UNIVERSITY OF LJUBLJANA
SCHOOL OF ECONOMICS AND BUSINESS

MASTER THESIS

THE EFFECT OF RATING ANALYST'S IDENTITY ON THE CREDIT RATING

Ljubljana, August 2020 ILLYA BONDARENKO

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LIST OF ABBREVIATIONS

EU – European Union

ESMA - European Securities and Markets Authority

CDO – Collateralized Debt Obligation

CFA – Chartered Financial Analyst

CPDO – Constant-Proportion Debt Obligation

CRA – Credit Rating Agency

IOSCO – International Organization of Securities Commission

KPI – Key Performance Indicator

MBA – Master of Business Administration

MS – Member State

NRSRO – A nationally recognized statistical ratings organization

SEC – Securities and Exchange Commission

US – United States

INTRODUCTION

Nowadays, credit ratings' main purpose is to provide information on the creditworthiness of corporate borrowers. Investors, as well as other market participants, are keen to use them as an indicator of default probability in the event of a new debt issue. Therefore, they have an immeasurable effect on firms' ability to access new capital as well as on the terms at which the company could borrow it. Given their visibility and commonality credit ratings represent an "entry ticket" to the financial markets for companies seeking funds, they can either attract or scare away potential investors, such as pension funds or hedge funds.

Despite their utmost importance to all the market participants, credit ratings were at the center of disputes since the global financial crisis, and even today the credibility of the ratings is often being followed by the chorus of concern. During the rise of structured finance products, the credit rating agencies rapidly expanded their rating business. Such an expansion came at the expense of rating accuracy, as top ratings were received by companies shortly before they collapsed (Bar-Isaac & Shapiro, 2011). Lack of sophistication of investors (Skreta & Veldkamp, 2009), regulatory arbitrage (White, 2010) and the various conflicts of interests and agency problems that credit rating agencies (hereafter: CRAs) faced (Bolton, Freixas, & Shapiro, 2012) were among the many potential causes widely discussed at the time. Before, during, and after the financial crisis of 2008, CRA critics were focusing on the three main issues regarding the integrity of the CRAs' operations (McVea, 2010):

1. Conflict of interest;
2. Flawed models and non-timely downgrades;
3. Lack of accountability.

The first issue is closely connected to the fee structure in the credit rating industry. The absolute dominance of the "issuer pays" model created the situation, where both the issuer and the rating agencies have an economic interest in ensuring the success of the issue: the issuer is interested in ensuring the sale of its securities, and the CRA is securing the flaw of fees from the issuers (McVea, 2010). Additionally, issuers may pressure the CRAs in order to receive higher ratings. The fee-based supplementary services provided by CRAs to the issuer, such as corporate consulting, may even further incentivize CRAs to issue beneficial ratings (Committee on Banking, Housing, and Urban Affairs, 2006). Secondly, the methodologies and models used by the CRAs are, by definition, based on assumptions. The varying quality of the underlying assumptions, however, may result in the subjective and often flawed forecasts. The acuteness of the issue was the most evident during the rise of the structured finance products, such as collateralized debt obligations (hereafter: CDOs). Last but not least, the last issue represents the discrepancy between the CRAs' historical lack of accountability and the scale of ratings' effect on the financial markets.

Each of the issues mentioned above was scrutinized by the researchers and regulated by the financial authorities: through the number legislative changes undertaken both in Europe and

US, rating agencies were pushed to rely on more quantitative and transparent rating techniques, therefore, limiting the potential rating inflation problem connected to the flawed and speculative models; specialized governing bodies possessing the regulatory power over the CRAs were established, in order to tackle the accountability issue; and, finally stricter reporting was supposed to limit the potential for conflicts of interest. However, even after the implementation of all regulatory changes and stricter monitoring practices, the perceived quality of the ratings did not improve dramatically, and various quality flaws indicated that the issues were not resolved yet (Jeon & Lovo, 2013).

While comparing, long-term corporate ratings issued for the same companies issued at the same time across agencies, we observe the within variation in ratings. Some share of the variation can be explained by the methodological differences as well as information asymmetry between the rating agencies, namely rating agency fixed effect. The legislative changes targeting the increasing transparency of the ratings mainly affected rating agencies' fixed effects. However, even when excluding the impact of agencies' fixed effects, it is hardly possible to explain the within variation in ratings completely.

According to Fracassi, Petry and Tate (2013), analyst fixed effects exist and account for 30% of the within variation in ratings. In other words, their research indicated that the rating biases of analysts greatly affect the credit spreads on the rated firms' outstanding debt and, consequently, the terms offered on new public debt issues. Moreover, researchers observed that in the long run, firms being rated by more pessimistic analysts tend to issue less debt, lean more on cash and equity financing, and grow slower than their peers covered by optimistic analysts (Fracassi, Petry, & Tate, 2013). When taking into consideration the analyst effects, it becomes obvious that attempting to solve the conflict of interest and accountability issues only on the company (CRA) level may not improve the quality of the ratings. In addition to regulating and governing the CRAs as a company, authorities have to take a closer look at the people issuing the ratings.

Throughout this thesis, I will try to evaluate the historical impact of the credit-rating agencies on the financial industry as well as to make a short introduction to the industry of credit ratings. I will try to assess the recent and the most significant regulation efforts in the US and EU and their impact on solving the issues of CRAs' accountability, conflicts of interest, and model accuracy. I will focus particularly on the European regulatory response to the credit rating crisis since it is the most relevant to the Slovenian companies. In this thesis, I will try to evaluate the applicability of the main conclusion provided by Fracassi, Petry and Tate (2013): "It is necessary to regulate the work of CRAs as well as the work of individual credit analysts".

Despite the scale of the analyst effects on the ratings and, therefore, on the cost of debt in general, their causes and determinants are still studied insufficiently. Whereas the impacts of various heuristics and biases on the judgments of equity analysts were scrutinized in-depth during the previous three decades. The nature of the credit rating is heavily dependent on an individual's analytical and forecasting skills, similar to the daily activities of equity analysts. The case of the revolving doors between the investment banks and CRAs just further draws the parallels between the equity and credit analysts required skillset and nature of the job. In my research, I will test whether the same behavioural tendencies and heuristics observed at the equity analysts' behaviour can be applied to the case of the credit rating analysts. I assume that by classifying some of the observable analyst traits and studying their impacts on the analysts' judgments it is possible to predict the rating quality as well as the analysts' impact on the rating itself.

I assume that the identity of the analyst can sufficiently affect the rating process: as the credit rating, may be regarded as a composite value achieved by processing various data on the firm's performance and outlook, consequentially, the input data may be perceived and analysed differently by different analysts. The main purpose of this thesis is to examine the effects that the individual analysts' characteristics have on the credit rating of the companies and consequentially on the cost of debt financing the companies will incur.

The goals of the master thesis are to determine the extent of the correlation of the credit rating from the analyst's identity/ if there is any, and to determine whether the analyst's behavioural heuristics are influencing the credit rating. In the first part of the thesis, the background of the credit rating history is presented, including the market structure and legislative environment before the financial crisis. The second section presents how the financial crisis and major CRAs mistakes are intertwined, as well as how the legislative environment has changed as a result of it. The third section discusses the role of the credit rating analysts in the credit rating process, draws parallels between the research on the equity analysts and the case of credit rating analysts and outlines the main hypotheses. In the fourth section the credit rating scores from the three major CRAs are presented. The fifth section outlines the methodology and the initial model used in this research, whereas the sixth section shortly presents the methodology of the Random Forest algorithm and describes the results of the data analysis. The seventh section discusses the research limitations which I have encountered. The last section concludes the thesis.

1 CREDIT RATING INDUSTRY ENVIRONMENT

Credit rating industry comprises of a huge variety of publicly traded securities (like corporate bonds, commercial papers, and municipal bonds), most of those are covered three major U.S. bond rating agencies: Moody's Investors Service, Standard & Poor's (S&P's) and Fitch, Inc. The credit ratings market structure did not change significantly throughout the last twenty years, representing an oligopoly (triopoly) controlled by the three major CRAs: S&P, Fitch, and Moody's collectively controlled 94.1% of total reported Nationally Recognized Statistical Rating Organizations' (hereafter: NRSRO) revenue in 2019 (SEC, 2019).

In the following sections, I will try to make an introduction to the credit rating industry and describe its main characteristics and structure.

1.1 Introduction to the Credit Rating Industry

In 1909 in the U.S., John Moody initiated the first bond-rating agency, which was mainly focused on railroad bonds (Sylla, 2001). Starting from the middle of the nineteenth century the main output of the credit reporting agencies was information on business standing and creditworthiness of all sorts of businesses in the U.S., sometimes presented as a commercial rating book (Jeon & Lovo, 2013). One example of such rating books was Poor's annual volume Manual of the Railroads of the United States, which was published starting from the year 1868 (Sylla, 2001). Due to the nature of U.S. economy at the time railroad corporations represented the first of America's big companies, operating multi-divisional businesses over large geographical expanses (Jeon & Lovo, 2013). At the beginning of the twentieth century Moody's was leading the railroad credit rating industry with its Analysis of Railroad Investments, in which it was covering railroads' assets, liabilities, and earnings and condensed the analysis into a single rating symbol (Sylla, 2001). This seemingly simplistic approach proved itself extremely popular, and later was adopted by Poor', Fitch, and Standard. Poor's and Standard merged in 1941 (Jeon & Lovo, 2011).

Throughout history various financial regulators were significantly influencing the accelerated development of the credit rating history (Coffee, 2006). In the year 1930, the Federal Reserve System adopted a system for evaluating the risk of a bank's entire portfolio of bonds based on credit ratings (Coffee, 2006). In 1931, the Office of the Comptroller of the Currency let banks report publicly traded bonds with a rating of BBB or better at book value; lower-rate bonds had to be reported at current market prices, which might be lower (The Financial Crisis Inquiry Commission, 2011). In other words, regulators were setting the reporting threshold utilizing the credit ratings scores and methodology without being able to regulate the process.

Since 1973, the Securities and Exchange Commission (hereafter: SEC) started to award Nationally Recognized Statistical Ratings Organizations status to the elected rating agencies (Jeon & Lovo, 2011). Until 2003, SEC recognized only these three agencies as nationally recognized statistical rating organizations (Jorion, Liu, & Shi, 2004). By 2020, their number has increased to nine (SEC, 2020).

