table (Appendix vi) shows the outcome of the first model application while the second table (Appendix v) shows how the results improved after eliminating the missfitting items. The fit of the item to the model can be observed in the columns "INFIT" and "OUTFIT".

Appendix v

```
TABLE 13.1 RASCH GLORIA2.xlsx                      ZOU037WS.TXT  Jul 23 2016 14:26
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  13 ITEM  2 CATS WINSTEPS 3.92.0

 PERSON: REAL SEP.: 1.59  REL.: .72 ... ITEM: REAL SEP.: 8.42  REL.: .99

         ITEM STATISTICS:  MEASURE 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
5	69	396	3.26	.16	1.52	4.8	4.47	6.9	.18	.50	85.7	85.6	05SATA
4	174	396	1.26	.13	1.33	5.1	1.68	4.9	.41	.57	68.7	75.5	04ROEC
12	194	396	.95	.12	1.40	6.3	1.56	4.6	.39	.57	59.4	74.4	12RETT
2	198	396	.89	.12	.86	-2.6	.82	-1.8	.64	.57	76.9	74.4	02AROA
1	245	396	.15	.13	.77	-4.4	.58	-4.4	.68	.56	81.4	75.4	01ROA_
8	269	396	-.25	.13	.66	-6.0	.51	-4.5	.70	.55	87.8	77.2	08SORA
11	284	396	-.51	.14	.87	-2.0	.72	-2.0	.60	.54	80.4	79.2	11WCTA
6	289	396	-.61	.14	.90	-1.5	.73	-1.8	.59	.53	80.1	79.9	06CURA
9	290	396	-.63	.14	.77	-3.5	.54	-3.4	.64	.53	84.1	80.0	09DERC
13	259	347	-.78	.15	.74	-3.6	.51	-3.3	.64	.52	85.9	80.9	13MVTL
3	310	396	-1.03	.15	.99	-.1	.78	-1.2	.53	.51	83.0	83.0	03INCR
10	312	396	-1.07	.15	1.14	1.7	1.06	.4	.45	.51	79.8	83.3	10CARA
7	335	396	-1.64	.17	1.02	.3	.62	-1.5	.49	.48	86.2	87.2	07QURA
MEAN	248.3	392.2	.00	.14	1.00	-.4	1.12	-.6			80.0	79.7	
P.SD	70.0	13.1	1.26	.01	.26	3.7	1.03	3.6			7.6	4.1	

```
TABLE 13.3 RASCH GLORIA2.xlsx                      ZOU037WS.TXT  Jul 23 2016 14:26
INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  13 ITEM  2 CATS WINSTEPS 3.92.0

        ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES:  MEASURE ORDER
```

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	DATA %	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
5	0	0	327	83	.73	1.65	.09	1.2	1.3	-.18	05SATA
	1	1	69	17	1.56	2.10	.25	3.3	5.0	.18	
4	0	0	222	56	.23	1.48	.10	1.1	1.1	-.41	04ROEC
	1	1	174	44	1.70	1.76	.13	1.6	2.1	.41	
12	0	0	202	51	.20	1.59	.11	1.3	1.4	-.39	12RETT
	1	1	194	49	1.59	1.66	.12	1.5	1.7	.39	
2	0	0	198	50	-.25	1.28	.09	.8	.6	-.64	02AROA
	1	1	198	50	2.00	1.44	.10	1.0	1.0	.64	
1	0	0	151	38	-.64	1.23	.10	.7	.5	-.68	01ROA_
	1	1	245	62	1.81	1.34	.09	.8	.7	.68	
8	0	0	127	32	-.92	1.13	.10	.6	.4	-.70	08SORA
	1	1	269	68	1.72	1.32	.08	.7	.7	.70	
11	0	0	112	28	-.81	1.36	.13	.8	.7	-.60	11WCTA
	1	1	284	72	1.54	1.43	.09	.9	.8	.60	
6	0	0	107	27	-.82	1.38	.13	.9	.7	-.59	06CURA
	1	1	289	73	1.51	1.45	.09	.9	.8	.59	
9	1	0	106	27	-1.00	1.20	.12	.7	.5	-.64	09DERC
	0	1	290	73	1.56	1.40	.08	.8	.8	.64	
13	0	0	88	25	-1.08	1.15	.12	.7	.4	-.64	13MVTL
	1	1	259	75	1.46	1.37	.09	.8	.7	.64	
	MISSING	***	49	12#	1.30	2.02	.29			.09	
3	1	0	86	22	-.89	1.42	.15	1.0	.7	-.53	03INCR
	0	1	310	78	1.37	1.52	.09	1.0	1.0	.53	
10	1	0	84	21	-.66	1.53	.17	1.2	1.0	-.45	10CARA
	0	1	312	79	1.29	1.59	.09	1.1	1.2	.45	
7	0	0	61	15	-1.17	1.27	.16	.9	.5	-.49	07QURA
	1	1	335	85	1.25	1.58	.09	1.1	1.1	.49	

Missing % includes all categories. Scored % only of scored categories

Appendix vi

```
TABLE 13.1 RASCH GLORIA2.xlsx                      ZOU134WS.TXT  Jul 23 2016 14:32
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  8 ITEM  2 CATS WINSTEPS 3.92.0

 PERSON: REAL SEP.: .88  REL.: .44 ... ITEM: REAL SEP.: 3.72  REL.: .93

        ITEM STATISTICS:  MEASURE 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
1	245	396	1.18	.16	1.36	4.8	1.40	2.9	.64	.74	57.4	72.7	01ROA_
8	269	396	.60	.15	.75	-4.0	.70	-3.4	.78	.71	79.1	72.8	08SORA
11	284	396	.24	.16	1.12	1.6	1.14	1.4	.65	.69	70.9	73.5	11WCTA
9	290	396	.10	.16	.62	-6.0	.53	-5.6	.79	.68	91.7	73.7	09DERC
13	259	347	-.13	.17	.68	-4.5	.58	-4.3	.76	.66	85.5	74.3	13MVTL
3	310	396	-.41	.16	1.28	3.3	1.39	2.8	.56	.64	68.7	75.9	03INCR
10	312	396	-.46	.16	1.11	1.4	1.31	2.3	.59	.64	76.5	76.2	10CARA
7	335	396	-1.13	.18	1.08	.9	.87	-.7	.57	.58	77.8	80.3	07QURA
MEAN	288.0	389.9	.00	.16	1.00	-.3	.99	-.6			76.0	74.9	
P.SD	28.2	16.2	.66	.01	.26	3.7	.34	3.2			9.9	2.4	

```
TABLE 13.3 RASCH GLORIA2.xlsx                      ZOU134WS.TXT  Jul 23 2016 14:32
INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  8 ITEM  2 CATS WINSTEPS 3.92.0

        ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES:  MEASURE ORDER
```

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
1	0	0	151	38	.03	1.53	.13	1.3	1.3	-.64	01ROA_
	1	1	245	62	2.52	1.38	.09	1.5	1.5	.64	
8	0	0	127	32	-.57	1.22	.11	.7	.6	-.78	08SORA
	1	1	269	68	2.58	1.16	.07	.8	.7	.78	
11	0	0	112	28	-.39	1.50	.14	1.2	1.2	-.65	11WCTA
	1	1	284	72	2.34	1.39	.08	1.1	1.0	.65	
9	1	0	106	27	-.88	1.09	.11	.6	.5	-.79	09DERC
	0	1	290	73	2.47	1.18	.07	.6	.6	.79	
13	0	0	88	25	-.93	1.08	.12	.6	.5	-.76	13MVTL
	1	1	259	75	2.35	1.29	.08	.7	.7	.76	
	MISSING	***	49	12#	1.93	1.76	.25			.07	
3	1	0	86	22	-.42	1.57	.17	1.4	1.5	-.56	03INCR
	0	1	310	78	2.12	1.56	.09	1.2	1.2	.56	
10	1	0	84	21	-.58	1.55	.17	1.2	1.4	-.59	10CARA
	0	1	312	79	2.15	1.51	.09	1.1	1.1	.59	
7	0	0	61	15	-.94	1.30	.17	1.0	.8	-.57	07QURA
	1	1	335	85	2.03	1.59	.09	1.1	1.1	.57	

Missing % includes all categories. Scored % only of scored categories

Appendix 5 - Preliminary PCA analysis per sector

In this Appendix are showed the preliminary outcomes of the PCA analysis for each sector.

Appendix 5.A- PCA analysis for Sector A

This table shows the PCA analysis for Sector A, after omitting all the missfitting data discussed in Chapter 4.2.1. We can see in the first part of the table that the "Unexplained variance in the 1st contrast" is 2.2289. In addition, in the second part of the table, it is useful to see that the correlations between equities measures determined on the base of the tentatively different item clusters is one. This is explained in the "Clusters" column, where the combinations between 1-2, 1-3, 2-3 contrasts present a correlation ("Disattenuated"+ Extra Correlation column) of 1.

Appendix vii

```
TABLE 23.0 RASCH GLORIA2.xlsx                    ZOU404WS.TXT  Jul 23 2016 16:50
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  2 CATS WINSTEPS 3.92.0
--------------------------------------------------------------------------------

    Table of STANDARDIZED RESIDUAL variance in Eigenvalue units = ITEM information units
                                           Eigenvalue   Observed   Expected
Total raw variance in observations     =      15.2633 100.0%         100.0%
 Raw variance explained by measures   =       5.2633  34.5%          34.0%
   Raw variance explained by persons  =       2.9914  19.6%          19.3%
   Raw Variance explained by items    =       2.2719  14.9%          14.7%
 Raw unexplained variance (total)     =      10.0000  65.5% 100.0%   66.0%
   Unexplned variance in 1st contrast =       2.2289  14.6%  22.3%
   Unexplned variance in 2nd contrast =       1.7815  11.7%  17.8%
   Unexplned variance in 3rd contrast =       1.2304   8.1%  12.3%
   Unexplned variance in 4th contrast =       1.0327   6.8%  10.3%
   Unexplned variance in 5th contrast =        .9116   6.0%   9.1%

      STANDARDIZED RESIDUAL VARIANCE SCREE PLOT

       VARIANCE COMPONENT SCREE PLOT
      +--+--+--+--+--+--+--+--+--+--+--+
  100%+  T                             +
      |                                |
V  63%+              U                 +
A     |                                |
R  40%+                                +
I     |     M                          |
A  25%+                                +
N     |                                |
C  16%+        P                       +
E     |           I     1              |
   10%+                    2           +
L     |                       3        |
O   6%+                          4     +
G     |                             5  |
|   4%+                                +
S     |                                |
C   3%+                                +
A     |                                |
L   2%+                                +
E     |                                |
D   1%+                                +
      |                                |
  0.5%+                                +
      +--+--+--+--+--+--+--+--+--+--+--+
        TV MV PV IV UV U1 U2 U3 U4 U5
         VARIANCE COMPONENTS

Approximate relationships between the PERSON measures
PCA       ITEM      Pearson       Disattenuated Pearson+Extr  Disattenuated+Extr
Contrast  Clusters  Correlation   Correlation   Correlation   Correlation
1         1 - 3     -0.0478       (-1.00)       0.2258        (1.00)
1         1 - 2      0.5222        1.0000       0.6694         1.0000
1         2 - 3      0.2993       (1.00)        0.5311        (1.00)
2         1 - 3      0.2427       (1.00)        0.4951         1.0000
2         1 - 2      0.2885       (1.00)        0.5401         1.0000
2         2 - 3      0.6510       (1.00)        0.7682         1.0000
3         1 - 3      0.1882       (1.00)        0.3847        (1.00)
3         1 - 2      0.3724       (1.00)        0.5795        (1.00)
3         2 - 3      0.5509       (1.00)        0.6982        (1.00)
4         1 - 3      0.2635       (1.00)        0.5331        (1.00)
4         1 - 2      0.4233       (1.00)        0.6217        (1.00)
4         2 - 3      0.4296       (1.00)        0.6534        (1.00)
5         1 - 3      0.5869       (1.00)        0.6991        (1.00)
5         1 - 2      0.5411       (1.00)        0.6693        (1.00)
5         2 - 3      0.6006        1.0000       0.7676         1.0000
```

Appendix 5.B- PCA analysis for Sector B

This table shows the PCA analysis for Sector A, after omitting all the missfitting data discussed in Chapter 4.2.2. We can see in the first part of the table that the "Unexplained variance in the 1st contrast" is 1.9306. In addition, in the second part of the table, it is useful to see that the correlations between equities measures determined on the base of the tentatively different item clusters is one. This is explained in the "Clusters" column, where the combinations between 1-2, 1-3, 2-3 contrasts present a correlation ("Disattenuated"+ Extra Correlation column) of 1.