By the early 1980s, the SEC limited money market funds to investments in securities that were given a high rating by at least two NRSROs, a similar approach was later adopted by the National Association of Insurance Companies in the insurance industry (Coffee, 2006). In a way, federal and state regulators outsourced the task of overseeing the capital structure of institutional investors (like state and federal banks, mutual funds, or insurance companies) to the NRSRO credit rating agencies (Jeon & Lovo, 2013). A similar approach was adopted by the international regulators: Basel II framework utilizes ratings produced by CRAs to determine the risk-weights for capital requirement (Bank for International Settlements, 2004). The SEC at the time was restricting money market funds to purchasing "securities that have received credit ratings from any two NRSROs… in one of the two highest short-term rating categories or comparable unrated securities" (The Financial Crisis Inquiry Commission, 2011). Partnoy in his paper (Partnoy, 1999) argues that such regulatory endorsement substituted investor due diligence with credit ratings: pension funds regulations that limit potential investment perimeter only to the "investment grade" instruments rated by the NRSRO, hereby, the legislative definition of "investment grade" is linked to the privately issued credit ratings. As a result of such a regulatory endorsement, ratings by NRSROs today are widely used as benchmarks in federal and state legislation, rules issued by financial and other regulators, foreign regulatory schemes, and private financial contracts (Committee on Banking, Housing, and Urban Affairs, 2006). Another result of such was the widespread practice for most issuers to purchase ratings from two or more rating agencies to comply with regulators' eligible portfolio standards for the institutional investors.

Initially, SEC's role was limited to just approval or rejection of the companies' applications to become an NRSRO; but if approved, a rating agency faced no further regulation (The Financial Crisis Inquiry Commission, 2011). Moody's standard disclaimer at the time reads (The Financial Crisis Inquiry Commission, 2011):

"The ratings… are, and must be construed solely as, statements of opinion and not statements of fact or recommendations to purchase, sell, or hold any securities."

Although CRAs were facing virtually no liability, historically, many institutional investors, such as university endowments and pension funds, and financial institutions relied on the credit ratings due to the lack of access to the informational sources that CRAs were utilizing as well as insufficient analytical capacity (Sylla, 2001). Credit ratings were altering even the private transactions: contracts may contain triggers that require the posting of collateral or immediate repayment, should a security or entity be downgraded (The Financial Crisis Inquiry Commission, 2011).

Over several decades, the credit rating industry was experiencing ever-increasing importance. The main driving force behind it were the bond markets, which were dramatically expanding (Committee on Banking, Housing, and Urban Affairs, 2006). This situation became even more pronounced during the period of the rice of the structured securities. According to Jerome Fons, Moody's former managing director (The Financial Crisis Inquiry Commission, 2011):

"Subprime residential mortgage-backed securities and their offshoots offer little transparency around composition and characteristics of the loan collateral…Loan-by-loan data, the highest level of detail, is generally not available to investors."

The process of developing an initial credit rating at the largest CRAs generally proceeds as follows (Committee on Banking, Housing, and Urban Affairs, 2006): analysts review company's financial statements and draft a preliminary rating; visit the management of the issuer and prepare a brief report explaining the rationale for the rating; and make a presentation to the rating committee, which then determines the final rating. Similar procedures are utilized by most of the CRAs while rating the corporate bonds, however, the rating process of the structure finance instruments gets significantly more complicated. While rating the corporate bonds credit rating analyst's skills and knowledge, as well as the perception of the input data have a major effect on both preliminary and the final ratings.

1.2 Barriers to Entry in the Credit Rating Industry

Two of the most distinctive characteristics of the Credit Rating industry are high barriers to entry and dominance of an issuer-pays pricing model. These barriers can be divided into natural and artificial (Jeon & Lovo, 2011). The obligatory recognition process as the NRSRO represents the artificial barrier. Despite the notable progress made by smaller rating agencies in gaining market share in some types of asset-backed securities over the past few years, various barriers to entry persist to exist in the industry, presenting competitive challenges for the smaller NRSROs (SEC, 2018). One of those barriers is minimum ratings requirement: it specifies the use of ratings of rating agencies in the investment management contracts of institutional fund managers and the investment guidelines of fixed income mutual fund managers, pension plan sponsors, and endowment fund managers (SEC, 2018). Another significant barrier is the inclusion requirements of some fixed income indices: to be included in many of these indices, securities must be rated by specific NRSROs (SEC, 2018). Inclusion and minimum rating requirements can be both classified as artificial requirements, however, according to Jeon and Lovo (2011), the persistent level of industry concentration even before the promulgation of NRSRO status suggests that a natural barrier to entry would exist in the industry even in the absence of artificial barriers.

In order to describe natural barriers and understand their origins I will utilize the model used by Jeon and Lovo (2011). In the infinite horizon model, each period an incumbent CRA competes with a market entrant. Incumbent (original) CRA, like Fitch or S&P's, has been present in the market for a long time and has proven its reliability and expertise, whereas a market entrant has not yet proven its expertise. In the credit rating industry, the more reliable the rater, the higher the issuer's expected profit (Jeon & Lovo, 2011). Therefore, both the difference in the reliability (a surrogate indicator of expertise) and the rating fees between the incumbent and entrant CRA are considered when the issuer decides whom to hire. Assuming that incumbent CRA's reputation is highly perceived by investors since their market tenure is sufficiently longer than the entrant's, and consequently the incumbents' ratings do have a greater effect on the investor's' behaviour than ratings from the newcomers (Jeon & Lovo, 2011). In other words, as long as public perception of the incumbent CRA's reputation maintains at high levels, the incumbent CRA will be preferred to be hired by the issuers. Therefore, the natural barriers in the credit rating market origin from the public's trust in the incumbent CRAs' reputation, due to their longer industry tenure.

According to the described model, to survive in the credit rating market newcomers, have to build up their reputation. The entrants can increase the public's perception of their expertise by getting hired by the issuers and produce the ratings that are correlated with the projects' outcome and private signals (Jeon & Lovo, 2011). In order to be hired newcomer has to sufficiently lower the offered rating fees in comparison to the incumbents' fees, thus creating the downward price pressure on the newcomers.

1.3 Fee, Market Structure and Business Model

Originally credit rating agencies were selling the rating books and individual rating reports via investors' subscriptions, representing the 'investor-pays' model (Sylla, 2001). As the credit rating industry was developing and expanding the prevalent pricing model also started to shift towards the 'issuer-paid' model. The main reason for the shift was the ever-increasing popularity of the high-speed photocopy machines that made it easier for non-subscribing investors to free-ride on the information in rating books (Jeon & Lovo, 2013).

According to the congressional testimony of John Coffee (2008, pp. 71-72), the CRA's fee is comprised of two parts:

"Today, the rating agencies receive one fee to consult with a client, explain its model, and indicate the likely outcome of the rating process; then, it receives a second fee to deliver the rating (If the client wishes to go forward once it has learned the likely outcome). The result is that client can decide not to seek the rating if it learns that it would be less favourable than it desires; the result is a loss of transparency to the market."

The CRA's fee structure has been criticized for two major reasons (Jeon & Lovo, 2013): first, because it allows issuers to shop for rating, by asking multiple CRAs for their rating quote and then publicizes only the most favourable ones; second, because CRAs may inflate the rating to charge additional fees from publicizing their ratings. The CRAs' incentives to produce higher ratings is described by the term "rating catering" (Park & Lee, 2017).

In their research Bolton, Freixas and Shapiro (2012) investigate the issues of the ratings shopping and conflict of interests: the results suggest that the higher competition has negative effects on the quality of the ratings. The pressure from the competition as well as from the investors is likely to result in the CRAs' incentives to inflate ratings. Besides, Park and Lee (2017) in their research observed that, when a bond issuer with incumbent CRAs hires an additional CRA, the newly hired CRA tends to produce higher ratings than those produced by the incumbent CRAs. Upgrades and downgrades can also be used as an instrument of rating catering (Park & Lee, 2017): the results suggest that the competitive pressure has an additional effect on the likelihood that CRAs upgrade ratings if the ratings they had assigned were lower than those of the newly-hired rivals. Some researchers, however, indicated the contradictory results: Morkoetter, Stebler and Westerfeld (2017) suggest that in the competitive situation of multiple ratings outstanding the rating effort of each rating agency is increasing, leading to more information being produced.

Market structure of the credit rating industry is a triopoly (Sylla, 2001), where Moody's, S&P's have been historically dominating the industry, later joined by Fitch (Jeon & Lovo, 2013). The cumulative market share of the three dominant CRAs in the U.S. stayed constant and amounted to around 94% during the last 5 years (SEC, 2019). In the European Union (hereafter: EU), these three major rating agencies accounted for 92.1% of the market for credit rating agencies by 2019 (ESMA, 2019). Moody' is the only publicly traded entity out of the three: since 2008, it was listed in the New York Stock Exchange (Jeon & Lovo, 2013).

1.4 Revolving Doors and Analyst Incentives

Revolving doors in this context refers to the frequent hiring of credit rating analysts by the firms they rate. The practice of the revolving doors – where monitors are hired by the industries they monitor – is extremely widespread in financial markets: bank regulators join financial institutions, risk controllers join trading floors (Kempf, 2020). Despite being common, the practice was followed by heavy criticism for being a source of economic distortion. After the financial crisis revolving doors was seen as a major contribution to the arising conflict of interests, weaker regulatory oversight, and as a result inflated credit rating (Robinbson, 2015). According to the Financial Crisis Inquiry Commission (2011):

"The pressure on rating agency employees was also intense as a result of the high turnover – a revolving door that has often left raters dealing with their old colleagues, this time as clients...Retaining employees was always a challenge, for the simple reason that the banks paid more. As a precaution, Moody's employees were prohibited from rating deals by a bank or issuer while they were interviewing for a job with that particular institution, but the responsibility for notifying management of the interview rested on the employee. After leaving Moody's, former employees were barred from interacting with Moody's on the same series of deals they had rated while in its employ, but there were no bans against working on the other deals with Moody's."

In other words, no specific control mechanism was established to limit the potential agency problem, as the reporting of the potential issues to managers wasn't organized as mandatory. The main concern arising was that the revolving doors practice may encourage potential employees to provide a beneficial rating for their potential employers. The alternative theory states that monitors are also hired for their expertise, therefore, they will have a greater incentive to invest in their industry qualifications or to signal their expertise during their employment as monitors (Kempf, 2020). The potential conflict of interest, however, was at least partially addressed by the Dodd-Frank act in 2010: the regulation introduced new provisions that require credit rating agencies to report analyst transfers to rated entities as well as to implement mandatory look-back reviews (SEC, 2010).

The two theories are not mutually exclusive, though, it is difficult to estimate the scale of those effects: whereas higher accuracy may lead to higher chances of employment, at the same time analysts may behave leniently and provide beneficial ratings, which may also increase the chances of employment. Kempf (2020) determined that analysts who are one standard deviation more accurate are 78% more likely to be hired by a prestigious underwriting investment bank than the average analyst who rates similar products at the same point in time.

Concerns about the industry labour market, especially the existence of lucrative well-paid alternatives, are likely to encourage the analysts to provide more accurate ratings, to improve the chances of their future employment. Therefore, restricting the possibility to be employed by better-paying investment bank may discourage the analysts to produce high accuracy ratings (Kempf, 2020). Disclosing all the analyst transfers as well as job interviews between analysts and rated entities is crucial in maintaining the quality of produced ratings.

1.5 Regulation Fair Disclosure (2000)

Credit Rating can be viewed as a "certifier product" or an information signal, which is not obligatory a subject of regulation due to the market discipline (Chiu, 2013). Market discipline in this context represents the quality test and the subsequent feedbacks of these information signals: users of the poor-quality ratings will disseminate information on their quality and stop using them. In real life, however, such a process of market discipline did not happen (Chiu, 2013). The failure of market discipline may be attributed to government intervention to the market of credit ratings. According to Kruck (2011), credit ratings have become an essential piece of information on risk measurement across various types of investment products. Moreover, the availability of such information drives investors to rely on these externally produced credit ratings, however, at the same time it prevents investors from being able to effectively scrutinize the quality of credit ratings (Chiu, 2013). Why? One of the factors was the long-standing credibility of the major CRAs. Second is the regulatory endorsement granted by governments. Regulation Fair Disclosure in this context represents the government intervention, which may result in the failure of the market discipline.

On October 23, 2000, the Securities and Exchange Commission implemented Regulation Fair Disclosure, prohibiting U.S. public companies from making selective, non-public disclosures to favoured investment professionals. Though it was aimed at levelling the playing field by eliminating the selective disclosures, however, its introduction was controversial (Jorion, Liu, & Shi, 2004). The Regulation was heavily criticized for impoverishing the information environment by decreasing the number of total disclosures and the quality of analysts' forecasts (Cornett, Tehranian, & Yalcin, 2007). Reg. FD, however, allowed companies to disclose financial information to credit rating agencies. The rationale for the exemption was that agencies are not selectively disseminating information and without the exemption, investors would receive lower-quality information from the rating agencies (Jorion, Liu, & Shi, 2004). The credit rating process is based on both access to public and non-public information by the CRA, however, when a rating is made public, the explanation given by the CRA refers only to the public information (Jorion, Liu, & Shi, 2004).

The Reg. FD significantly affected the power of the credit rating effects on the investors' behaviour (Jorion, Liu, & Shi, 2004): studies identified that the stock market reaction to upgrades (generally insignificant in prior studies) became significant after the implementation of Reg. FD. In other words, market participants commenced to assign higher informational value to the credit rating and, therefore, the extent of the market reaction on the rating action, such as upgrade or downgrade, has also increased.

Moody' argued that Reg. FD has just preserved the "status quo ante" (Jorion, Liu, & Shi, 2004). The implementation of Reg. FD provided the CRAs with a long-term strategic advantage, significantly increasing the informational effect of the rating actions.

1.6 Credit Rating Agency Reform Act of 2006

During the years after the Reg. FD implementation major CRAs were enjoying the unregulated power to determine the cost of borrowing for the corporations not only in the U.S. but around the globe. However, the rising criticism of the CRAs' ability to warn investors about several of the largest bankruptcies in U.S. history was pushing regulators to review the situation (Committee on Banking, Housing, and Urban Affairs, 2006). Corporate scandals and the following bankruptcies of Enron and WorldCom signified the SEC's inability to efficiently regulate and monitor the CRAs' operations under the current NRSRO system.

First of all, there was rising congressional concern regarding the SEC's authority to oversee and regulate the credit rating industry (Congressional Research Service, 2006). In response, Congress began the process considering the legislative framework to efficiently regulate CRAs. On September 22, 2006, the Credit Rating Agency Reform Act of 2006 was passed (Coffee, 2010). Only after more than 30 years of monitoring operations on the credit rating market, the SEC was granted limited authority to oversee NRSROs (The Financial Crisis Inquiry Commission, 2011). Besides, for the first time terms, such as credit rating, credit rating agency, NRSRO, and qualified institutional buyer, were given the legal definition (Congressional Research Service, 2006).

The reform was altering the SEC's registration procedure, focusing on improving the transparency of the process. By changing the registration procedure, the reform intended to eliminate the artificial barriers to entry present in the industry. Though the academic research suggested the contradictory results regarding the effect of the increased competition, regulators believed that a higher number of rating providers and subsequently lower prices will improve the quality of the produced ratings (The Financial Crisis Inquiry Commission, 2011). The Reform Act was forcing the SEC to admit any new NRSRO application, in case the applicant could make an adequate showing of competence (Congressional Research Service, 2006). As a result, the number of NRSROs has increased up to ten by the beginning of 2007. Section four of the act amended the list of documentation that CRAs were required to submit (Committee on Banking, Housing, and Urban Affairs, 2006):

"A credit rating agency that wants to become an NRSRO must furnish an application that contains the following required information: rating statistics over the short-, mid-, and long-term periods; procedures and methodologies that the rating agency uses…; policies or procedures to prevent the misuse of material non-public information; organizational structure; whether the rating agency has a code of ethics and, if not, the reasons; conflicts of interest related to the issuance of ratings…; a list of the 20 largest issuers and subscribers that use the rating services…"

CRAs were required to provide the Commission with the extended disclosures regarding the methodologies used, however, methodologies reported upon the registration were not further monitored (Coffee, 2010).

2 THE CREDIT RATING CRISIS

Structured finance securities were ruling the financial markets by December 2008, accounting for over $11 trillion worth of outstanding U.S. bond market debt (Benmelech & Dlugosz, 2009). The three major CRAs were assigning predominantly high ratings to the structured finance securities: roughly 60% of all global structured products were AAA-rated (Fitch Ratings, 2007). Converting illiquid assets into liquid securities, started the fire of the financial innovation in the pre-crisis years and gave rise to exotic financial instruments that found their way, either directly or indirectly, onto commercial and investment bank balance sheets (Cerbioni, Fabrizi, & Parbonetti, 2015).

The monetary policy of the Federal Reserve, along with capital flows from abroad, created conditions in which a housing bubble was developing (The Financial Crisis Inquiry Commission, 2011). Lending standards began to deteriorate as the housing bubble was luring borrowers, mortgage brokers, appraisers, originators, securitizes, investors and credit rating agencies with higher returns (The Financial Crisis Inquiry Commission, 2011). In 2008, the creditworthiness of the structured finance securities began to deteriorate dramatically, followed by the series of rating downgrades. The CRAs were heavily criticized for the sluggishness in adjusting their ratings, especially those assigned to the structured finance securities. Major scientific articles argued that the issuance of new financial instruments, such as MBSs, played a prominent role in the crisis because they induced the financial sector to misallocate resources to real estate (Diamond & Rajan, 2009). Princeton economist, Alan Blinder wrote:

“Part of the answer is that the securities, especially the now-notorious C.D.O.s, for collateralized debt obligations, were probably too complex for anyone’s good. Investors placed too much faith in the rating agencies which, to put it mildly, failed to get it right. It is tempting to take the rating agencies out for a public whipping. But it is more constructive to ask how the rating system might be improved” (Blinder, 2007).

Despite the prevailing public opinion and heavy criticism, that rating agencies were not liable for misstatements in securities registrations because courts ruled that their ratings were opinions, protected by the First Amendment (The Financial Crisis Inquiry Commission, 2011).

In the following sections, I will try to briefly describe the concept of securitization, to review what happened to the structured finance and the role of CRAs in the mortgage market collapse. I will observe the role of the CRAs on the example of Moody’s Investors Service, as, since the company is publicly traded, there were more publicly available documents and disclosures.

2.1 Structured Finance Background

The beginnings of the structured finance market can be traced to the inaugural issue of the mortgage-based securities by Bank of America in 1977 (Fishman & Kendall, 1999). Since then the securitization market was developing and extending at ever-growing pace: by January 2008, 111,988 individual rated tranches were outstanding worldwide, with structured finance becoming the largest financial market in the world (Benmelech & Dlugosz, 2009).

Securitization facilitated an expansion of the U.S. mortgage market and modified the structure of the value chain within which financial assets, risk, and liquidity were managed (Heilpern, Haslam, & Andresson, 2009). Beginning in the mid-1990s private-label securitization practices began to expand in the market due to the wider availability of the standardized data with loan-level information on mortgage performance (The Financial Crisis Inquiry Commission, 2011). Several companies developed an easy-to-use automated system for mortgage underwriting for use by lenders, such as Desktop Underwriter or Loan prospector applications (The Financial Crisis Inquiry Commission, 2011).

Permissive regulatory conditions together with favourable accounting treatments incentivized banks to actively participate in securitization transactions. Corporations, like Citigroup, Lehman Brothers, and Morgan Stanley were actively acquiring smaller subprime lenders (The Financial Crisis Inquiry Commission, 2011). Selling complex collateralized products to investors allowed the bank executives to increase banking returns and their bonuses in a relatively short period (Heilpern, Haslam, & Andresson, 2009). The extreme forms of securitization process reached during the pre-crisis period increased the complexity and opacity of securities available in the financial market and made it difficult to assess their risk level (Cerbioni, Fabrizi, & Parbonetti, 2015). The basic securitization process was altered and additionally complicated, which resulted in the creation of ABS collateralized debt obligations (ABS CDOs) and similar securities.