Appendix viii

```
TABLE 23.0 RASCH GLORIA2.xlsx                     ZOU763WS.TXT   Jul 28 2016 15: 5
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  9 ITEM  2 CATS WINSTEPS 3.92.0
------------------------------------------------------------------------------------

    Table of STANDARDIZED RESIDUAL variance in Eigenvalue units = ITEM information units
                                          Eigenvalue   Observed   Expected
 Total raw variance in observations     =      13.8533 100.0%         100.0%
  Raw variance explained by measures   =       4.8533  35.0%          34.5%
    Raw variance explained by persons  =       2.8565  20.6%          20.3%
    Raw Variance explained by items    =       1.9968  14.4%          14.2%
  Raw unexplained variance (total)     =       9.0000  65.0% 100.0%   65.5%
    Unexplned variance in 1st contrast =       1.9306  13.9%  21.5%
    Unexplned variance in 2nd contrast =       1.8481  13.3%  20.5%
    Unexplned variance in 3rd contrast =       1.2784   9.2%  14.2%
    Unexplned variance in 4th contrast =       1.0152   7.3%  11.3%
    Unexplned variance in 5th contrast =        .8842   6.4%   9.8%

      STANDARDIZED RESIDUAL VARIANCE SCREE PLOT

       VARIANCE COMPONENT SCREE PLOT
      +--+--+--+--+--+--+--+--+--+--+--+
  100%+  T                             +
      |                                |
V  63%+           U                    +
A     |                                |
R  40%+                                +
I     |     M                          +
A  25%+                                +
N     |        P                       |
C  16%+                                +
E     |           I     1  2           |
   10%+                                +
L     |                    3           |
O   6%+                       4  5     +
G     |                                |
|   4%+                                +
S     |                                |
C   3%+                                +
A     |                                |
L   2%+                                +
E     |                                |
D   1%+                                +
      |                                |
  0.5%+                                +
      +--+--+--+--+--+--+--+--+--+--+--+
        TV MV PV IV UV U1 U2 U3 U4 U5
       VARIANCE COMPONENTS

 Approximate relationships between the PERSON measures
 PCA       ITEM      Pearson       Disattenuated Pearson+Extr  Disattenuated+Extr
 Contrast  Clusters   Correlation   Correlation   Correlation   Correlation
 1         1 - 3      0.3083        1.0000        0.6280        1.0000
 1         1 - 2      0.3574        (1.00)        0.5738        (1.00)
 1         2 - 3      0.0985        (1.00)        0.4554        (1.00)
 2         1 - 3      0.3820        (1.00)        0.6027        (1.00)
 2         1 - 2      0.2150        (1.00)        0.5736        1.0000
 2         2 - 3      0.2805        (1.00)        0.5718        (1.00)
 3         1 - 3     -0.0026       (-1.00)        0.3235        (1.00)
 3         1 - 2      0.0982        (1.00)        0.4491        (1.00)
 3         2 - 3      0.3850        (1.00)        0.6507        (1.00)
 4         1 - 3      0.4307        (1.00)        0.7246        (1.00)
 4         1 - 2      0.5610        (1.00)        0.7362        (1.00)
 4         2 - 3      0.5576        (1.00)        0.7354        (1.00)
 5         1 - 3      0.4501        (1.00)        0.7200        (1.00)
 5         1 - 2      0.5516        (1.00)        0.7478        (1.00)
 5         2 - 3      0.6678        (1.00)        0.8315        1.0000
```

Appendix 5.C- PCA analysis for Sector C

This table shows the PCA analysis for Sector A, after omitting all the missfitting data discussed in Chapter 4.2.3. We can see in the first part of the table that the "Unexplained variance in the 1st contrast" is 1.92. In addition, in the second part of the table, it is useful to see that the correlations between equities measures determined on the base of the tentatively different item clusters is one. This is explained in the "Clusters" column, where the combinations between 1-2, 1-3, 2-3 contrasts present a correlation ("Disattenuated"+ Extra Correlation column) of 1.

Appendix ix

```
TABLE 23.0 RASCH GLORIA2.xlsx                    ZOU134WS.TXT  Jul 23 2016 14:32
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  8 ITEM  2 CATS WINSTEPS 3.92.0
--------------------------------------------------------------------------------

    Table of STANDARDIZED RESIDUAL variance in Eigenvalue units = ITEM information units
                                          Eigenvalue   Observed   Expected
 Total raw variance in observations    =     11.4572 100.0%         100.0%
  Raw variance explained by measures   =      3.4572  30.2%          30.1%
    Raw variance explained by persons  =      1.8987  16.6%          16.5%
    Raw Variance explained by items    =      1.5585  13.6%          13.6%
  Raw unexplained variance (total)     =      8.0000  69.8% 100.0%   69.9%
    Unexplned variance in 1st contrast =      1.9262  16.8%  24.1%
    Unexplned variance in 2nd contrast =      1.7998  15.7%  22.5%
    Unexplned variance in 3rd contrast =      1.4323  12.5%  17.9%
    Unexplned variance in 4th contrast =       .9766   8.5%  12.2%
    Unexplned variance in 5th contrast =       .7904   6.9%   9.9%

      STANDARDIZED RESIDUAL VARIANCE SCREE PLOT

       VARIANCE COMPONENT SCREE PLOT
      +--+--+--+--+--+--+--+--+--+--+--+
  100%+  T                             +
      |                                |
V 63%+              U                  +
A     |                                |
R 40%+                                 +
I     |                                |
A 25%+     M                           +
N     |                                |
C 16%+        P        1               +
E     |          I        2            |
  10%+                       3         +
L     |                         4      |
O  6%+                             5   +
G     |                                |
|  4%+                                 +
S     |                                |
C  3%+                                 +
A     |                                |
L  2%+                                 +
E     |                                |
D  1%+                                 +
      |                                |
 0.5%+                                 +
      +--+--+--+--+--+--+--+--+--+--+--+
         TV MV PV IV UV U1 U2 U3 U4 U5
        VARIANCE COMPONENTS

Approximate relationships between the PERSON measures
PCA       ITEM      Pearson     Disattenuated Pearson+Extr  Disattenuated+Extr
Contrast  Clusters  Correlation  Correlation  Correlation    Correlation
1         1 - 3     -0.2059     (-1.00)       0.2369         (1.00)
1         1 - 2      0.1714      (1.00)       0.4529         (1.00)
1         2 - 3      0.1059      (1.00)       0.4945         (1.00)
2         1 - 3      0.0202      (1.00)       0.4322         (1.00)
2         1 - 2      0.4276      (1.00)       0.6526         (1.00)
2         2 - 3      0.3372      (1.00)       0.6728         (1.00)
3         1 - 3      0.0893      (1.00)       0.3900         (1.00)
3         1 - 2      0.5311      (1.00)       0.7195         (1.00)
3         2 - 3      0.0849      (1.00)       0.4870         (1.00)
4         1 - 3      0.5840      (1.00)       0.7090         (1.00)
4         1 - 2      0.2174      (1.00)       0.4837         (1.00)
4         2 - 3      0.0848      (1.00)       0.5371         (1.00)
5         1 - 3      0.2163      (1.00)       0.4858         (1.00)
5         1 - 2     -0.0132     (-1.00)       0.3247         (1.00)
5         2 - 3      0.1828      (1.00)       0.5958         (1.00)
```

Appendix 6- Final model - Sector A

This Appendix showed the results from the final model selected for Sector A discussed in 4.4.1. In the first table (Appendix x) is presented an analysis of the reliability of the model for the items and persons, while in the second table (Appendix xi) they are represented the outcomes for the item difficulties.

Appendix x

```
TABLE 3.1 RASCH GLORIA7.xlsx                        ZOU792WS.TXT  Jul 29 2016 17:37
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  9 ITEM  7 CATS WINSTEPS 3.92.0
```

SUMMARY OF 484 MEASURED PERSON

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	25.7	8.9	-.03	.27	1.01	-.1	1.05	-.1
P.SD	12.6	.3	.84	.11	.69	1.5	.76	1.5
S.SD	12.6	.3	.84	.11	.69	1.5	.76	1.5
MAX.	53.0	9.0	3.15	1.00	4.21	4.1	4.94	4.3
MIN.	2.0	8.0	-2.33	.21	.06	-4.8	.07	-4.6

```
 REAL RMSE    .33 TRUE SD    .77  SEPARATION  2.35  PERSON RELIABILITY  .85
MODEL RMSE    .30 TRUE SD    .78  SEPARATION  2.65  PERSON RELIABILITY  .88
 S.E. OF PERSON MEAN = .04

              DELETED:     836 PERSON
PERSON RAW SCORE-TO-MEASURE CORRELATION = .96
CRONBACH ALPHA (KR-20) PERSON RAW SCORE "TEST" RELIABILITY = .88  SEM = 4.43
```

SUMMARY OF 9 MEASURED ITEM

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	1381.6	478.9	.00	.03	.99	-.9	1.04	-.2
P.SD	217.3	14.5	.23	.00	.37	6.4	.40	6.0
S.SD	230.5	15.3	.24	.00	.39	6.7	.42	6.3
MAX.	1883.0	484.0	.25	.03	1.45	6.2	1.50	6.3
MIN.	1168.0	438.0	-.54	.03	.50	-9.7	.50	-8.9

```
 REAL RMSE    .04 TRUE SD    .22  SEPARATION  6.23  ITEM   RELIABILITY  .97
MODEL RMSE    .03 TRUE SD    .23  SEPARATION  6.73  ITEM   RELIABILITY  .98
 S.E. OF ITEM MEAN = .08

              DELETED:       4 ITEM
ITEM RAW SCORE-TO-MEASURE CORRELATION = -.98
Global statistics: please see Table 44.
UMEAN=.0000 USCALE=1.0000
```

Appendix xi

```
TABLE 13.1 RASCH GLORIA7.xlsx                    ZOU946WS.TXT  Jul 24 2016 13:47
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
```

PERSON: REAL SEP.: 2.61 REL.: .87 ... ITEM: REAL SEP.: 6.03 REL.: .97

ITEM STATISTICS: MEASURE 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
3	1168	484	.26	.03	.98	-.3	1.21	2.8	.73	.72	43.4	30.4	03INCR
10	1204	484	.22	.03	1.07	1.1	1.13	1.7	.67	.72	27.7	30.3	10CARA
11	1259	484	.15	.03	1.47	6.6	1.56	6.8	.60	.72	24.6	30.3	11WCTA
13	1177	438	.09	.04	.50	-9.5	.50	-8.3	.84	.72	40.4	29.7	13MVTL
9	1317	484	.08	.03	1.34	5.0	1.38	4.9	.61	.72	30.2	29.5	09DERC
8	1334	484	.06	.03	.38	-9.9	.41	-9.9	.86	.71	42.1	29.4	08SORA
1	1406	484	-.02	.03	.50	-9.9	.49	-9.1	.84	.71	40.5	29.5	01ROA_
4	1480	484	-.10	.03	1.51	7.2	1.66	7.9	.58	.70	17.6	29.4	04ROEC
2	1540	484	-.17	.03	.59	-7.8	.57	-7.2	.81	.70	39.5	30.0	02AROA
5	1883	484	-.58	.04	1.62	8.2	1.66	7.5	.55	.66	19.0	32.2	05SATA
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	

```
TABLE 13.3 RASCH GLORIA7.xlsx                    ZOU946WS.TXT  Jul 24 2016 13:47
INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
```

ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES: MEASURE ORDER

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	DATA %	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
3	6	0	93	19	-1.01	.50	.05	.6	.7	-.52	03INCR
	5	1	96	20	-.41	.34	.03	.6	.6	-.20	
	4	2	95	20	-.14	.34	.03	.5	.4	-.05	
	3	3	55	11	.18	.43	.06	.6	.6	.09	
	2	4	54	11	.42	.44	.06	.6	.6	.18	
	1	5	45	9	1.02	.50	.08	.4	.4	.38	
	0	6	46	10	1.02*	1.51	.22	4.5	5.5	.38	
10	6	0	77	16	-.57	.59	.07	1.3	1.3	-.25	10CARA
	5	1	99	20	-.49	.60	.06	1.1	1.2	-.25	
	4	2	84	17	-.42	.56	.06	1.2	1.4	-.19	
	3	3	67	14	-.18	.58	.07	1.7	1.7	-.06	
	2	4	75	15	.22	.54	.06	1.1	1.1	.12	
	1	5	56	12	.81	.64	.09	.9	.7	.34	
	0	6	26	5	2.18	.72	.14	.4	.4	.58	
11	0	0	97	20	-.59	.64	.07	1.4	1.6	-.30	11WCTA
	1	1	90	19	-.55	.58	.06	1.1	1.1	-.27	
	2	2	63	13	-.35	.57	.07	1.4	1.4	-.13	
	3	3	56	12	-.06	.50	.07	1.0	1.0	.00	
	4	4	66	14	.22	.67	.08	1.5	1.7	.11	
	5	5	61	13	.82	.99	.13	1.2	1.4	.36	
	6	6	51	11	.90	1.00	.14	1.7	2.2	.36	
13	0	0	75	17	-1.01	.51	.06	.7	.7	-.47	13MVTL
	1	1	66	15	-.69	.41	.05	.4	.5	-.29	
	2	2	69	16	-.35	.34	.04	.5	.4	-.14	
	3	3	69	16	-.12	.34	.04	.6	.5	-.03	
	4	4	65	15	.32	.36	.05	.4	.3	.17	
	5	5	58	13	.70	.50	.07	.5	.4	.32	
	6	6	36	8	1.87	.78	.13	.6	.5	.63	
	MISSING	***	46	10#	.06	.80	.12			.04	
9	6	0	72	15	-.85	.65	.08	1.2	1.1	-.37	09DERC
	5	1	79	16	-.43	.43	.05	1.1	1.0	-.19	
	4	2	82	17	-.28	.69	.08	1.9	2.2	-.12	
	3	3	66	14	.04	.52	.06	1.1	1.0	.04	
	2	4	79	16	.01*	.50	.06	1.4	1.3	.03	
	1	5	76	16	.71	.85	.10	1.5	1.4	.36	
	0	6	30	6	1.31	1.41	.26	2.6	2.5	.38	
8	0	0	85	18	-1.02	.46	.05	.6	.7	-.50	08SORA
	1	1	78	16	-.71	.36	.04	.4	.4	-.32	
	2	2	53	11	-.35	.28	.04	.3	.3	-.12	
	3	3	73	15	-.07	.28	.03	.4	.3	-.01	
	4	4	88	18	.18	.30	.03	.5	.4	.12	
	5	5	63	13	.70	.27	.03	.2	.2	.32	
	6	6	44	9	1.91	.69	.10	.4	.4	.68	

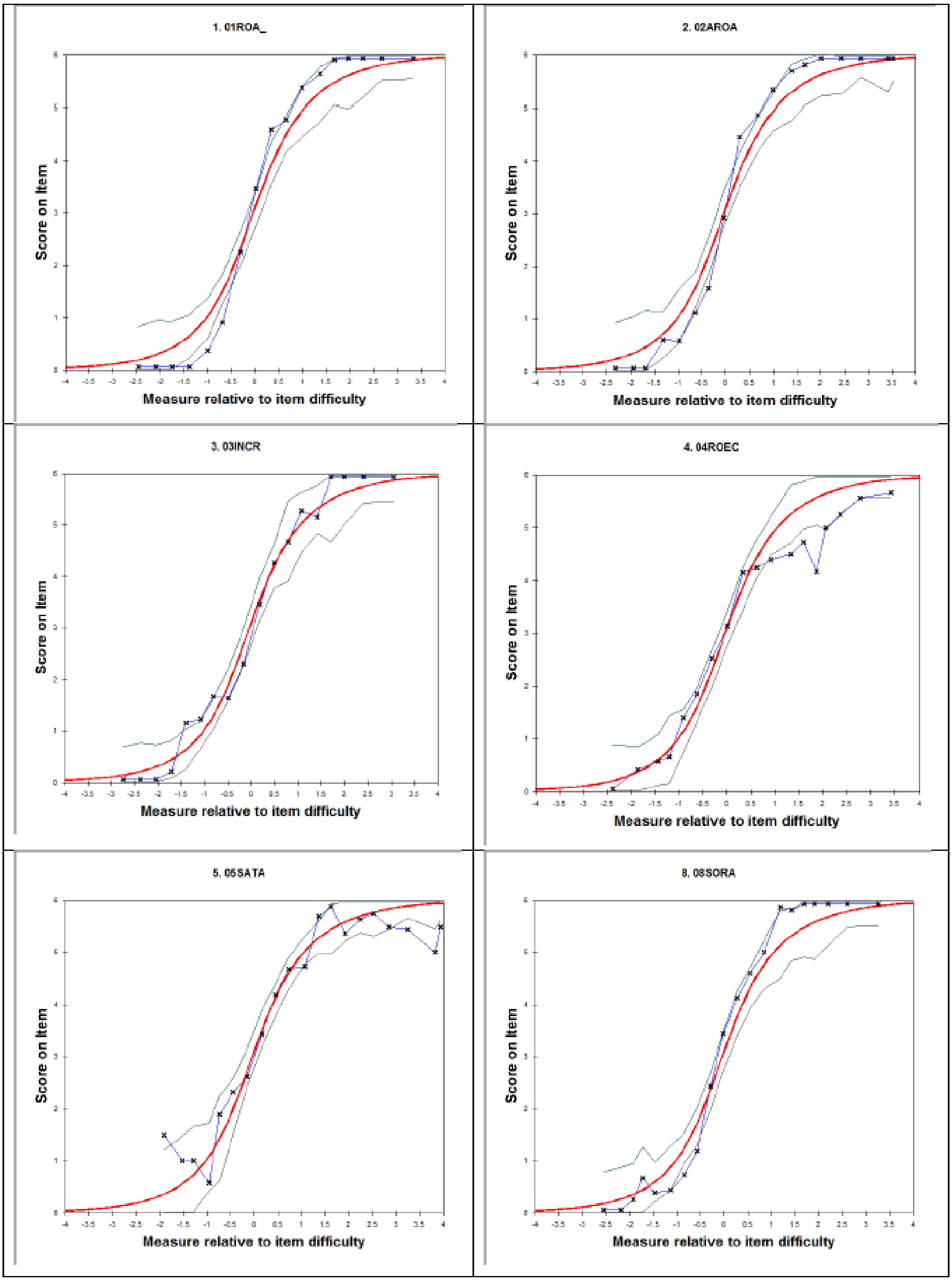
1	0	0	82	17	-1.10	.49	.05	.7	.7	-.52	01ROA_
	1	1	74	15	-.70	.21	.02	.3	.3	-.31	
	2	2	60	12	-.33	.23	.03	.3	.2	-.12	
	3	3	66	14	-.10	.20	.03	.2	.1	-.02	
	4	4	65	13	.26	.34	.04	.4	.3	.13	
	5	5	68	14	.52	.42	.05	.6	.5	.25	
	6	6	69	14	1.37	.91	.11	.8	.8	.64	
4	0	0	76	16	-.97	.56	.07	.9	.9	-.44	04ROEC
	1	1	66	14	-.55	.41	.05	1.0	.9	-.22	
	2	2	59	12	-.21	.54	.07	1.7	1.8	-.07	
	3	3	64	13	.08	.58	.07	1.5	1.6	.05	
	4	4	68	14	.31	.88	.11	2.0	2.5	.16	
	5	5	74	15	.34	.92	.11	1.8	2.2	.18	
	6	6	77	16	.63	.96	.11	1.4	1.8	.32	
2	0	0	62	13	-1.11	.53	.07	.7	.7	-.45	02AROA
	1	1	68	14	-.71	.35	.04	.6	.6	-.30	
	2	2	68	14	-.54	.34	.04	.4	.4	-.22	
	3	3	57	12	-.20	.24	.03	.3	.2	-.06	
	4	4	65	13	.08	.32	.04	.4	.3	.05	
	5	5	79	16	.47	.40	.04	.5	.5	.25	
	6	6	85	18	1.20	.91	.10	.8	.8	.63	
5	0	0	44	9	-.90	.39	.06	1.1	1.2	-.30	05SATA
	1	1	52	11	-.83	.67	.09	1.5	1.4	-.30	
	2	2	43	9	-.55	.56	.09	1.3	1.4	-.17	
	3	3	41	8	-.13	.51	.08	1.8	1.8	-.03	
	4	4	41	8	.01	.79	.12	2.0	2.8	.02	
	5	5	120	25	.12	.90	.08	1.5	2.0	.10	
	6	6	143	30	.52	.82	.07	1.2	1.3	.41	

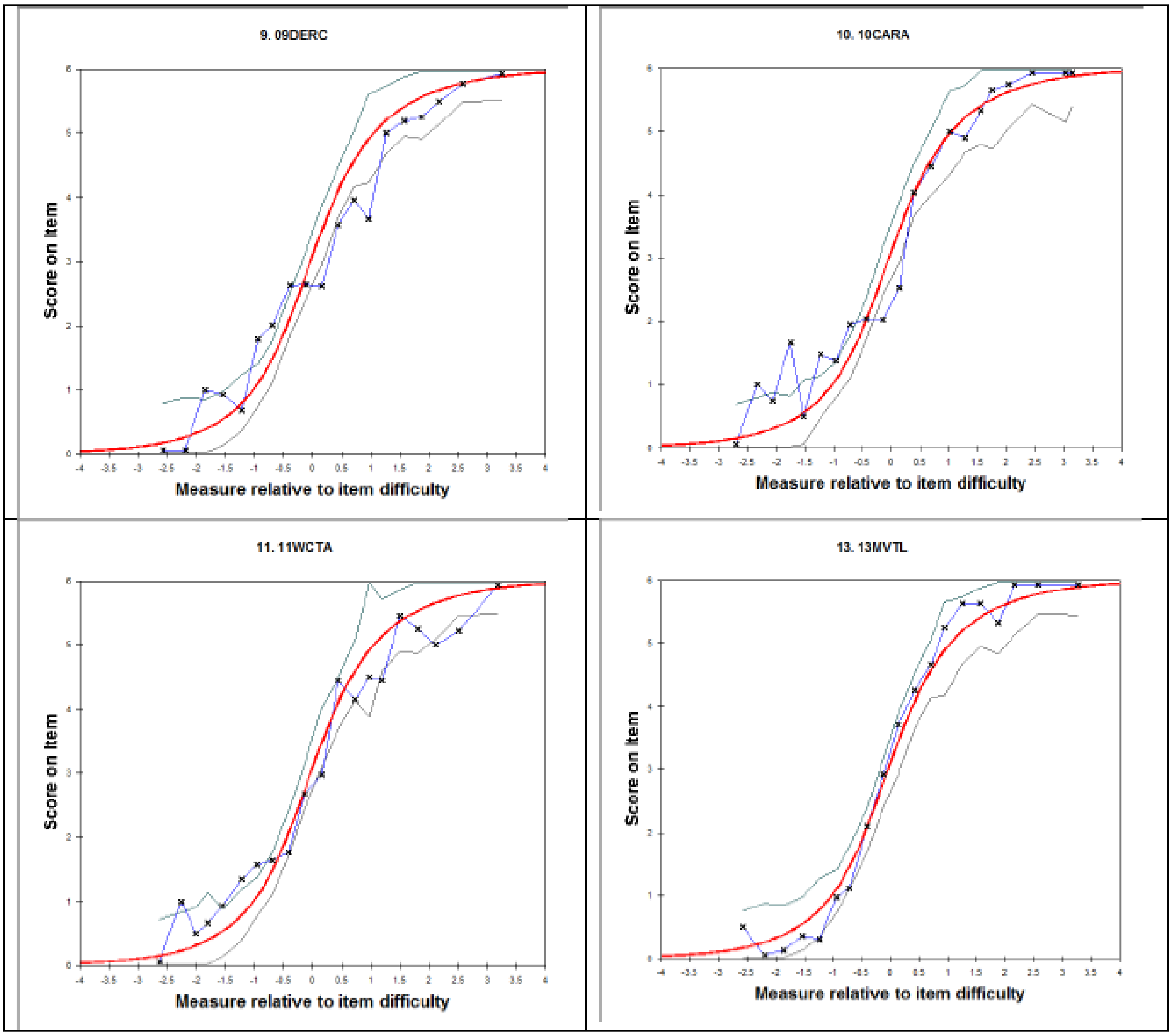
* Average ability does not ascend with category score
# Missing % includes all categories. Scored % only of scored categories

Appendix 6.A- Item characteristic curves- Sector A

In this Appendix, we present the item characteristic curves for Sector A for each variable used in the model. The graphics show how the items fit with the data at the extreme (OUTFIT) and in the middle (INFIT).The grey lines represents the interval confidence, while the blue line the actual observations. A good fit will be observed when the blue line will be in the middle of the two grey lines.