2.2 CRAs and Information Asymmetry

As the securitization process was becoming more and more complex for an average investor, they became to assign a higher weight to the ratings provided by the major CRAs during their decision-making process (Jeon & Lovo, 2013). In other words, the average investor was simply unable to estimate the risk-return qualities of the structured financial instruments; credit ratings were becoming one of the main criteria while assessing the investment. The loan tranches were assigned the same letter ratings (grades), equivalent to those used in the corporate bonds' ratings. The main purpose of the credit rating is to provide a user with the means of comparing risks across various asset classes and time. Therefore, the risk of triple-A rated mortgage security was supposed to be similar to the risk of a triple-A corporate bond (The Financial Crisis Inquiry Commission, 2011). Despite this seemingly straightforward logic, by 2008, 73% of the mortgage-backed rated triple-A securities were downgraded to junk; this rating action of unprecedented scale affected mostly exclusively the MBS market (The Financial Crisis Inquiry Commission, 2011).

Federal and state rules required or encouraged financial firms and institutional investors to make investments based on the ratings produced by major CRAs, leading to undue reliance on those ratings (The Financial Crisis Inquiry Commission, 2011). Throughout the years each of the major credit rating agencies was adjusting their rating models due to ever-changing financial market conditions. Moody's, particularly, since the mid-1990s has been utilizing three models for rating mortgage-based securities (Stein, Das, Ding, & Chinchalkar, 2010). The first one was developed in 1996 and was used for rating residential mortgage-based securities. At the beginning of the 2000s, Moody's was following its strict policies regarding the quality of the ratings, it can be observed on the example of the collateralized debt obligations: no CDO could achieve a triple-A rating from Moody's if collateral consisted entirely from mortgages. The reason for that was a long-standing "diversity score", which was preventing securities with homogeneous collateral pools from winning the highest ratings (Jones, 2008). According to Moody's (Moody's Investor Service, 2007):

"Moody's Diversity Score is a measure to estimate the diversification in a portfolio… The Diversity Score is obtained from the CDO's monthly surveillance reports. More precisely in terms of modelling, the Diversity Score measures the number of uncorrelated and identical assets that would have a similar loss distribution the actual portfolio of correlated assets."

Nor Fitch, nor S&P were utilizing similar indicators. In 2003, Moody's created a new model, called M3 Prime, which was utilized for rating prime, jumbo and Alt-A deals (The Financial Crisis Inquiry Commission, 2011). By 2004, the diversity score was abolished. This decision, approved by the Moody's credit committee, led to the dramatic increase in the number of mortgages CDOs which Moody's was hired to rate (Jones, 2008). In August 2006, Moody's European Division, managed by Frederic Devon, awarded the AAA rating to the first "constant-proportion debt obligation" (hereafter: CPDO) developed by the Dutch bank ABN AMRO (Moosa, 2016). It was followed by S&P, which also awarded triple-A grade to the security (Jones, 2008). About two weeks after those first ratings came out, Fitch, which was not hired to rate any CPDOs, said it couldn't understand how they had been achieved: its models had put CPDO bonds barely above junk grade (Moosa, 2016). After the other banks realized the perspectives of this new financial product, they started to develop their versions of the CPDO. Moody's and S&P were hired to rate the majority of CPDOs (Jones, 2008). CPDOs were reported to represent the most lucrative individual instrument for the CRAs. The statement about the CPDO quality provided by Fitch did not influence the market, as CPDO was rated as top investment-grade security by Moody's and S&P. According to Moosa (2016), at a time Moody's has realized that one of the analysts did a mistake: a small error in the computer coding that Moody's used to run its CPDO performance stimulation had thrown the results way off. Error or computer "bug" hasn't been disclosed to investors, instead, the rating model was corrected in a way that new CPDO could still get a AAA score. In 2007, Moody's residential mortgage bond team in the US found potential problems undermining the quality of the ratings: from January on it started to track a disturbing rise in the number of subprime mortgages going delinquent (Jones, 2008). Despite the alarming trend Moody's was slow to react and did not make any amendments to its model outlook. In their 2007 special report Moody's described the situation as following (Moody's Investors Service, 2007):

"The recent weakening of credit performance of subprime residential mortgage loans that were originated in 2006 has become the focus of much attention…Mortgage lenders have begun to pull back from the subprime market while several specialized subprime lenders have closed down."

However, the conclusion part of the same document states:

"Given the assumptions, we found that the effects were generally mild to moderate for SF CDOs with exposure to subprime RMBS up to the observed average but could be severe for the most heavily exposed transactions."

In other words, Moody's did not see the need to make any adjustments until further signals. There are three key measures that rating agencies use to assess the soundness of a mortgage-backed bond (Jones, 2008): delinquency rate is the first, the second one shows the number of people delinquent for more than 90 days, and the third shows the number of foreclosures. Soon after publishing its report in March 2007, Moody's started to track the ever-increasing number of consistently missed payments. On the second of August, Moody's publicly announced its rating methodology update (Moody's Investors Service, 2007). The main changes included the new delinquency assumptions, which resulted in a serious of unprecedented downgrades: on August 16, Moody's released the results of its revised methodology (Jones, 2008). 691 mortgage bonds were downgraded at once and similar rating actions were followed by Fitch and S&P.

Moody’s as well as Fitch and S&P was denying any wrongdoings from their side and was addressing originators as one of the main causes of the crisis (Moody's Investors Service, 2007):

“As we have frequently commented on in recent years, originators of subprime loans have loosened underwriting guidelines and materially increased the layering of risk… declines in home price appreciation nationwide also have played a role in these early defaults…”

Nonetheless, it is evident, that CRAs were relying on the flawed and outdated models to issue their ratings, failed to perform meaningful due diligence on the assets underlying the securities, and, moreover, continued to rely on those models even after it became obvious that the models were wrong (The Financial Crisis Inquiry Commission, 2011).

2.3 Dodd-Frank Financial Reform Bill (2010)

S&P as well as other major CRAs was claiming that their credit ratings were “a uniform measure of credit quality globally and across all types of debt instruments” (S&P, 2007), without taking any legal responsibility for their quality. Despite the ratings’ status as a “uniform measure” and all the reassuring statements, the major CRAs are criticized for being a central figure in the financial crisis. Particularly, their handling of the structured finance securities ratings was followed with a chorus of concern, after a series of unprecedented downgrades in 2007 and 2008 (Jeon & Lovo, 2013).

Outdated rating models together with the fact, that CRAs were not adequately regulated by the Securities and Exchange Commission or any other regulator to ensure the quality of their ratings, led to the major inflation of the ratings (The Financial Crisis Inquiry Commission, 2011). The mass downgrades and defaults that followed underlined the need to scrutinize the quality of ratings issued by the CRAs. In response to the financial crisis and obscure credit rating agencies regulation, in July 2010, Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dimitrov, Palia, & Tang, 2015).

The document outlined a series of broad reforms to the market of credit ratings, it delegated the responsibility of developing the specific rules and regulations to the SEC (Dimitrov, Palia, & Tang, 2015). In other words, most of the control provisions and governance reform were drawn to be finalized as of April 2014 (Toscano, 2020). Two regulatory provisions, however, were implemented already by 2013 (Dimitrov, Palia, & Tang, 2015): 1) Dodd-Frank significantly increased CRAs’ liability for issuing inaccurate ratings, by lessening the pleading standards for private actions against CRAs (Section 939); 2) the law made it easier for the SEC to impose sanctions on CRAs and to bring claims against CRAs for material misstatements and fraud (Section 933).

Historically, major CRAs were able to successfully claim that credit ratings constitute opinions protected as free speech under the First Amendment (Coffee, 2010). Such a defence requires plaintiffs to prove that CRAs issued ratings with the knowledge they are false or with reckless disregard for their accuracy, effectively preventing most lawsuits from proceeding to trial (Dimitrov, Palia, & Tang, 2015). The drastic change that was brought with the Dodd-Frank Act consists of the following: in order to proceed with the lawsuit to trial plaintiffs must only provide evidence that CRAs knowingly or recklessly failed to conduct a reasonable investigation of the rated security. Section 939 of the Act makes CRAs liable as experts for material misstatements and omissions in registration statements filed with the SEC (Dimitrov, Palia, & Tang, 2015). In response to that CRAs refused to consent to have their ratings included in the registration statements for both structured finance products and corporate bonds (Coffee, 2010). Due to the refusal, the market for asset-backed securities declined significantly, leading the SEC to suspend Section 939 only for the structured finance products.

Provisions of Section 933 specifically stated that CRAs' statements are no longer considered forward-looking for the purpose of the safe harbour provisions of the Securities and Exchange Act of 1934 (Dimitrov, Palia, & Tang, 2015). In other words, these changes allowed the SEC to punish the CRAs for fraud and material misstatements. CRAs are now obliged to disclose the information on internal controls, rating methodologies, third-party due diligence in their annual reports (Coffee, 2010).

2.4 Regulatory Governance of CRAs in the EU

Similar to the case of the US and SEC, for the long time the European Union did not have the regulatory authority with a legal binding force over the credit rating agencies. "Statement of Principles Regarding the Activities of Credit Rating Agencies" (hereafter: IOSCO Principles), published in September 2003 by the International Organization of Securities Commission (hereafter: IOSCO), represented the first regulatory attempt in the EU. It laid out high-level objectives but left open the matters of implementation (Deipenbrock & Andenas, 2011). More detailed guidance was issued by the end of 2004 – the "Code of Conduct Fundamentals". At the time IOSCO did not have a law-making power, therefore, both IOSCO Code Principles and Fundamentals were viewed only as a set of recommendations. Moreover, the IOSCO Code Fundamentals were defined in an abstract manner leaving room for interpretation (Deipenbrock & Andenas, 2011). Such a lenient regulation can be at least partly explained by the high international credibility of the major CRAs as well as an example of colleagues from overseas: until 2006, SEC also did not exercise any real regulatory power over the CRAs.

When the first edition of the IOSCO Code Fundamentals was published in 2004, the EU adopted a respective self-regulatory regime with the major CRAs operating in the EU (Deipenbrock & Andenas, 2011). Established on June 6, 2001, The Committee of European

Securities Regulators (CESR) had to oversee the compliance with the IOSCO Code Fundamentals and report on it annually (ESMA, 2019). Throughout this period the European Union and consequently its institutions were seeking to maintain and strengthen a market-driven correction mechanism rather than trying to establish the regulatory governing body, which would possess the legal authority over the CRAs. In other words, the authorities were attempting to harness the private investors to promote the public good, by spreading the information on ratings' quality and ignoring the CRAs with inflated ratings (McVea, 2010). CESR was one of the main advocates of the market-driven approach, proposing the establishment of the international rather than European standard-setting and monitoring body (Deipenbrock & Andenas, 2011).

The financial crisis of 2008 has proven that the intended self-governing regime was a failure. The ever-rising need for monitoring the credit rating industry appeared especially acute to the European regulators after the collapse of Lehman Brothers in the autumn same year. By 2008, the US regulators had already implemented the Credit Rating Agency Reform Act of 2006, which was further amended by the Dodd-Frank financial bill. In December 2009, the European Parliament the Council accepted the new European Regulation on Credit Rating Agencies No.1060/2009 (Deipenbrock & Andenas, 2011). The Official Journal of the European Union emphasizes the lack of control over the CRAs and particularly the fact that major CRAs were based outside of the EU (The Official Journal of the European Union, 2009):

"Currently, most credit rating agencies have their headquarters outside the Community. Most Member States do not regulate the activities of credit rating agencies or the conditions for the issuing of credit ratings… The Commission will continue to work with its international partners to ensure convergence of the rules applying to credit rating agencies."

Curious detail regarding the regulations of the smaller CRAs was added to the initial text of regulation (The Official Journal of the European Union, 2009):

"In order to take account of the specific condition of credit rating agencies that have fewer than 50 employees, the competent authorities should be able to exempt such credit rating agencies from some of the obligations laid down by this Regulation…"

If taking to account that the majority of criticism was focused on the three major CRAs, the European authorities were trying to prevent the smaller CRAs from being hurt by the regulation. Considering all of the facts mentioned above, I can assume that by making such an exemption, authorities were trying to prevent the regulation from hindering the small EU-based credit agencies.

In 2010, the European System of Financial Supervision was created, followed by the Single Supervisory Mechanism (Chiu, 2014). In January 2011, CESR was replaced as a monitoring authority with the European Securities and Markets Authority (hereafter: ESMA). The appointment signified the drastic change in the regulatory regime: market-driven mechanism was replaced by the strong grip of regulating authority. ESMA's competences were significantly broadened in comparison with CESR's: in contrast to the predecessor, ESMA possessed an authority to draft technical standards, emergency powers as well as competences regarding overseeing the systemic risk of cross border financial institutions (Deipenbrock & Andenas, 2011). ESMA amended the European CRA Regulation in 2011 and, later, in 2013 (ESMA, 2019).

The European CRA Regulation obliged agencies to disclose information regarding the procedures and methodologies used to issue and review ratings, policies and procedures to identify, manage and disclose any conflicts of interest, information regarding ratings analysts, compensation and performance evaluation arrangements and services other than rating activities the CRAs intend to provide (Deipenbrock & Andenas, 2011). Moreover, CRAs had to report in-depth information on its structure, corporate governance, subsidiaries, and ownership, similarly to the CRA Reform Act of 2006. After all the required information being reported, the governing body decides on CRAs' registration. In case CRA's registration application is approved, the information which was provided during the registration process shall not be disclosed afterward (Deipenbrock & Andenas, 2011). According to the CESR Annual Report of 2010 (CESR, 2010) by December 2010, 45 legal entities applied for certification and only one has been registered. By the 14th of November 2019, there were 34 registered CRAs not including the subsidiaries (ESMA, 2019).

In addition to the disclosure requirements, the European CRA Regulation comprised the requirements for the CRAs' rating methodologies. According to Article 8 (3) (The Official Journal of the European Union, 2009):

"A credit rating agency shall use rating methodologies that are rigorous, systematic, continuous, and subject to validation based on historical experience, including back-testing."

Conflicts of interest connected to the "issuer-pays" model were not addressed in the 2009 European CRA Regulation. Member States had to appoint their respective authorities which would implement the monitoring and regulation over the CRAs as well as develop the national penalty laws applicable to violations of the CRA Regulation (Deipenbrock & Andenas, 2011). In other words, ESMA was intended to be an exclusively responsible authority for the registration and supervision of the registered rating agencies, however, the implementation of the rules and operational decision-making would be executed by the respectable authorities in each EU Member State (hereafter: MS).

On the 21st of May 2013, The European Parliament and the Council presented the new amendment to the current European CRA Regulation. The amendment to the Regulation supported a move towards decreasing the dependence on the credit ratings and encouraged investors to conduct their own due diligence (The Official Journal of the European Union, 2013):

“Over-reliance on credit ratings should be reduced and all the automatic effects deriving from credit ratings should be gradually eliminated. Credit institutions and investment firms should be encouraged to put in place internal procedures in order to make their own credit risk assessment and should encourage investors to perform due diligence exercise. Within the framework this Regulation provides that financial institutions should not solely or mechanically rely on credit ratings.”

Despite the text of the Regulation decreasing the dependence on the CRA-issued ratings represented a difficult task since the financial infrastructure and operations of the EU were deeply intertwined with the usage of externally issued ratings. For example, the Basel Committee issued a new post-crisis Basel III Capital Accord to address gaps and weaknesses in previous Accords, but Basel III does not abolish Basel II and retains the approaches to measuring credit and market risk that incorporate the use of ratings (Deipenbrock & Andenas, 2011). EMSA continued its strategy to foster the growth of the EU-based CRAs by introducing the rotation mechanism and various means of financial support as well as addressing the conflicts of interest issue arising due to the “issuer-pays” model (The Official Journal of the European Union, 2013):

“In order to increase competition in a market that has been dominated by three credit rating agencies, measures should be taken to encourage the use of smaller credit rating agencies…The credit rating market shows that, traditionally, credit rating agencies and rated entities enter into long-lasting relationships. This raises the risk of familiarity, as the credit rating agency may become too sympathetic to the desires of the rated entity… The Commission should put forward, by the end of 2013, a report regarding the feasibility of a network of smaller credit rating agencies in order to increase competition in the market. That report should evaluate Union financial and non-financial support and incentives for the creation of such a network… It is appropriate to introduce rotation on the credit rating market for re-securitizations.”

Though the intentions to organize the supportive network for the smaller CRAs were clearly outlined in the text of the Regulation, the report of the European Commission on the matter, published in 2014, rejected the feasibility of the proposition (European Comission, 2014):

“The analysis of the feasibility of the options for the creation of a network of smaller CRAs has identified multiple market obstacles for the establishment of an integrated network as well as some obstacles limiting the potential scope of a cooperation network.”

Amendment to the Regulation also attempted to limit the discrepancies in ratings arising due to rating methodologies modifications or updates and to force CRAs to take into consideration the feedback from issuers and investors when updating the methodology (The Official Journal of the European Union, 2013):

“It is important to ensure that modifications to the rating methodologies do not result in less rigorous methodologies. For that purpose, issuers, investors and other interested parties should have the opportunity to comment on any intended change to rating methodologies.”

The most significant and questionable change, however, covered the accountability of the CRAs to investors. Article 35a of the Regulation states (The Official Journal of the European Union, 2013):

“Where a credit rating agency has committed, internationally or with gross negligence, any of the infringements listed in Annex III having an impact on a credit rating, an investor or issuer may claim damages from the credit rating agency for damage caused to it… An investor may claim damages… where it establishes that it has reasonably relied on… or otherwise with due care, on a credit rating for a decision to invest into, hold onto or divest from a financial instrument covered by that credit rating.”

The Regulation for the first time held the CRAs accountable for the quality of ratings under the condition that investors would be able to prove that CRA had infringed the regulation intentionally or with gross negligence (Deipenbrock & Andenas, 2011). Such a condition puts the burden of proof and all the costs associated with it on the shoulders of investors.

The European response to the credit rating crisis though came later than the US regulatory framework, attempted to address the main issues associated with the CRAs: conflict of interest, flawed models and non-timely downgrades, and lack of accountability. Although actual regulation was written in an obscure way, CRAs became obligated to report the key assumptions used in their models as well as maintain the rating model updated and subjected to validation. The times when CRAs could change the compositions of their models indefinitely to achieve targeted ratings were over. The regulatory changes passed in the EU were resembling the CRA Reform Act of 2006 both in the targets and the instruments utilized. EMSA, however, obtained greater authority than SEC, because it was empowered to evaluate the methodologies and procedures used by CRAs (Coffee, 2010). The accountability issue was addressed, by granting the right to sue CRA to investors. Conflict of interest was addressed by establishing the obligatory rotation of the CRAs on the re-securitization issuing. Moreover, ESMA became the authorized monitoring body, similarly to the SEC in the United States (hereafter: US). Regulators were seeking to resolve the issues mentioned above on the CRA or entity level, effectively ignoring the individuals behind the ratings. Though information about the rating analysts is mandatory to report during the registration process after the process is finished the reported information is not reviewed or updated. The European authorities were considering the lack of EU-based CRAs as a competitive disadvantage for the rated European entities (Deipenbrock & Andenas, 2011), therefore several attempts were made to foster competitiveness, development, and growth of the European CRAs.

In my opinion increasing the competition in the market and increasing the number of EU-based CRAs will only partially solve the issue of unreliable and inflated ratings. First, the composition of the credit rating industry is such that the dominance of the "issuer-pays" model is by itself results in the conflict of interests and putting the regulatory pressure on the CRAs will not be sufficient enough to solve the issue completely. Second, the natural barrier to entry is present on the market: the huge reputational advantage of the three incumbent CRAs. For the European companies to improve their perceived reputation they have to achieve longer industry tenure, which is possible only by putting lower price tags on their ratings than the three major CRAs. Without the lower prices on their ratings, the EU-based CRAs would not be able to get hired by the issuers, except if the newcomers would produce the more beneficial ratings (which contradicts with the intentions of the regulatory authorities). The long-term financial support from the European authorities will be necessary for the EU-based CRAs to survive and establish its presence on the market. The academical research suggested contradictory results regarding the benefits of higher competition: a higher number of CRAs present on the market may incentivize issuers to shop for higher ratings. Third, in addition to the incumbent conflict of interest arising between CRA and rated entity, the agency problem on the level of individuals is present. If the European authorities will try to change the dominant pricing model on the market it most likely will result in the powerful opposition from both issuers and CRAs, as well as tremendous costs and complexities associated with the transition. Considering the actual market conditions, I believe, the best alternative to the pricing model transition is to focus the regulative efforts on the individuals behind the ratings: instead of attempting to influence the behaviour and incentives of CRAs, authorities have to regulate the behaviour of individual credit rating analysts.