Appendix xii





Appendix 6.B – Andrich threshold- Sector A

This table shows the Andrich threshold for sector A. The Andrich threshold is a measure which shows if the items are ordered and therefore they form an ordinated scale. As we can see from the table the Andrich threshold has an ascending order, indicating that the measures are not disordered.

Appendix xiii

```
TABLE 3.2 RASCH GLORIA7.xlsx                          ZOU946WS.TXT  Jul 24 2016 13:47
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
```

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.

Appendix 6.C- Item map- Sector A

This Appendix shows the item map for sector A. This is a synthesis of the results obtained as we can observe on the left the measure obtained by each persons and on the right the corresponding item value for each measure. For instance, a value of 6 in Interest Coverage it is reached only by person with a measure of 2.7. In addition, this table also shows which are the items in which is more difficult to score a high value. For instance, a person need to score 2.7 to get a 6 in interest coverage, while a score of 1.9 is needed to score the same value in Sales to Total assets.

Appendix xiv

```
TABLE 12.8 RASCH GLORIA7.xlsx                     ZOU946WS.TXT  Jul 24 2016 13:47
INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
-----------------------------------------------------------------------------------

MEASURE     PERSON - MAP - ITEM - Measures for category scores (maximum probability of observing a category)
                  <more>|<rare>
  4                     +
                        |
                        |
                        |
                      . |
                      . |
  3                     +
                        |
                    .## |                                                             03I .6
                        |                                                             10C .6
                        |                                                             11W .6
                        |                                                             08S .6
                        |                                                             09D .6
                        |                                                             13M .6
                        |                                                             01R .6
                      # |                                                             02A .6
                        |                                                             04R .6
                        |
  2                   . +
                      . |                                                             05S .6
                     .# T
                     .# |
                        |
                     .# |
                     .# |                                                   03I .5
                        |                                                   10C .5
                        |                                                   11W .5
                      . |                                                   08S .5
                        |                                                   09D .5
                        |                                                   13M .5
  1                  .# +                                                   01R .5
                        |                                                   04R .5
                   #### S|                                                  02A .5
                     .# |
                 .##### |                                         03I .4
                        |                                         10C .4
                 .##### |T                                        08S .4    05S .5
                        |                                         09D .4
                        |                                         11W .4
                        |                                         13M .4
                  .#### |                                         01R .4
                 .##### |S                              03I .3    02A .4
                        |                                         04R .4
                 .##### |                               10C .3
                        |                               11W .3
  0          .######### M+M                             01R .3
                        |                               08S .3
                        |                               09D .3
                        |                               13M .3
                ####### |                      03I .2   04R .3
            .########## |S                     10C .2   02A .3    05S .4
                        |                      11W .2
                ####### |                      08S .2
                        |
                        |                        09D .2
                        |                        13M .2
               ######## |T                       01R .2
                        |                        04R .2
                .###### |                        02A .2   05S .3
               ######## |             03I .1
                        |             10C .1
                 ###### |             11W .1
                        |             13M .1
 -1                  ## S+            01R .1     05S .2
                        |             08S .1
                        |             09D .1
                   .### |             04R .1
                      # |             02A .1
                     .# |
                    .## |
                      . |             05S .1
                        |
                      # T|
 -2                     +   03I .0
                        |   10C .0
                      . |   08S .0
                        |   09D .0
                        |   11W .0
                        |   13M .0
                        |   01R .0
                        |   02A .0
                        |   04R .0
                      . |
                        |
                        |   05S .0
 -3                     +
                  <less>|<freq>
EACH "#" IS 4: EACH "." IS 1 TO 3
```

Appendix 7- Final model- Sector B

This Appendix showed the results from the final model selected for Sector B discussed in 4.4.2. In the first table is presented an analysis of the reliability of the model for the items and persons, while in the second table they are represented the outcomes for the item difficulties.

Appendix xv

SUMMARY OF 440 MEASURED (EXTREME AND NON-EXTREME) PERSON

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	23.0	9.0	-.43	.34				
P.SD	12.3	.1	1.27	.12				
S.SD	12.3	.1	1.28	.12				
MAX.	54.0	9.0	5.68	1.84				
MIN.	1.0	8.0	-3.77	.28				

REAL RMSE .41 TRUE SD 1.21 SEPARATION 2.98 PERSON RELIABILITY .90
MODEL RMSE .36 TRUE SD 1.22 SEPARATION 3.43 PERSON RELIABILITY .92
S.E. OF PERSON MEAN = .06

PERSON RAW SCORE-TO-MEASURE CORRELATION = .97
CRONBACH ALPHA (KR-20) PERSON RAW SCORE "TEST" RELIABILITY = .92 SEM = 3.40

SUMMARY OF 9 MEASURED (NON-EXTREME) ITEM

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	1124.2	439.3	.00	.04	.99	-.6	1.04	.0
P.SD	121.3	1.9	.24	.00	.32	4.9	.35	5.0
S.SD	128.6	2.0	.25	.00	.34	5.2	.38	5.3
MAX.	1409.0	440.0	.23	.05	1.54	7.1	1.63	7.7
MIN.	1009.0	434.0	-.56	.04	.56	-8.0	.57	-7.3

REAL RMSE .05 TRUE SD .23 SEPARATION 4.90 ITEM RELIABILITY .96
MODEL RMSE .04 TRUE SD .23 SEPARATION 5.21 ITEM RELIABILITY .96
S.E. OF ITEM MEAN = .08

DELETED: 4 ITEM
ITEM RAW SCORE-TO-MEASURE CORRELATION = -1.00
Global statistics: please see Table 44.
UMEAN=.0000 USCALE=1.0000

Appendix xvi

TABLE 13.1 RASCH GLORIA7.xlsx   ZOU992WS.TXT Jul 28 2016 16:31
INPUT: 1320 PERSON 13 ITEM REPORTED: 440 PERSON 9 ITEM 7 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 2.98 REL.: .90 ... ITEM: REAL SEP.: 4.90 REL.: .96

ITEM STATISTICS: MEASURE 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
9	1009	440	.23	.05	1.12	1.7	1.07	1.0	.75	.77	36.9	35.4	09DERC
13	1021	434	.18	.05	.58	-7.5	.57	-7.3	.87	.77	47.6	35.6	13MVTL
10	1052	440	.15	.04	.96	-.5	.94	-.9	.80	.77	40.3	35.6	10CARA
8	1068	440	.11	.04	.56	-8.0	.63	-6.2	.86	.77	48.3	35.7	08SORA
11	1070	440	.11	.04	1.54	7.1	1.63	7.7	.66	.77	33.5	35.7	11WCTA
3	1097	440	.06	.04	1.07	1.1	1.47	6.0	.70	.77	34.9	35.6	03INCR
1	1146	440	-.04	.04	.73	-4.5	.74	-4.2	.82	.77	46.0	35.9	01ROA_
2	1246	440	-.24	.04	.97	-.4	.98	-.3	.79	.76	34.6	35.8	02AROA
5	1409	440	-.56	.04	1.40	5.4	1.35	4.6	.67	.74	33.5	36.5	05SATA
MEAN	1124.2	439.3	.00	.04	.99	-.6	1.04	.0			39.5	35.8	
P.SD	121.3	1.9	.24	.00	.32	4.9	.35	5.0			5.9	.3	

TABLE 13.3 RASCH GLORIA7.xlsx   ZOU992WS.TXT Jul 28 2016 16:31
INPUT: 1320 PERSON 13 ITEM REPORTED: 440 PERSON 9 ITEM 7 CATS WINSTEPS 3.92.0

ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES: MEASURE ORDER

ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
9	6	0	87	20	-1.65	.71	.08	1.0	1.0	-.48	09DERC
	5	1	75	17	-.99	.74	.09	1.4	1.4	-.20	
	4	2	77	18	-.68	.77	.09	1.2	1.2	-.09	
	3	3	87	20	-.19	.69	.07	1.0	.9	.09	
	2	4	65	15	.27	.71	.09	1.1	1.0	.23	
	1	5	35	8	1.19	1.11	.19	1.0	1.0	.37	
	0	6	14	3	2.71	1.68	.47	1.7	1.4	.45	
13		***	6	1#	-.15	1.04	.47			.03	13MVTL
	0	0	78	18	-1.83	.63	.07	.7	.7	-.51	
	1	1	85	20	-1.21	.49	.05	.6	.6	-.30	
	2	2	79	18	-.69	.47	.05	.5	.4	-.09	
	3	3	68	16	-.13	.53	.06	.5	.5	.10	
	4	4	66	15	.29	.50	.06	.6	.6	.24	
	5	5	38	9	1.06	.56	.09	.6	.6	.36	
	6	6	20	5	2.97	1.13	.26	.6	.6	.59	
10	6	0	91	21	-1.71	.67	.07	.9	.9	-.51	10CARA
	5	1	66	15	-1.11	.52	.06	.7	.7	-.22	
	4	2	80	18	-.72	.65	.07	.9	.9	-.11	
	3	3	76	17	-.08	.62	.07	.7	.7	.13	
	2	4	56	13	.06	.73	.10	1.3	1.3	.15	
	1	5	52	12	.91	.84	.12	1.0	.9	.38	
	0	6	19	4	2.68	1.44	.34	1.0	.9	.52	
8	0	0	58	13	-1.94	.63	.08	.6	.6	-.46	08SORA
	1	1	92	21	-1.20	.43	.05	.5	.5	-.31	
	2	2	97	22	-.71	.51	.05	.6	.5	-.12	
	3	3	70	16	-.39	.71	.09	1.1	1.5	.02	
	4	4	62	14	.42	.46	.06	.4	.3	.27	
	5	5	42	10	1.11	.62	.10	.5	.5	.39	
	6	6	19	4	2.95	1.17	.28	.6	.6	.56	
11	0	0	84	19	-1.58	.77	.09	1.2	1.2	-.44	11WCTA
	1	1	64	15	-1.11	.67	.08	1.1	1.2	-.22	
	2	2	74	17	-.55	.73	.09	1.2	1.2	-.04	
	3	3	95	22	-.28	.77	.08	1.2	1.3	.06	
	4	4	60	14	.21	.86	.11	1.4	1.4	.20	
	5	5	45	10	.86	1.17	.18	1.5	1.6	.34	
	6	6	18	4	1.62	2.50	.61	5.8	6.1	.33	
3	6	0	65	15	-1.73	.52	.07	.8	.9	-.42	03INCR
	5	1	73	17	-1.24	.53	.06	.6	.7	-.28	
	4	2	75	17	-.64	.68	.08	.9	1.3	-.07	
	3	3	94	21	-.36	.85	.09	1.3	2.0	.03	
	2	4	78	18	.25	1.16	.13	1.7	2.6	.25	
	1	5	50	11	1.44	1.06	.15	.6	.7	.53	
	0	6	5	1	.43*	2.65	1.33	4.8	7.9	.07	
1	0	0	57	13	-1.92	.75	.10	.9	.9	-.45	01ROA_