3 EFFECTS OF INDIVIDUALS ON THE ECONOMIC PERFORMANCE

At the beginning of this chapter, I will try to present the initial hypothesis why credit rating analysts matter in determining the credit rating, and subsequently, I will try to describe the development of theories about the influence of individuals on the forecasting results, in order to apply the principles and conclusions ensued from this research to the context of work of a credit rating analyst. I assume that the conclusions of the research on equity analysts can be at least partially applied to the case of credit rating analysts due to the similar nature and requirements of the job, which can be indicated by the common revolving door practice: historically credit rating analysts are often employed in the investment banks and financial institutions (Kempf, 2020).

3.1 The Role of Credit Analysts

Throughout the years CRAs were stating that companies' fundamentals were at the center of scrutiny while rating the firms. However, the identity of an analyst may matter if analysts gather different information or interpret the same information differently (Fracassi, Petry, & Tate, 2013). Similarly, to the managers in the decision-making process of the company, analysts face uncertainty while making rating recommendation. And even if the information gathering process is standardized within the agency, different analysts may provide different interpretations for the same information (Fracassi, Petry, & Tate, 2013). Another analogy with managers' role comes from the potential agency problem: analysts may develop a long-term relationship with the management of covered firms leading to the potential conflict of interests. The Dodd-Frank Act, however, limited the probability of such conflicts of interest arising (Dimitrov, Palia, & Tang, 2015).

In their paper Fracassi, Petry and Tate (2013) measured the effects of individual analysts on long-term credit ratings using the regression model. The model contained fixed effects for each firm-quarter and each of the three rating agencies (Fracassi, Petry, & Tate, 2013). In their initial model, each analysts' rating was compared only to peers who rate the same company at the same time period. By performing such a resampling, researchers corrected their estimates of analyst effects for non-random matching of analysts to the firms. Those observed analyst effects cannot be properly explained due to the major differences in the quality of private information collected by analysts who cover the same firm, instead analyst fixed effects are intended to capture a systematic tendency for analysts to be either relatively more optimistic or pessimistic than peers across the set of firms that they rate (Fracassi, Petry, & Tate, 2013). The result of the initial testing showed that the analyst fixed effect was observed to have higher explanatory power than the agency fixed effects. In other words, based on the model analysts' identity had a larger effect on the variation in ratings across agencies than the effects of CRA that covered the rated firm. Analyst fixed effects explained from 29.55% to 31.57% of the variation in rating across agencies covering the same firm.

Such a scale of explained variation indicates the existence of analyst-specific biases on credit ratings. These individual biases, insignificant at first glance, carry through to companies' cost of capital and, subsequently, their financing policies. By measuring the link between analyst biases and the credit spreads on firms' outstanding debt, Fracassi, Petry and Tate established, that market does not fully account for analyst biases in ratings, hence, the coefficient estimate on the analyst effect was significantly different from zero. The tests indicated that the market undoes only about 29% of the effect of analyst biases on ratings.

After establishing the existence and significance of the analyst-specific effects, resulting from individual biases, Fracassi, Petry and Tate utilized a logit regression of debt issuance on credit ratings to test whether these effects do influence the companies' financial policies. Test results suggested that analyst biases had a significant negative effect on the odds of debt issuance: one notch increase in relative analyst pessimism decreases the odds of debt issuance by 27%. As analyst pessimism increases, so does the price at which firms raise new public debt; which is consistent with the previous finding. According to Fracassi, Petry and Tate (2013, p. 5):

“We find some evidence that firms with more pessimistic analysts hold larger cash reserves, perhaps in response to the higher cost of debt capital. Moreover, we estimate a significant one percentage point lower growth rate in sales for a one-notch increase in ratings due to analyst pessimism. Thus, analyst rating biases only affect the composition of the firm’s liabilities but appear to affect real decisions in a way that affects the firm’s ability to grow”.

In this thesis, I will try to replicate the results achieved by Fracassi, Petry and Tate (2013). Therefore, I assume that credit ratings cannot be fully explained by the firm, macroeconomic and agency factors captured by firm and agency fixed effects, hence our primary hypothesis is as following:

- Hypothesis 1: Individual analyst’s characteristics have an effect on the credit rating received by the company.

3.2 Forecast Accuracy and Analysts’ Experience

At the end of the 20th century, M. B. Clement (1999)in his paper focused on estimating the influence of analysts’ professional traits (such as experience, a surrogate variable representing one’s ability and skill) and employer size (a surrogate for resources available to the analyst) on the equity analysts’ forecasting behaviour. Prior research (e.g. O'Brien, 1990; Richards, 1976) did not provide evidence of the existence of the systematic difference in the analysts’ forecast performance. Because of the mixed results provided by several major studies at the time (e.g. Brown & Rozeff, 1980; Coggin & Hunter, 1989; Butler & Lang, 1991) determinants of the analysts’ forecast accuracy were hardly studied.

Clement (1999) suggested that analysts' characteristics may be used in predicting the differences in forecasted values, the paper represented a breakthrough and ground for further research examining determinants of analysts’ forecast accuracy. His main hypotheses regarding the ability of an individual analyst were presented as follows (Clement, 1999):

- Holding resources (employer size) and portfolio complexity (number of firms and industries followed) constant, forecast accuracy increases with forecasting experience.
- Holding resources (employer size) and portfolio complexity (number of firms and industries followed) constant, forecast accuracy increases with firm-specific forecasting experience.

In order to construct the model, which would include the unobservable characteristics (like a skill or ability), it is necessary to determine the applicable indicators. In the case of ability, Clement (1999) assumed that analyst labour market functions as a contest, where analysts showing better performance continues and the weaker performers are forced to leave the profession. Therefore, analysts with greater industry tenure are supposed to perform better on average (unless an analyst was able to keep his position due to luck). The following assumption is consistent with the learning curve model (Anzanello & Fogliatto, 2011): analysts' general skills and knowledge improve as the repetition of certain tasks occur. In addition to the improvements in analysts' general knowledge and skills, firm-specific skills develop with a greater analyst's experience (Clement, 1999): if analyst covers the firm for the longer period of time, he might gain a better understanding of the idiosyncrasies of particular firm's reporting practices or he might establish better relationships with insiders and thereby gain better access to managers' private information. The results of tests suggested that forecast accuracy tended to increase with experience and employer size and decrease with the number of firms and industries followed by an analyst. Some of the results from later research indicate that firm-specific experience has an opposite effect on the rating accuracy: according to Fracassi, Petry and Tate (2013, p. 6) the rating quality deteriorates with the length of time analysts have covered a particular firm; particularly, ratings become more optimistic and less accurate over a 3-year horizon.

The main implication of the results achieved by Clement was outlining the potential area for future research: modelling analysts' characteristics may be useful in predicting forecast accuracy.

Katherine Schipper (1991) suggested two major points regarding further forecast accuracy research, that have shaped the direction of the subsequent research on the topic:

- She suggested that the research regarding analysts' earnings forecasts was focused too narrowly on the statistical properties of the forecasts, without considering the full decision context and economic incentives affecting these properties. Schipper suggested that a more complete description of analysts' economic incentives and the role of earnings forecasts in the full decision context of analysts should lead to richer hypotheses regarding the statistical properties of the earnings forecasts.
- The second major point was that the research on the statistical properties of analysts' earnings forecasts focuses on outputs from, rather than inputs to, analysts' decision processes. Schipper called for more research into how analysts do use accounting information and their own earnings forecasts in making decisions.

Schipper's commentary together with the results from the more recent studies (Stickel, 1992; Sinha, Brown, & Das, 1997) documented the systematic differences, made the idea of further research into the factors influencing analysts' forecast accuracy became broadly accepted. Particularly, Sinha, Brown, and Das (1997) suggested that systematic ex-post differences exist in analysts forecast accuracy: by performing a series of ex-ante tests of forecast accuracy, they observed that analysts classified as superior in one period continue to be classified as superior in later periods, but analysts classified as inferior in one period do not continue to be classified as inferior in later periods. Moreover, results suggested that some analysts' earnings forecasts should be weighted higher than others when formulating composite earnings expectations. This suggestion is predicated on the assumption that capital markets distinguish between analysts who are ex-ante superior, and that they utilize this information when formulating stock prices (Sinha, Brown, & Das, 1997). Despite the strong evidence of the existence of the systematic differences, researchers did not yet attempt to explain the observed differences.

P. O'Brown (1990) calls for research into whether some analysts are better forecasters than others, whether the market's earnings expectations reflect these differences, and the degree to which consensus forecasts drawn from analyst tracking services such as I/B/E/S reflect investor expectations. Earnings forecasting was chosen as the only analysed activity due to its quantitative nature and that it can be compared with observable earnings outcomes. The study did not explore any significant differences between the analysts, in other words, individual analysts failed to exhibit a consistent difference in their forecasting ability.

Since 1992, two questions of the utter importance for the future models and research were investigated (Ramnath, Rock, & Shane, 2008):

- What information affects the development of analysts' earnings forecasts and recommendations?
- How do analysts transform information into target prices and stock recommendations?

Researchers started to focus on the way analysts process information (e.g., Block, 1999), rather than just studying the inputs analysts use in their forecasting job. Jacob, Lys, and Neale (1997) examined the contributions of experience and brokerage house variables on analyst forecasting attributes including forecast accuracy, frequency, and horizon. The results supported the hypothesis that the employer's size (here, surrogate for various brokerage house variables) is positively associated with the forecast accuracy, however, no evidence that experience is positively associated with the forecast accuracy was found. In contrast, the research carried out by Mikhail, Walther, and Willis (1997) did find evidence of positive associations between forecast accuracy and both employer's size and experience. The results were supported by Clement (1999) performing the tests on a larger sample and a broader set of variables included. Firm-specific forecasting experience was found to relate to the accuracy of forecasts produced by the analyst as well as with the profitability of stock recommendations. However, it is hardly possible to determine how this firm-specific experience was obtained since it is hardly feasible to separate the learning effects from the effects of improved access to management information as analyst gains experience (Mikhail, Walther, & Willis, 1997).