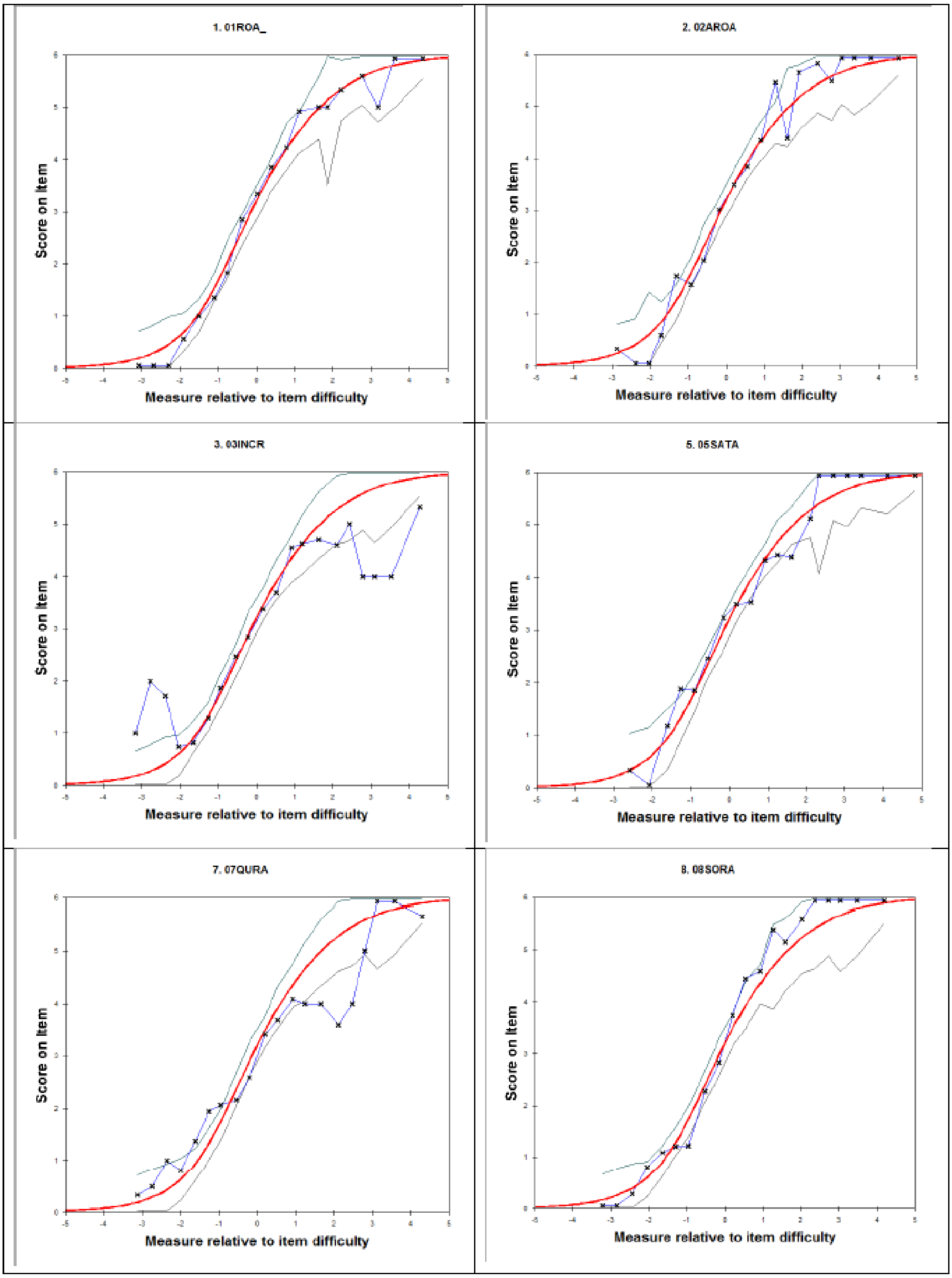
	1	1	79	18	-1.25	.55	.06	.9	.8	-.30	
	2	2	85	19	-.91	.58	.06	.7	.7	-.18	
	3	3	79	18	-.30	.46	.05	.4	.4	.05	
	4	4	66	15	.21	.62	.08	.7	.7	.21	
	5	5	48	11	1.03	.90	.13	.7	.7	.40	
	6	6	26	6	2.10	1.41	.28	1.0	1.1	.50	
2	0	0	54	12	-1.90	.76	.10	1.0	1.0	-.43	02AROA
	1	1	60	14	-1.15	.55	.07	1.2	1.2	-.22	
	2	2	79	18	-.97	.70	.08	1.1	1.1	-.20	
	3	3	88	20	-.59	.65	.07	1.0	.9	-.06	
	4	4	69	16	-.09	.54	.07	.8	.8	.12	
	5	5	52	12	.74	.73	.10	.7	.7	.34	
	6	6	38	9	2.00	1.31	.21	.9	1.0	.59	
5	0	0	46	10	-1.75	.80	.12	1.4	1.4	-.35	05SATA
	1	1	32	7	-1.21	.87	.16	2.2	2.3	-.17	
	2	2	57	13	-1.31*	.59	.08	.7	.7	-.27	
	3	3	94	21	-.62	.81	.08	1.4	1.4	-.07	
	4	4	115	26	-.12	.82	.08	1.1	1.1	.14	
	5	5	55	13	.06	.84	.11	1.6	1.5	.15	
	6	6	41	9	1.76	1.54	.24	1.1	1.1	.55	

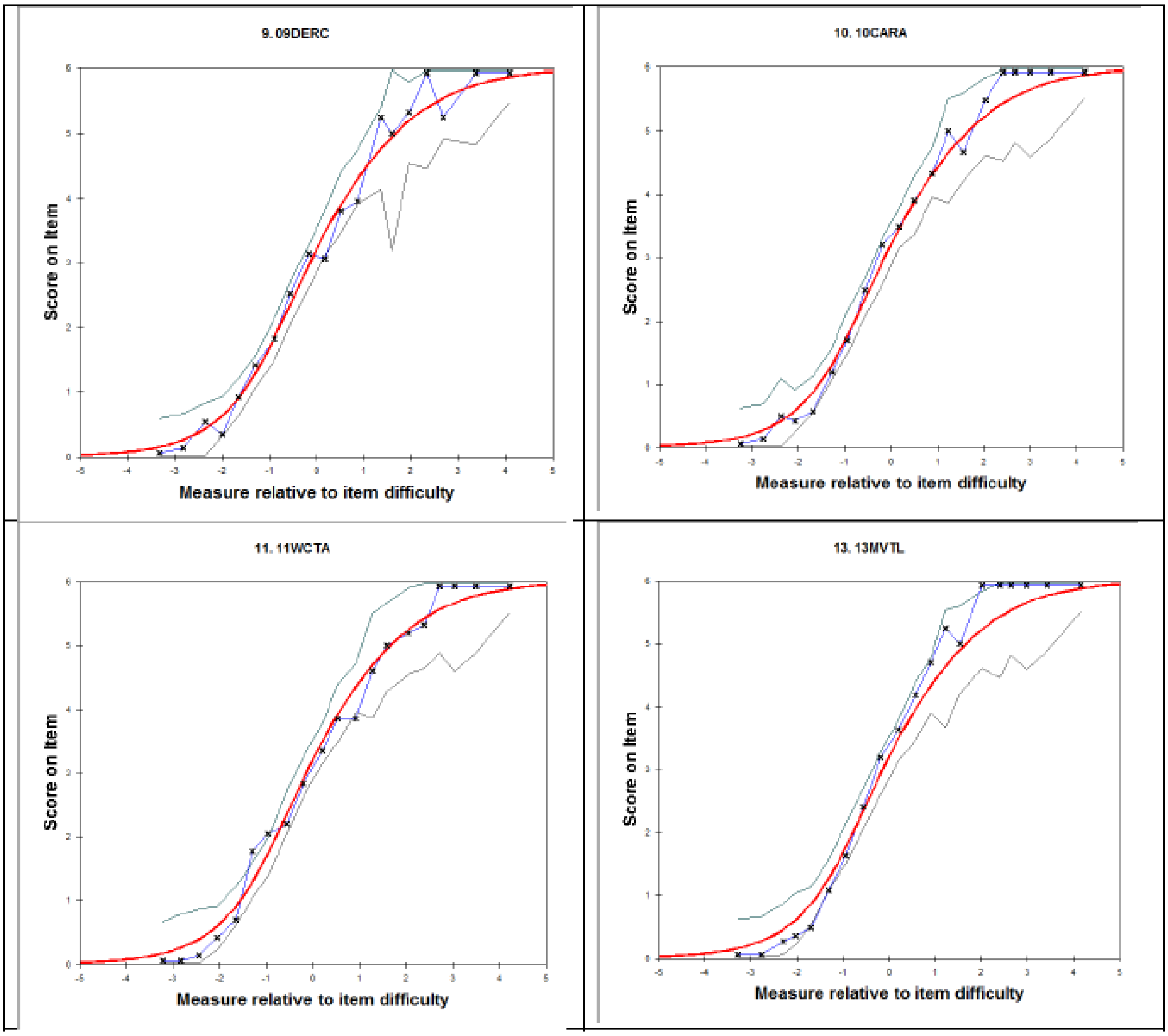
* Average ability does not ascend with category score
# Missing % includes all categories. Scored % only of scored categories

Appendix 7.A- Item characteristic curves- Sector B

In this Appendix, we present the item characteristic curves for Sector b for each variable used in the model. The graphics show how the items fit with the data at the extreme (OUTFIT) and in the middle (INFIT). The grey lines represents the interval confidence, while the blue line the actual observations. A good fit will be observed when the blue line will be in the middle of the two grey lines.

Appendix xvii





Appendix 7.B- Andrich Threshold- Sector B

This table shows the Andrich threshold for sector B. The Andrich threshold is a measure which shows if the items are ordered and therefore they form an ordinated scale. As we can see from the table the Andrich threshold has an ascending order, indicating that the measures are not disordered.

Appendix xviii

TABLE 3.2 RASCH GLORIA7.xlsx ZOU470WS.TXT Jul 24 2016 13:51
INPUT: 1320 PERSON 13 ITEM REPORTED: 440 PERSON 10 ITEM 7 CATS WINSTEPS 3.92.0

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	666	15	-1.60	-1.55	.97	.99	NONE	(-2.88)	0
1	1	723	16	-1.09	-1.13	.97	.96	-1.42	-1.56	1
2	2	793	18	-.71	-.73	.93	.96	-1.02	-.79	2
3	3	820	19	-.30	-.29	.97	1.08	-.55	-.15	3
4	4	712	16	.20	.17	.98	1.10	.08	.60	4
5	5	461	10	.77	.77	.94	.94	.89	1.66	5
6	6	219	5	1.88	1.96	1.51	1.40	2.03	(3.32)	6
MISSING		6	0	-.23						

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

Appendix 7.C- Item map- Sector B

This Appendix shows the item map for sector B. This is a synthesis of the results obtained as we can observe on the left the measure obtained by each persons and on the right the corresponding item value for each measure. For instance, a value of 6 in Solvency ratio is reached only by person with a measure of 3.9. In addition, this table also shows which are the items in which is more difficult to score a high value. For instance, a person need to score 3.8 to get a 6 in Debt to equity ratio, while a score of 2.9 is needed to score the same value in Sales to Total asset.

Appendix xix

```
TABLE 12.8 RASCH GLORIA7.xlsx                    ZOU470WS.TXT  Jul 24 2016 13:51
INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
-------------------------------------------------------------------------------------

MEASURE     PERSON - MAP - ITEM - Measures for category scores (maximum probability of observing a category)
             <more>|<rare>
   5               +
                   |
                   |
                   |
                .  |
                   |
   4               +
                   |
                .  |                                                    08S .6
                   |                                                    09D .6
                   |                                                    10C .6
                   |                                                    11W .6
                   |                                                    13M .6
                   |                                                    01R .6
                   |                                                    03I .6
                   |                                                    07Q .6
                .  |                                                    02A .6
   3               +
                .  |                                                    05S .6
                   |
                .  |
                .  |
               .#  |
   2               +
                . T|                                            08S .5
                   |                                            09D .5
                   |                                            10C .5
                   |                                            11W .5
                   |                                            13M .5
               .#  |                                            01R .5
                   |                                            03I .5
                   |                                            07Q .5
                .  |                                            02A .5
                #  |
               .#  |                                            05S .5
   1         .###  +
              .##  |                                    09D .4
                   |                                    13M .4
                   |
              ### S|                                  03I .4
                   |                                  07Q .4
                   |                                  08S .4
                   |                                  10C .4
                   |                                  11W .4
            .####  |T                                 01R .4
          .######  |                                  02A .4
            .####  |S
    0     #######  +M                         08S .3  05S .4
                   |                          09D .3
                   |                          10C .3
                   |                          11W .3
                   |                          13M .3
             .###  |S                         01R .3
                   |                          03I .3
                   |                          07Q .3
     .########### M|                          02A .3
            .####  |T                 09D .2
           .#####  |                  03I .2  05S .3
                   |                  08S .2
                   |                  10C .2
                   |                  11W .2
                   |                  13M .2
            .####  |                  01R .2
                   |                  07Q .2
  -1 ############  +                  02A .2
        #########  |
            #####  |          09D .1  05S .2
                   |          13M .1
           .##### S|          03I .1
                   |          07Q .1
                   |          08S .1
                   |          10C .1
                   |          11W .1
              ###  |          01R .1
               .#  |          02A .1
  -2         ####  +          05S .1
                #  |
                   |
                .  |
                # T|  09D .0
                   |  10C .0
                   |  13M .0
                   |  01R .0
                   |  03I .0
                   |  07Q .0
                   |  08S .0
                   |  11W .0
  -3               +
                .  |  02A .0
                   |  05S .0
                   |
                   |
                   |
  -4               +
             <less>|<freq>
 EACH "#" IS 4: EACH "." IS 1 TO 3
```

Appendix 8- Final model- Sector C

This Appendix showed the results from the final model selected for Sector C discussed in 4.4.3. In the first table is presented an analysis of the reliability of the model for the items and persons, while in the second table they are represented the outcomes for the item difficulties.