The following assumption was made regarding the applicability of previously mentioned findings to the case of credit rating analytics' accuracy: I assumed that it is possible to apply the findings regarding the factors influencing equity analysts' accuracy to the case of credit rating analysts, due to the similar nature of the profession as well as a high emphasis on ones' forecasting and analytical abilities in both cases. This similarity is evident from the case of high employees' turnover between rating agencies and investment banks (Story, 2010): during the mortgage boom, companies like Goldman Sachs offered generous pay-packages to analysts who had been working at much lower pay at the rating agencies.

Based on the findings mentioned above I formulated the following hypotheses regarding the credit rating analysts' rating accuracy:

- Hypothesis 2: Analyst's industry tenure and forecasting experience have an effect on the credit rating received by the company.

I used the number of prior years in which an analyst has been covering the firm as a proxy for firm-specific experience, as well as the number of years during which an analyst was working in the industry as a proxy for the industry tenure (forecasting experience). Older research suggests the positive effects of the firm-specific experience on the quality of the forecasts, however, the more recent papers (Fracassi, Petry, & Tate, 2013) reject such views. Initially I assumed the positive effects of the industry tenure on forecast accuracy.

3.3 Optimism in Ratings and Other Analysts' Characteristics

Apart from accuracy, the analyst's optimism has a major effect on ratings. Many research papers on the topic find that analysts tend to be optimistic rather than pessimistic (Krolikowski, Chen, & Mohr, 2016). Whether the origins of it lie in the belief of possession of the superior analytical or forecasting skills or abundance of the private information, overly optimistic forecasts tend to backfire at the analysts in the long run. In the context of the credit rating industry, an over-optimistic forecast can lead to inflated and misrepresentative ratings. Therefore, I believe, it is crucial to study the analysts' characteristics which tend to increase or decrease the optimism.

Fracassi, Petry and Tate (2013) in their research observed that analysts with Master of Business Administration (hereafter: MBA) and with longer industry tenure tend to provide less optimistic ratings that are more accurate over a 2- or 3- year horizon, consistent with higher skill or less bias. Based on that, I formulate the following hypotheses:

- Hypothesis 3: Analyst's MBA diploma has an effect on the credit rating received by the company.

In 2009, De Franco and Zhou (2009) were comparing the performance of the equity analysts with and without a Chartered Financial Analyst (hereafter: CFA) designation. CFA charter holder status can be achieved after passing a series of examinations with the CFA Institute, along with meeting other criteria. CFA designation is widely spread among the financial professionals: both equity and credit analysts are pursuing the charter holder status in order to gain various employment benefits as well as gain valuable financial knowledge and skills.

The demand for CFA designation was gradually growing over the last few decades. According to the CFA Institute, in 1990, there were 10,000 charter holders worldwide, by 2008 – 89,000; and by 2020 there were over 154,000 charter holders (CFA Institute, 2020). After conducting a series of tests researchers achieved the following results (De Franco & Zhou, 2009):

"We find evidence that charter holder forecasts are timelier than those of non-charter holders. The results for accuracy are mixed. Charter holders' forecasts are more accurate if we control for the day of the forecast and less accurate if we do not. There is some evidence that charter holders act more boldly and less opportunistically…"

Mixed results for accuracy can be partially explained with the possibility that non-charter holders could have acquired valuable accounting or finance skills via MBA, Ph.D., industry experience, or other examination-based certifications. In addition to the direct comparison between charter holders and non-charter holders, researchers were able to analyse the performance of the same analysts before and after attaining the charter holder status (De Franco & Zhou, 2009):

"We also find evidence that charter holders become timelier relative to non-charter holders in the period after obtaining their charter. These results provide support for a human-capital explanation, in which CFA charter holders improve their productivity during the CFA program."

Based on the research results, I can assume that CFA designation will have a similar effect on the productivity and accuracy of the credit rating analysts, due to the similar nature of the knowledge and skills required. Therefore, I formulate the following hypotheses:

- Hypothesis 4: Analyst's CFA designation has an effect on the credit rating received by the company.

Despite the mixed results regarding the improvements in accuracy, I assume that gaining additional accounting and finance skills will have a positive effect on the analyst's efficiency and, subsequently, rating accuracy.

In May 2010, the research by Alok Kumar was published in the Journal of Accounting Research. The paper was investigating the systematic differences between the forecasting style and abilities of female and male equity analysts. The research indicated the following results (Kumar, 2010):

"I posit that only female analysts with superior forecasting abilities enter the profession due to a perception of discrimination in the analyst labour market. Consistent with the self-selection hypothesis, I find that female analysts issue bolder and more accurate forecasts, where the accuracy is higher in market segments with a lower concentration of female analysts. The Female-male accuracy differences are robust and cannot be explained by non-random distribution of female analysts across stocks, industries, or brokerage firms."

Besides, the results show that female analysts on average get less coverage in the media than their male peers. Interestingly, the market at least partially does recognize the accuracy difference by stronger responses to updates from the female analysts even despite the fewer media coverage.

In this thesis, I do not intend to research whether gender discrimination is present in the credit rating industry, instead, I attempt to test whether gender has an effect on one's perception of input data and forecasting abilities and, consequently, the rating quality. Therefore, based on the results indicated by the previous research (Kumar, 2010) I formulate the following hypotheses:

- Hypothesis 5: Analyst's gender has an effect on the credit rating received by the company.

4 MAJOR CRA'S RATING SYSTEM

The main dependent variable of this research is a credit rating, based on a quantitative analysis assessment of the creditworthiness of a borrower. According to Fitch (Fitch Ratings, 2019):

"Fitch's credit ratings relating to issuers are an opinion on the relative ability of an entity to meet financial commitments, such as interest, preferred dividends, repayment of principal, insurance claims or counterparty obligations."

In other words, the credit rating expresses the default risk, and as an "opinion" it should not be interpreted as a buy or sell recommendation. Since Moody's adopted the single symbol rating system at the beginning of the twentieth century, Fitch and S&P followed with the similar systems. In the scientific literature on the credit quality the terms "investment grade" and "speculative grade" commonly mentioned. Historically the terms were used as a shorthand to describe the categories 'AAA' to 'BBB' ("investment grade") and 'BB' to 'D' ("speculative grade") (Fitch Ratings, 2019). Investment grade category usually consists of bonds with a low to moderate level of risk, whereas speculative of "junk" category is supposed to indicate higher default probability to investors. The historic default of AAA-rated securities is well under one percent in any given ten-year period, whereas for B-rated securities, the ten-year default probability equals 45% (Committee on Banking, Housing, and Urban Affairs, 2006).

Figure 1: Credit Rating System and Letter Rating Conversion

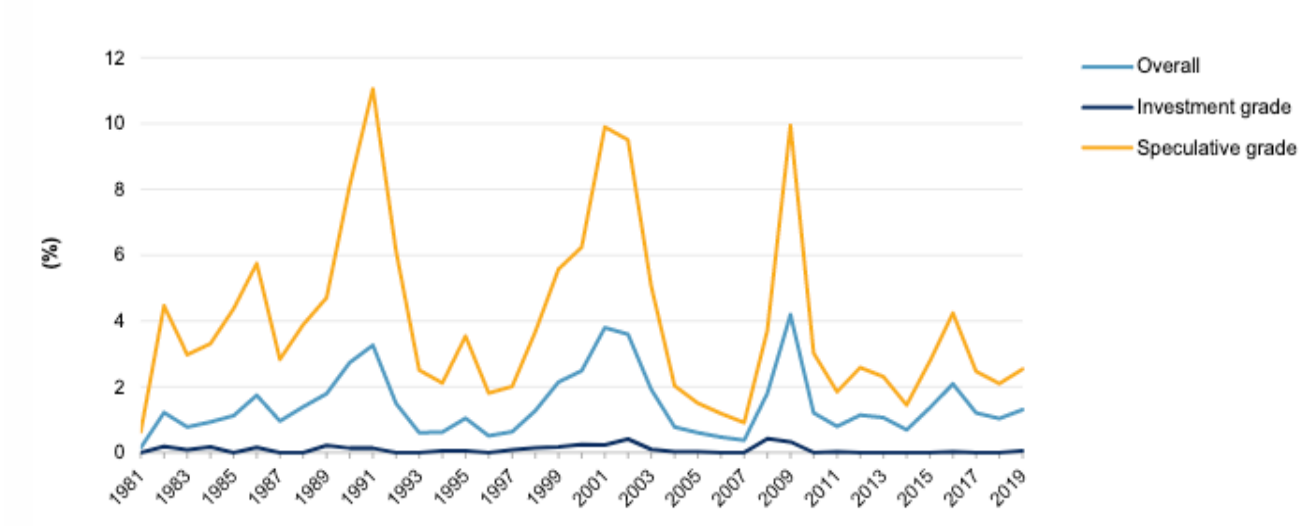
Moody's	S&P	Fitch	
Aaa	AAA	AAA	Prime
Aa1	AA+	AA+	High grade
Aa2	AA	AA	
Aa3	AA-	AA-	
A1	A+	A+	Upper medium grade
A2	A	A	
A3	A-	A-	
Baa1	BBB+	BBB+	Lower medium grade
Baa2	BBB	BBB	
Baa3	BBB-	BBB-	
Ba1	BB+	BB+	Non-investment grade speculative
Ba2	BB	BB	
Ba3	BB-	BB-	
B1	B+	B+	Highly speculative
B2	B	B	
B3	B-	B-	
Caa1	CCC+	CCC	Substantial risk
Caa2	CCC		Extremely speculative
Caa3	CCC-		Default imminent with little prospect for recovery
Ca	CC	CC	
	C	C	
C	D	D	In default
/			
/			

"Junk"

Source: Wolfstreet.com (2020).

According to the 2020 Annual Global Study on the default and rating transition by S&P (S&P Global, 2020) 118 defaults occurred in the year 2019: out of them only two companies possessed an investment-grade rating. In fact, for the first time in three years, there were defaults from companies that started the year with investment-grade ratings (S&P Global, 2020). The 2019 default figures correspond with the trend observable from the Default Rates statistics in the Figure 2: the default probability of the investment-grade rated companies represents just a fraction of such of the companies rated with the speculative-grade.

Figure 2:Global Default Rates: Investment Grade Versus Speculative Grade



Source: S&P Global (2020).