Appendix xx

TABLE 3.1 RASCH GLORIA4.xlsx ZOU471WS.TXT Jul 29 2016 21:48
INPUT: 1320 PERSON 13 ITEM REPORTED: 396 PERSON 8 ITEM 4 CATS WINSTEPS 3.92.0

SUMMARY OF 346 MEASURED (NON-EXTREME) PERSON

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	15.8	7.9	.80	.53	.97	.0	.96	.0
P.SD	5.5	.3	1.12	.19	.48	1.1	.48	1.1
S.SD	5.5	.3	1.12	.19	.48	1.1	.48	1.1
MAX.	23.0	8.0	2.82	1.01	2.54	3.0	2.55	3.0
MIN.	2.0	7.0	-2.05	.37	.14	-3.8	.13	-3.8

REAL RMSE .59 TRUE SD .95 SEPARATION 1.62 PERSON RELIABILITY .72
MODEL RMSE .56 TRUE SD .97 SEPARATION 1.74 PERSON RELIABILITY .75
S.E. OF PERSON MEAN = .06

MAXIMUM EXTREME SCORE: 50 PERSON 12.6%
DELETED: 924 PERSON

SUMMARY OF 396 MEASURED (EXTREME AND NON-EXTREME) PERSON

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	16.7	7.9	1.21	.69				
P.SD	5.7	.3	1.49	.47				
S.SD	5.7	.3	1.49	.47				
MAX.	24.0	8.0	4.04	1.84				
MIN.	2.0	7.0	-2.05	.37				

REAL RMSE .85 TRUE SD 1.22 SEPARATION 1.43 PERSON RELIABILITY .67
MODEL RMSE .84 TRUE SD 1.24 SEPARATION 1.48 PERSON RELIABILITY .69
S.E. OF PERSON MEAN = .08

PERSON RAW SCORE-TO-MEASURE CORRELATION = .92
CRONBACH ALPHA (KR-20) PERSON RAW SCORE "TEST" RELIABILITY = .85 SEM = 2.23

SUMMARY OF 8 MEASURED (NON-EXTREME) ITEM

	TOTAL SCORE	COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD
MEAN	828.3	389.9	.00	.07	1.00	-.3	.95	-.7
P.SD	75.0	16.2	.34	.00	.26	3.5	.26	3.0
S.SD	80.2	17.3	.36	.00	.28	3.7	.28	3.2
MAX.	964.0	396.0	.64	.08	1.37	4.4	1.28	3.1
MIN.	706.0	347.0	-.64	.07	.60	-5.9	.53	-5.6

REAL RMSE .07 TRUE SD .33 SEPARATION 4.38 ITEM RELIABILITY .95
MODEL RMSE .07 TRUE SD .33 SEPARATION 4.63 ITEM RELIABILITY .96
S.E. OF ITEM MEAN = .13

DELETED: 5 ITEM
ITEM RAW SCORE-TO-MEASURE CORRELATION = -.87
Global statistics: please see Table 44.
UMEAN=.0000 USCALE=1.0000

Appendix xxi

TABLE 13.1 RASCH GLORIA4.xlsx ZOU137WS.TXT Jul 24 2016 13:53
INPUT: 1320 PERSON 13 ITEM REPORTED: 396 PERSON 8 ITEM 4 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 1.43 REL.: .67 ... ITEM: REAL SEP.: 4.38 REL.: .95

ITEM STATISTICS: MEASURE 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
1	706	396	.64	.07	1.31	3.9	1.28	3.1	.66	.73	40.5	45.7	01ROA_
8	799	396	.22	.07	.73	-4.0	.66	-4.4	.76	.69	60.1	48.2	08SORA
9	836	396	.04	.07	.89	-1.5	.80	-2.2	.70	.67	56.1	50.0	09DERC
11	836	396	.04	.07	1.11	1.4	1.18	1.8	.62	.67	43.6	50.0	11WCTA
13	744	347	-.06	.07	.60	-5.9	.53	-5.6	.76	.65	62.7	50.9	13MVTL
10	870	396	-.12	.07	1.12	1.6	1.04	.4	.62	.65	50.6	51.2	10CARA
3	871	396	-.13	.07	1.37	4.4	1.26	2.5	.57	.65	40.2	51.2	03INCR
7	964	396	-.64	.08	.83	-2.1	.89	-.9	.60	.58	58.1	60.0	07QURA
MEAN	828.3	389.9	.00	.07	1.00	-.3	.95	-.7			51.5	50.9	
P.SD	75.0	16.2	.34	.00	.26	3.5	.26	3.0			8.5	3.9	

TABLE 13.3 RASCH GLORIA4.xlsx ZOU137WS.TXT Jul 24 2016 13:53
INPUT: 1320 PERSON 13 ITEM REPORTED: 396 PERSON 8 ITEM 4 CATS WINSTEPS 3.92.0

ITEM CATEGORY/OPTION/DISTRACTOR FREQUENCIES: MEASURE ORDER

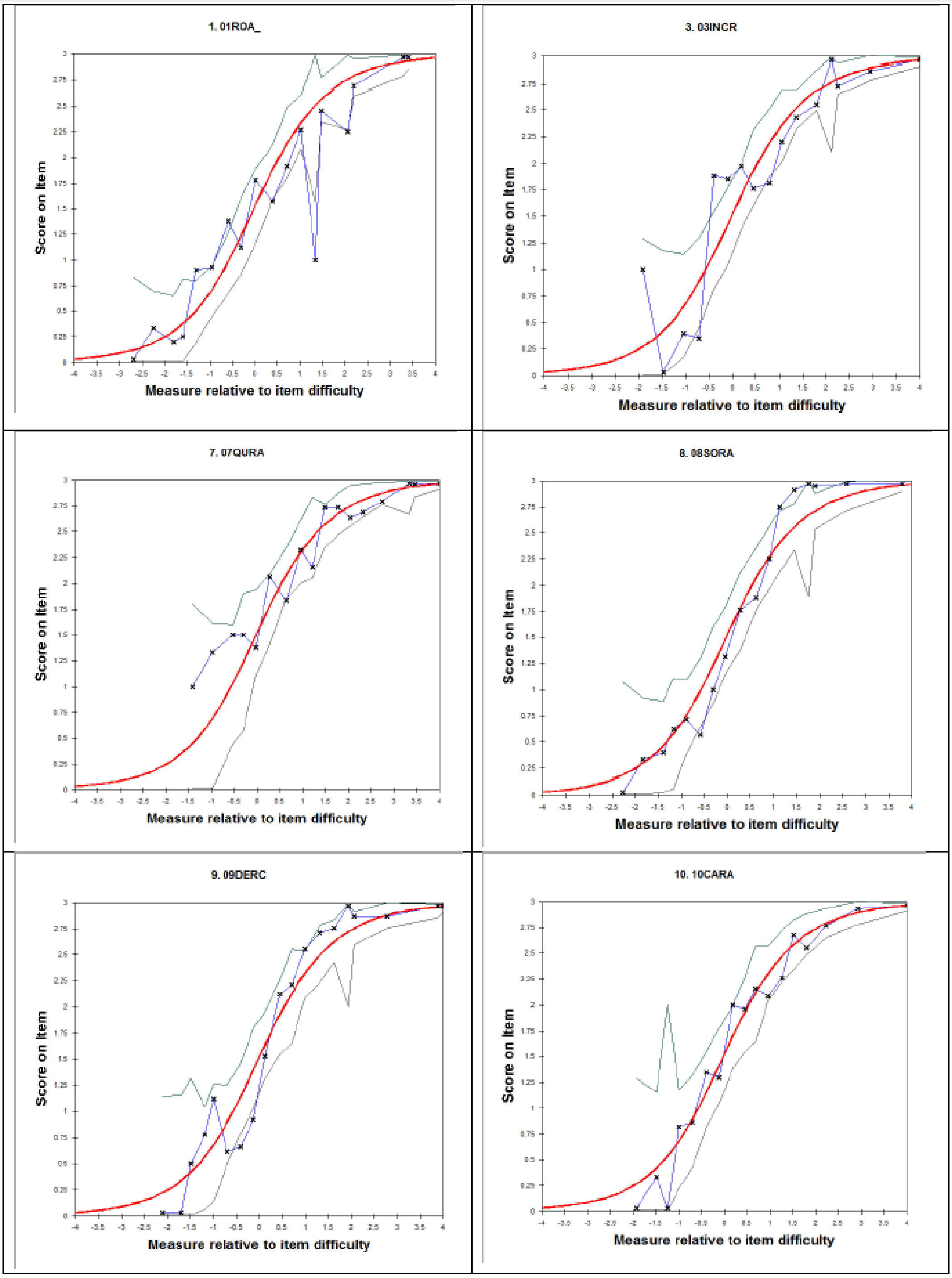
ENTRY NUMBER	DATA CODE	SCORE VALUE	DATA COUNT	%	ABILITY MEAN	P.SD	S.E. MEAN	INFT MNSQ	OUTF MNSQ	PTMA CORR.	ITEM
1	0	0	79	20	-.13	.83	.09	1.3	1.3	-.45	01ROA_
	1	1	72	18	.39	.91	.11	1.3	1.3	-.26	
	2	2	101	26	1.07	.98	.10	1.3	1.2	-.05	
	3	3	144	36	2.44	1.35	.11	1.3	1.3	.62	
8	0	0	57	14	-.37	.63	.08	1.0	.9	-.43	08SORA
	1	1	70	18	-.15	.62	.07	.5	.4	-.42	
	2	2	78	20	.67	.65	.07	.6	.5	-.18	
	3	3	191	48	2.39	1.12	.08	.6	.6	.77	
9	3	0	56	14	-.35	.50	.07	1.0	.9	-.42	09DERC
	2	1	50	13	-.43*	.59	.08	.4	.3	-.42	
	1	2	84	21	.83	.82	.09	.8	.9	-.13	
	0	3	206	52	2.18	1.24	.09	.8	.8	.68	
11	0	0	31	8	-.58	.67	.12	.9	.8	-.35	11WCTA
	1	1	81	20	.08	.75	.08	1.1	1.0	-.38	
	2	2	97	24	1.08	1.00	.10	1.4	1.6	-.05	
	3	3	187	47	2.06	1.44	.11	1.3	1.3	.54	
13	0	0	41	12	-.66	.48	.08	.7	.6	-.45	13MVTL
	1	1	47	14	-.27	.46	.07	.4	.3	-.39	
	2	2	80	23	.56	.63	.07	.5	.4	-.22	
	3	3	179	52	2.19	1.12	.08	.6	.6	.75	
	MISSING	***	49	12#	1.65	1.71	.25			.11	
10	3	0	42	11	-.40	.68	.11	1.2	1.1	-.37	10CARA
	2	1	42	11	-.16	.77	.12	1.0	.8	-.31	
	1	2	108	27	.73	.87	.08	1.0	1.0	-.19	
	0	3	204	52	2.07	1.39	.10	1.1	1.1	.60	
3	3	0	48	12	-.53	.64	.09	1.0	1.0	-.43	03INCR
	2	1	38	10	.21	.73	.12	1.5	1.2	-.22	
	1	2	97	24	.93	.89	.09	1.1	1.2	-.10	
	0	3	213	54	1.90	1.49	.10	1.5	1.5	.50	
7	0	0	2	1	-.64	.34	.34	.9	.8	-.09	07QURA
	1	1	59	15	-.34	.61	.08	.9	.6	-.43	
	2	2	100	25	.48	.98	.10	1.3	1.2	-.28	
	3	3	235	59	1.92	1.37	.09	.9	.9	.58	

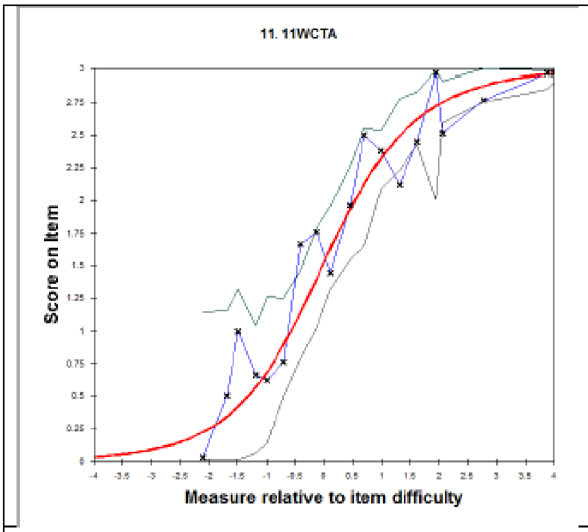
* Average ability does not ascend with category score
\# Missing % includes all categories. Scored % only of scored categories

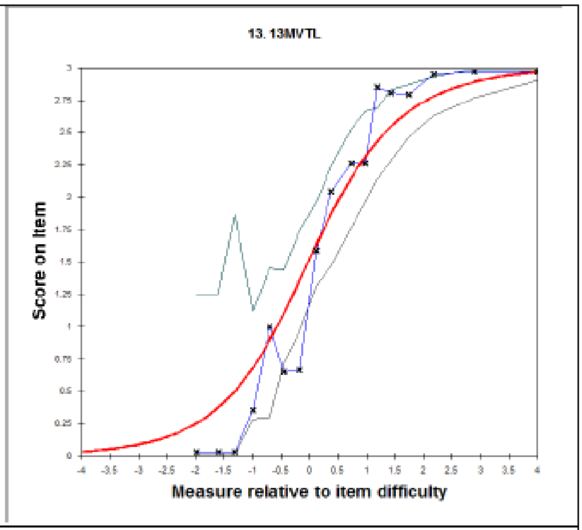
Appendix 8.A- Item characteristic curves- Sector C

In this Appendix, we present the item characteristic curves for Sector C for each variable used in the model. The graphics show how the items fit with the data at the extreme (OUTFIT) and in the middle (INFIT). The grey lines represents the interval confidence, while the blue line the actual observations. A good fit will be observed when the blue line will be in the middle of the two grey lines.

Appendix xxii







Appendix 8.B- Andrich threshold- Sector C

This table shows the Andrich threshold for sector C. The Andrich threshold is a measure which shows if the items are ordered and therefore they form an ordinated scale. As we can see from the table the Andrich threshold has an ascending order, indicating that the measures are not disordered.

Appendix xxiii

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	356	11	-.54	-.56	1.02	.95	NONE	(-1.99)	0
1	1	459	15	-.10	-.01	.89	.75	-.55	-.57	1
2	2	745	24	.81	.72	.96	1.04	-.15	.53	2
3	3	1559	50	1.56	1.58	1.07	1.04	.70	(2.05)	3
MISSING		49	2	1.71						

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

Appendix 8.C- Item map- Sector C

This Appendix shows the item map for sector C. This is a synthesis of the results obtained as we can observe on the left the measure obtained by each persons and on the right the corresponding item value for each measure. For instance, a value of 3 in Return on Asset is reached only by person with a measure of 2.8. In addition, this table also shows which are the items in which is more difficult to score a high value. For instance, a person need to score 2.8 to get a 3 in ROA, while a score of 1.3 is needed to score the same value in the Quick ratio. Finally, in this table we can observe that there are not indicator able to value the persons with measure of 3.

Appendix xxiv

```
TABLE 12.8 RASCH GLORIA4.xlsx                    ZOU137WS.TXT   Jul 24 2016 13:53
INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  8 ITEM  4 CATS WINSTEPS 3.92.0

MEASURE     PERSON - MAP - ITEM - Measures for category scores (maximum probability of observing a category)
              <more>|<rare>
   3 .############ T+
                    |
           .######  |
                 #  |                                   01ROA_ .3
                    |
                    |
                    |
                    |                                   08SORA .3
                    |
        .#########  |                                   09DERC .3
                    |                                   11WCTA .3
   2             .  +                                   13MVTL .3
                   S|                                   03INCR .3
                    |                                   10CARA .3
                    |
          .#######  |
                 #  |
                    |
            .#####  |                                   07QURA .3
                    |
                 .  |                        01ROA_ .2
           .######  |
   1             .  +
             .####  |
                 . M|                        08SORA .2
               ###  |T
              .###  |                        09DERC .2
                    |                        11WCTA .2
                    |                        13MVTL .2
               ###  |                        03INCR .2
                    |                        10CARA .2
               ###  |S
                 .  |
            .#####  |             01ROA_ .1
   0           ###  +M
                 .  |                        07QURA .2
               .##  |
              #### S|S
              .###  |             08SORA .1
                    |             09DERC .1
                    |             11WCTA .1
               ###  |             13MVTL .1
                    |T            03INCR .1
                    |             10CARA .1
               .##  |
                .#  |
  -1             .  +
                ##  |
                 .  |             07QURA .1
                    |
                 . T|  01ROA_ .0
                 .  |
                    |
                 .  |
                    |  08SORA .0
                    |  09DERC .0
                    |  11WCTA .0
  -2                +
                 .  |  03INCR .0
                    |  10CARA .0
                    |  13MVTL .0
                    |
                    |
                    |
                    |
                    |  07QURA .0
                    |
                    |
                    |
  -3                +
              <less>|<freq>
EACH "#" IS 4: EACH "." IS 1 TO 3
```

Appendix 9- Relationship between the Rasch ratings and Bloomberg default risk

This Appendix will present the outcome for each Sector regarding the relationship between the Bloomberg default risk and the Rasch ratings.

Appendix 9.A- Sector A results

Here are showed the outcome of the model for Sector A after plugging the Bloomberg default risk (14RATI) in the model. In particular from the first (Appendix xxv) we can observe the reliability and difficulties of the model and the Andrich threshold, which is ordered. On the other hand, in the second table (Appendix xxvi) we can observe the final outcome of relationship between the Rasch ratings and the Bloomberg default risk. For instance, we can observe that to a Rasch rating of -0.68 (MEAN MEASURE column) correspond a Bloomberg rating of HY1 considering 24 observations (PERSON COUNT Column).

Appendix xxv

```
TABLE 13.1 RASCH GLORIA7 con rating.xlsx        ZOU130WS.TXT  Jul 26 2016 11:21
 INPUT: 1320 PERSON  14 ITEM  REPORTED: 484 PERSON  11 ITEM  20 CATS WINSTEPS 3.92.0

 PERSON: REAL SEP.: 2.14  REL.: .82 ... ITEM: REAL SEP.: 3.96  REL.: .94

        ITEM STATISTICS:  MEASURE 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	G
11	953	433	.29	.04	1.30	4.3	1.31	4.0	.57	.66	27.5	29.5	11WCTA	1
13	961	402	.11	.04	.50	-9.4	.50	-8.7	.85	.64	38.6	28.1	13MVTL	1
4	1018	407	.10	.04	1.28	3.9	1.31	4.0	.59	.68	21.6	29.7	04ROEC	1
8	1070	440	.10	.04	.54	-9.1	.54	-8.3	.85	.64	32.5	27.7	08SORA	1
1	992	415	.09	.04	.54	-8.8	.54	-8.0	.86	.64	40.7	28.0	01ROA_	1
3	1168	391	.07	.04	1.27	3.9	1.61	7.3	.56	.64	28.6	29.3	03INCR	1
10	1204	407	-.02	.04	.87	-2.1	.87	-1.9	.69	.67	31.2	30.0	10CARA	1
2	1030	399	-.05	.04	.60	-7.3	.60	-6.7	.82	.64	31.8	27.6	02AROA	1
9	1317	412	-.14	.04	1.20	2.9	1.17	2.4	.56	.64	30.6	30.5	09DERC	1
14	3625	463	-.27	.03	1.46	6.0	1.58	7.5	.57	.72	20.5	25.9	14RATI	0
5	1025	341	-.30	.04	1.54	6.7	1.44	5.2	.48	.62	21.1	28.9	05SATA	1
MEAN	1305.7	410.0	.00	.04	1.01	-.8	1.04	-.3			29.5	28.6		
P.SD	741.2	29.5	.17	.00	.39	6.3	.42	6.3			6.4	1.3		

```
SUMMARY OF CATEGORY STRUCTURE.  Model="R"
FOR GROUPING "1" ITEM NUMBERS: 1-5 8-11 13
```

CATEGORY LABEL	SCORE	OBSERVED COUNT	%	OBSVD AVRGE	SAMPLE EXPECT	INFIT MNSQ	OUTFIT MNSQ	ANDRICH THRESHOLD	CATEGORY MEASURE	
0	0	521	13	-1.19	-1.07	.78	.84	NONE	(-2.72)	0
1	1	768	19	-.82	-.83	.93	.88	-1.34	-1.37	1
2	2	676	17	-.57	-.60	.97	.93	-.59	-.71	2
3	3	614	15	-.32	-.35	.78	.71	-.38	-.24	3
4	4	666	16	-.04	-.06	.88	.89	-.29	.30	4
5	5	700	17	.33	.32	.98	1.02	.07	1.48	5
6	6	102	3	.82	.98	2.07	2.30	2.54	(3.70)	0
MISSING		793	16	.07						

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

Appendix xxvi

```
TABLE 28.1 RASCH GLORIA7.xlsx                          ZOU931WS.TXT  Jul 24 2016 14:48
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
```

Subtotal specification is: PSUBTOTAL=@15DEFA

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	***
20	.61	.23	.99	1.02	.54	2.43	.86	
24	-.68	.13	.61	.62	-.57	1.86	.78	HY1
14	-1.06	.13	.45	.47	-1.08	1.02	.51	HY2
6	-1.15	.23	.52	.57	-.96	1.14	.57	HY3
4	-.54	.26	.45	.52	-.46	1.56	.71	HY4
1	-1.08	-	.00	-	-1.08	.00	.00	HY6
30	-.39	.12	.65	.66	-.54	2.35	.85	IG10
1	1.75	-	.00	-	1.75	.00	.00	IG2
11	.45	.08	.26	.28	.40	.51	.21	IG3
43	.57	.13	.87	.88	.45	2.58	.87	IG4
64	-.03	.10	.80	.80	-.19	2.77	.89	IG5
87	.17	.09	.85	.85	.05	2.81	.89	IG6
75	.13	.10	.87	.88	-.08	2.81	.89	IG7
56	-.20	.11	.81	.82	-.28	2.79	.89	IG8
48	-.49	.13	.88	.89	-.61	2.63	.87	IG9

SUBTOTAL RELIABILITY: inestimable
UMEAN=0 USCALE=1

Appendix 9.B- Sector B results

Here are showed the outcome of the model for Sector B after plugging the Bloomberg default risk (14RATI) in the model. In particular from the first (Appendix xxvii) we can observe the reliability and difficulties of the model and the Andrich threshold, which is ordered. On the other hand, in the second table (Appendix xxviii) we can observe the final outcome of relationship between the Rasch ratings and the Bloomberg default risk. For instance, we can observe that to a Rasch rating of -1.54 (MEAN MEASURE column) correspond a Bloomberg rating of HY1 considering 13 observations (PERSON COUNT Column).

Appendix xxvii

TABLE 13.1 RASCH GLORIA7 con rating.xlsx ZOU827WS.TXT Jul 28 2016 16:43
INPUT: 1320 PERSON 14 ITEM REPORTED: 440 PERSON 10 ITEM 21 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 2.48 REL.: .86 ... ITEM: REAL SEP.: 5.99 REL.: .97

ITEM STATISTICS: MEASURE 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	G
13	901	414	.33	.05	.56	-8.0	.56	-7.6	.87	.70	43.5	34.5	13MVTL	1
11	962	422	.31	.05	1.31	4.3	1.34	4.6	.65	.71	30.3	34.8	11WCTA	1
8	954	421	.26	.05	.63	-6.4	.66	-5.7	.82	.70	41.1	34.6	08SORA	1
1	990	414	.14	.05	.67	-5.7	.66	-5.7	.81	.70	41.8	34.8	01ROA_	1
9	1009	353	.07	.05	.97	-.4	1.00	.0	.68	.69	33.7	35.0	09DERC	1
2	1018	402	-.03	.05	.89	-1.7	.89	-1.6	.74	.69	30.8	34.2	02AROA	1
3	1097	375	-.03	.05	.91	-1.3	.95	-.7	.66	.69	39.7	35.3	03INCR	1
10	1052	349	-.04	.05	.94	-.8	.96	-.5	.71	.68	35.0	35.1	10CARA	1
5	1163	399	-.34	.05	1.34	4.6	1.35	4.6	.57	.69	28.8	35.2	05SATA	1
14	3606	434	-.66	.04	1.64	8.0	1.73	8.9	.63	.78	22.1	29.9	14RATI	0
MEAN	1275.2	398.3	.00	.05	.99	-.7	1.01	-.4			34.7	34.4		
P.SD	780.2	28.1	.29	.00	.33	4.9	.35	5.0			6.5	1.5		

TABLE 3.2 RASCH GLORIA7 con rating.xlsx ZOU586WS.TXT Aug 4 2016 12:56
INPUT: 1320 PERSON 14 ITEM REPORTED: 440 PERSON 10 ITEM 21 CATS WINSTEPS 3.92.0

SUMMARY OF CATEGORY STRUCTURE. Model="R"
FOR GROUPING "1" ITEM NUMBERS: 1-3 5 8-11 13

CATEGORY LABEL	SCORE	OBSERVED COUNT	%	OBSVD AVRGE	SAMPLE EXPECT	INFIT MNSQ	OUTFIT MNSQ	ANDRICH THRESHOLD	CATEGORY MEASURE	
0	0	377	11	-1.82	-1.69	.83	.87	NONE	(-3.35)	0
1	1	626	18	-1.25	-1.28	.93	.93	-1.99	-1.90	1
2	2	703	20	-.91	-.90	.86	.86	-1.21	-1.04	2
3	3	751	21	-.47	-.48	.95	.98	-.76	-.34	3
4	4	637	18	-.01	-.03	.91	.91	-.10	.51	4
5	5	417	12	.63	.57	.89	.93	.67	2.13	5
6	6	38	1	1.21	1.46	1.65	1.32	3.38	(4.53)	0
MISSING		411	10	-.47						

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

Appendix xxviii

```
TABLE 28.1 RASCH GLORIA7.xlsx                          ZOU992WS.TXT  Jul 28 2016 16:31
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 440 PERSON  9 ITEM  7 CATS WINSTEPS 3.92.0
```

Subtotal specification is: PSUBTOTAL=@15DEFA

EXTREME AND NON-EXTREME PERSON SCORES

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
440	-.43	.06	1.27	1.28	-.49	3.43	.92	***
6	-.15	.47	1.04	1.14	.04	2.82	.89	
13	-1.54	.29	1.02	1.06	-1.37	2.09	.81	HY1
6	-2.01	.23	.52	.57	-1.86	.69	.32	HY2
1	-1.57	-	.00	-	-1.57	.00	.00	HY4
1	.96	-	.00	-	.96	.00	.00	IG1
27	-1.19	.19	.95	.97	-1.28	2.55	.87	IG10
5	2.03	.56	1.13	1.26	2.60	2.10	.82	IG2
17	.91	.30	1.18	1.22	1.08	2.96	.90	IG3
50	.37	.15	1.07	1.08	.11	2.95	.90	IG4
60	-.31	.13	.99	1.00	-.42	2.96	.90	IG5
79	-.25	.17	1.50	1.51	-.49	3.43	.92	IG6
71	-.61	.12	1.00	1.01	-.64	2.95	.90	IG7
64	-.81	.11	.89	.90	-.99	2.63	.87	IG8
40	-.87	.19	1.19	1.21	-1.15	3.25	.91	IG9

SUBTOTAL RELIABILITY: inestimable
UMEAN=0 USCALE=1

Appendix 9.C- Sector C results

Here are showed the outcome of the model for Sector B after plugging the Bloomberg default risk (14RATI) in the model. In particular from the first (Appendix xxix) we can observe the reliability and difficulties of the model and the Andrich threshold, which is ordered. On the other hand, in the second table (Appendix xxx) we can observe the final outcome of relationship between the Rasch ratings and the Bloomberg default risk. For instance, we can observe that to a Rasch rating of -0.86 (MEAN MEASURE column) correspond a Bloomberg rating of HY1 considering 3 observations (PERSON COUNT Column).

Appendix xxix

TABLE 13.1 RASCH GLORIA4 con rating.xlsx ZOU075WS.TXT Jul 26 2016 12:39
INPUT: 1320 PERSON 14 ITEM REPORTED: 396 PERSON 9 ITEM 17 CATS WINSTEPS 3.92.0

PERSON: REAL SEP.: 1.44 REL.: .67 ... ITEM: REAL SEP.: 11.02 REL.: .99

ITEM STATISTICS: MEASURE 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	G
1	274	252	1.40	.09	1.00	.1	.98	-.3	.59	.57	48.4	51.6	01ROA_	1
8	226	205	1.07	.10	1.04	.5	1.03	.4	.49	.52	46.8	50.2	08SORA	1
11	275	209	.98	.10	1.03	.4	1.07	.8	.39	.59	50.7	50.8	11WCTA	1
13	207	168	.72	.11	.77	-2.5	.75	-2.7	.68	.52	56.5	50.3	13MVTL	1
7	259	161	.17	.12	.89	-1.1	.91	-.9	.16	.57	55.3	53.3	07QURA	1
14	3670	382	.08	.04	1.03	.4	1.01	.2	.79	.80	32.4	31.7	14RATI	0
10	870	354	-1.44	.10	.96	-.5	.88	-1.4	.61	.50	66.0	62.5	10CARA	1
9	836	340	-1.46	.10	1.08	1.0	1.01	.1	.60	.50	61.0	62.7	09DERC	1
3	871	348	-1.52	.10	1.33	3.8	1.20	2.2	.44	.46	60.7	63.3	03INCR	1
MEAN	832.0	268.8	.00	.10	1.01	.2	.98	-.2			53.1	53.0		
P.SD	1041.6	82.4	1.11	.02	.14	1.6	.12	1.3			9.4	9.2		

SUMMARY OF CATEGORY STRUCTURE. Model="R"
FOR GROUPING "1" ITEM NUMBERS: 1 3 7-11 13

CATEGORY LABEL	SCORE	OBSERVED COUNT	%	OBSVD AVRGE	SAMPLE EXPECT	INFIT MNSQ	OUTFIT MNSQ	ANDRICH THRESHOLD	CATEGORY MEASURE	
0	0	210	10	-1.53	-1.47	.91	.89	NONE	(-3.04)	0
1	1	459	23	-.21	-.51	1.45	1.43	-1.80	-1.08	1
2	2	745	37	.70	1.03	1.14	.99	-.28	.96	2
3	3	623	31	2.82	2.61	.65	.74	2.08	(3.25)	0
MISSING		1131	36	.62						

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

Appendix xxx

```
TABLE 28.1 RASCH GLORIA4.xlsx                     ZOU137WS.TXT  Jul 24 2016 13:53
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 396 PERSON  8 ITEM  4 CATS WINSTEPS 3.92.0
```

Subtotal specification is: PSUBTOTAL=@15DEFA

EXTREME AND NON-EXTREME PERSON SCORES

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
396	1.21	.08	1.49	1.49	1.12	1.48	.69	***
14	1.36	.41	1.48	1.53	1.16	1.31	.63	
3	-.86	.28	.39	.48	-1.13	.00	.00	HY1
2	-1.05	.60	.60	.85	-1.05	.72	.34	HY2
1	.23	-	.00	-	.23	.00	.00	HY3
10	2.62	.57	1.70	1.79	3.43	.71	.33	IG1
5	-.33	.22	.44	.49	-.16	.51	.21	IG10
21	1.26	.36	1.59	1.63	1.12	1.51	.70	IG2
37	1.77	.29	1.72	1.75	2.11	1.27	.62	IG3
63	1.90	.16	1.29	1.30	1.68	.89	.44	IG4
73	1.48	.16	1.39	1.40	1.12	1.21	.59	IG5
75	.95	.14	1.22	1.23	.91	1.52	.70	IG6
41	1.02	.21	1.31	1.33	.73	1.45	.68	IG7
36	.20	.19	1.13	1.15	-.09	1.82	.77	IG8
15	-.12	.23	.86	.89	-.30	1.72	.75	IG9

SUBTOTAL RELIABILITY: inestimable
UMEAN=0 USCALE=1

Appendix 10- Relationship between the Rasch ratings and CEO power

In this Appendix, we are going to present the results of the analysis of the variance in relation to CEO power. The results for each sector are presented below.

Appendix 10.A- Sector A results

In this Appendix is represented the analysis of the variance for sector A. In particular in the ANOVA table we can observe the F-tests, which resulted in the rejection of the null hypothesis (which is that mean of the distribution are all the same) and therefore demonstrating the negative relationship between CEO power and credit ratings.

Appendix xxxi

```
TABLE 28.1 RASCH GLORIA7.xlsx                        ZOU931WS.TXT  Jul 24 2016 14:48
 INPUT: 1320 PERSON  13 ITEM  REPORTED: 484 PERSON  10 ITEM  7 CATS WINSTEPS 3.92.0
```

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					

Appendix 10.B- Sector B results

In this Appendix is represented the analysis of the variance for sector B. In particular in the ANOVA table we can observe the F-tests, which resulted in non-significant result on the relation of the Rasch ratings with CEO power.

Appendix xxxii

TABLE 28.1 RASCH GLORIA7.xlsx ZOU992WS.TXT Jul 28 2016 16:31
INPUT: 1320 PERSON 13 ITEM REPORTED: 440 PERSON 9 ITEM 7 CATS WINSTEPS 3.92.0

Subtotal specification is: PSUBTOTAL=@14CEOP

EXTREME AND NON-EXTREME PERSON SCORES

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
440	-.43	.06	1.27	1.28	-.49	3.43	.92	*
89	-.56	.09	.84	.84	-.42	2.49	.86	0
351	-.40	.07	1.36	1.36	-.57	3.57	.93	1

SUBTOTAL RELIABILITY: .02
UMEAN=0 USCALE=1

PERSON CODE	CODE	MEAN DIFFERENCE MEASURE	S.E.	t	Welch-2sided d.f.	Prob.
0	1	-.16	.12	-1.43	219	.155

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@14CEOP	1.92	1.00	1.92	1.18	.2776
Error	712.14	438.00	1.63		
Total	714.05	439.00	1.63		
Fixed-Effects Chi-squared: 2.0381 with 1 d.f., prob. .1534					

NON-EXTREME PERSON SCORES ONLY

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
439	-.45	.06	1.24	1.24	-.49	3.45	.92	*
89	-.56	.09	.84	.84	-.42	2.49	.86	0
350	-.42	.07	1.32	1.32	-.57	3.60	.93	1

SUBTOTAL RELIABILITY: .00
UMEAN=0 USCALE=1

PERSON CODE	CODE	MEAN DIFFERENCE MEASURE	S.E.	t	Welch-2sided d.f.	Prob.
0	1	-.15	.11	-1.29	212	.198

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@14CEOP	1.53	1.00	1.53	.99	.6796
Error	675.04	437.00	1.54		
Total	676.57	438.00	1.54		
Fixed-Effects Chi-squared: 1.6642 with 1 d.f., prob. .1970					

Appendix 10.C- Sector C results

In this Appendix is represented the analysis of the variance for sector C. In particular in the ANOVA table we can observe the F-tests, which resulted in the rejection of the null hypothesis (which is that mean of the distribution are all the same) and therefore demonstrating the negative relationship between CEO power and credit ratings.

Appendix xxxiii

TABLE 28.1 RASCH GLORIA4.xlsx ZOU137WS.TXT Jul 24 2016 13:53
INPUT: 1320 PERSON 13 ITEM REPORTED: 396 PERSON 8 ITEM 4 CATS WINSTEPS 3.92.0

Subtotal specification is: PSUBTOTAL=@14CEOP

EXTREME AND NON-EXTREME PERSON SCORES

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
396	1.21	.08	1.49	1.49	1.12	1.48	.69	*
274	1.38	.09	1.49	1.49	1.37	1.37	.65	0
122	.81	.13	1.42	1.43	.48	1.66	.73	1

SUBTOTAL RELIABILITY: .85
UMEAN=0 USCALE=1

PERSON CODE	CODE	MEAN DIFFERENCE MEASURE	S.E.	t	Welch-2sided d.f.	Prob.
0	1	.58	.16	3.67	241	.000

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@14CEOP	28.24	1.00	28.24	13.03	.0006
Error	854.03	394:00	2.17		
Total	882.27	395.00	2.23		
Fixed-Effects Chi-squared: 13.4810 with 1 d.f., prob. .0002					

NON-EXTREME PERSON SCORES ONLY

PERSON COUNT	MEAN MEASURE	S.E. MEAN	P.SD	S.SD	MEDIAN	MODEL SEPARATION	MODEL RELIABILITY	CODE
346	.80	.06	1.12	1.12	.84	1.74	.75	*
235	.95	.07	1.12	1.12	1.12	1.65	.73	0
111	.49	.10	1.05	1.06	.26	1.82	.77	1

SUBTOTAL RELIABILITY: .85
UMEAN=0 USCALE=1

PERSON CODE	CODE	MEAN DIFFERENCE MEASURE	S.E.	t	Welch-2sided d.f.	Prob.
0	1	.46	.12	3.71	228	.000

ANOVA - PERSON Source	Sum-of-Squares	d.f.	Mean-Squares	F-test	Prob>F
@14CEOP	16.00	1.00	16.00	13.17	.0006
Error	418.06	344.00	1.22		
Total	434.06	345.00	1.26		
Fixed-Effects Chi-squared: 13.7650 with 1 d.f., prob. .0002					