5 EMPIRICAL RESEARCH

5.1 Methodology

The methods used in the following chapters of the thesis were chosen based on the literature review of the most common indicators of risk used in the assessment of the credit quality of the corporate debt. In my research, I focused on the Long Term Senior Unsecured Debt, therefore, selecting the final publicly published credit rating as a dependent variable. To test the validity of the hypotheses outlined in the previous chapters, I intend to construct the model, where the final published credit rating will be explained using the sets of independent variables. These sets of explanatory variables were selected to represent the company's performance during the financial year corresponding with the timeframe of the rating process, key analyst's traits (a surrogate for analyst's identity) as well as the fixed agency effects (depending on which CRA was in charge for the rating).

5.1.1 Initial Model

To validate the hypotheses stated in the previous chapters, it is necessary to test and analyse the correlation structure between the final published credit rating score and analyst-specific fixed effects. Bertrand and Schoar (2003) used the following regression model to test the correlation between the firm's policies and corporate manager's effects separately from the firm's effects:

$$y_{it} = a_t + \gamma_i + \beta X_{it} + \lambda_{CEO} + \lambda_{CFO} + \lambda_{Others} + \varepsilon_{it} \quad (1)$$

As equation (1) shows, y_{it} represented one the corporate policy variables, a_t represented the company's year fixed effects, γ_i were firm fixed effects, X_{it} represented a vector of time-verying firm level controls and ε_{it} was an error term (Bertrand & Schoar, 2003). The remaining three variables represent the key part of the model which allowed the separate analysis of the manager's fixed effects. Though the research was focused on studying the fixed effects of managers in the context of test the assumed managers' homogeneity, the developed model can be used also for analysing the fixed effects of the credit rating analysts.

Fracassi, Petry and Tate (2013) utilized similar model in their research on the credit analysts:

$$Rating_{ijt} = a_{jt} + \beta_i + \gamma_{analyst} + \varepsilon_{ijt} \tag{2}$$

As equation (2) shows, $Rating_{ijt}$ represented the long-term issuer rating for the firm j in quarter *t* by rating agency *i*, a_{jt} was a firm-quarter fixed effect, β_i was a rating agency fixed effect and ε_{ijt} was an error term. The remaining variable of interest was a dummy variable for each sample analyst: it would take the value of 1 only under the condition that analyst was covering the firm *j* in quarter *t* for agency *i* and zero otherwise (Fracassi, Petry, & Tate, 2013). Using dummy variables allowed to test the researchers' null hypothesis:

"Over-reliance on credit ratings should be reduced and all the automatic effects deriving provides that financial institutions should not solely or mechanically rely on credit ratings."

In this thesis, I intended to use the model developed by Fracassi, Petry and Tate (2013) with adjustments on the analyst-related explanatory variable: instead of using a dummy variable for each analyst, I attempted to represent the analyst effects with a set of explanatory variables connected to the analyst's key traits of interest. In the following chapters I used the following equation:

$$Rating_i = a_i + \beta_i + \gamma_{analyst} + \varepsilon_i \tag{3}$$

As equation (3) shows, $Rating_{ijt}$ represented the long-term issuer rating for the firm *i*, a_i was a firm's yearly fixed effect, β_i is a rating agency fixed effect and ε_i was an error term. $\gamma_{analyst}$, the explanatory variable of interest is represented by multiple variables of analyst's key traits. The key difference between my approach and the one used by scholars in the preceding research is that instead of attempting to measure the impact of analyst effects, I attempt to study the correlation between the individual traits and the published ratings. The dummy variable for each analyst was replaced with the set of variables of traits with unique combinations of values which supposed to represent each analyst separately.

5.1.2 Universal Rating

As it was described in the previous chapters, the rating systems used by the major CRAs despite the vast similarity contain discrepancies. Therefore, conversion to the universal rating shall be applied to meaningfully compare the ratings from different CRAs. Due to the similarity of the model equation, I used the conversion utilized by Fracassi, Petry and Tate (2013) in their research: thereby, the investment-grade will be represented with ratings from 1 to 10, and speculative-grade with ratings from 11 to 21.

Table 1: Credit Rating System and Letter Rating Conversion

Credit Rating	Letter Rating		
	Standard & Poor's	Moody's	Fitch
1	AAA	Aaa	AAA
2	AA+	Aa1	AA+
3	AA	Aa2	AA
4	AA-	Aa3	AA-
5	A+	A1	A+
6	A	A2	A
7	A-	A3	A-
8	BBB+	Baa1	BBB+
9	BBB	Baa2	BBB
10	BBB-	Baa3	BBB-
11	BB+	Ba1	BB+
12	BB	Ba2	BB
13	BB-	Ba3	BB-
14	B+	B1	B+
15	B	B2	B
16	B-	B3	B-
17	CCC+	Caa1	CCC+
18	CCC	Caa2	CCC
19	CCC-	Caa3	CCC-
20	CC, C	Ca	CC, C
21	D	C	D, DD, DDD

Source: Fracassi, Petry and Tate (2013).

5.1.3 Data Collection

In my research, I will try to analyse the correlation between analyst effects and credit rating of the unsecured senior corporate debt. Since the credit rating score received by the company influences the company's cost of additional debt capital and, subsequently, the ability to access it; I decided to study the long-term issuer ratings. In order to collect the data on the rated debt issues, I used the Bloomberg Terminal accessible at the library of the Faculty of

Economics, University of Ljubljana. Using the terminal command <CRPR> which allows for analysis of the creditworthiness of a corporation since it displays both current and historical credit ratings from several available credit rating agencies at once. The command should be followed by the company's ticker name (e.g. <CVX> stands for Chevron).

Table 2: Sample of rated senior unsecured debt issuings.

Company	Rating period/year	Announcement date	Analyst/Head-analyst	Rating agency	Rating
3M	2016	14.09.2016	Carissa LaTorre	S&P	AA-
3M	2016	14.09.2016	Rene Lipsch	Moody's	A1
3M	2014	29.05.2014	Carissa LaTorre	S&P	AA-
3M	2015	13.05.2015	Carissa LaTorre	S&P	AA-
3M	2014	29.05.2014	Edwin Wiest	Moody's	Aa2
3M	2015	13.05.2015	Rene Lipsch	Moody's	Aa3
AXP	2019	19.08.2019	Michael Taiano	Fitch	A/F1
AXP	2019	21.05.2019	Warren Kornfeld	Moody's	A3
AXP	2019	16.05.2019	Rian Pressman	S&P	BBB+
AXP	2017	08.11.2017	Warren Kornfeld	Moody's	A3
AXP	2017	26.10.2017	Rian Pressman	S&P	BBB+
AXP	2017	08.09.2017	Michael Taiano	Fitch	A
AAPL	2017	02.02.2017	Gerald Granovsky	Moody's	Aa1
AAPL	2017	04.05.2017	Andrew Chang	S&P	AA+
AAPL	2016	28.07.2016	Andrew Chang	S&P	AA+
AAPL	2016	28.07.2016	Gerald Granovsky	Moody's	Aa1

Source: Own work based on Bloomberg Terminal.

In order to simplify the data collection and to at least partially mitigate the size differences of the companies, I chose to select to the sample the publicly rated debt obligations from the components and former components of Dow Jones Industrial Average, issued during the last ten years. In order to get the data on the credit analysts which covered the firm in the selected period, I matched the ratings to the rating action announcements published on Moody's, Fitch, and S&P Global rating websites, filtering them by the company name, type of debt and announcement date. The rating action announcements included the name(s) of the head/senior analyst(s). The categories selected in the sample are shown in Table 2.

After this step, I was extracting the analyst's key characteristics and information from the analyst's public LinkedIn profile. In the context of this research, the most important sections of the LinkedIn profile would be Experience, Education and Licenses and Certifications. For example, the section of Experience provides the possibility to estimate the total industry tenure of the individual credit rating analyst. The section of Licenses and Certifications will be supplemented with the data from the official CFA Institute's Members Directory which is available online. Searching by analyst name allows the identification of whether the analyst possesses a CFA Charter and additionally at least partially verifies the information from the analyst's public LinkedIn profile.

Due to the fact that data collection and matching were performed manually, a significant amount of published ratings were lost because it was not possible to retrieve the complete set of data on the analyst due to the incomplete LinkedIn profile or its absence.

5.1.4 Firm's Fixed Effect

In order to capture the effect of the company's performance during the rating period, I used the set of explanatory variables, which supposed to represent the company's fixed effects. Early research papers in this area did not acknowledge the impact of rating changes on the stock performance (Pinches & Singleton, 1978); however, after the more recent papers indicated a significant impact of rating announcements on the stocks (Zaima & McCarthy, 1988), the whole new area of research was born as a result: economists were trying to identify the core determinants of credit ratings. The CRAs' methodology has been often regarded as obscure and, even though nowadays the CRAs are obliged to disclose the core assumptions and the logic incorporated in their models (Deipenbrock & Andenas, 2011). Packer (2002) was studying the determinants of credit ratings issued to Japanese corporations by foreign and local credit agencies. The sample comprised of credit ratings issued to non-financial corporations based in Japan. The main conclusion of the research was that variables representing size, profitability, retained earnings and leverage were the most important in determining the rating.

Bissoondoyal-Bheenick (2005) studied the main financial determinants of the credit ratings on the sample of ratings assigned to companies based in Australia by Standard and Poor's and Moody's:

"The main finding of this paper is that of the quantitative variables used in the analysis, a company's rating appears to be largely determined by its size, profitability, and leverage measures. This obviously suggests that the information publicly available in the financial statements do play a role in the analysis undertaken by the rating agencies."

In my analysis, I will focus on the information available in the financial statements published by companies as the main proxy for the company's financial and operational performance. Due to the fact that the companies selected in the sample operate in the different industries, the inclusion of the company's industry positioning, role in the sector, or the regulatory environment to the model would not be meaningful; since the requirements and averages fluctuate significantly across industries. Therefore, I selected the following key performance indicators (hereafter: KPIs):

1. Return on assets;
2. Return on equity;
3. Debt to total capital ratio;
4. Debt to equity ratio;
5. Net sales growth (in comparison to the previous recorded financial year).

Return on assets and equity are supposed to represent the profitability of the company since they are better suited for the inter-industry comparison and analysis than the net profit margin. They indicate how successful a rated company is in generating returns and profits on the invested funds. The net sales growth variable is supposed to represent an internal growth rate. Debt to total capital and debt to equity ratios are used as a measure of a company's leverage. These two variables demonstrate how the capital structure of the rated company was financed. These variables are related to profitability variables since the capital structure of a firm can be considered as of high quality if the firm has a high return on equity and its modest dividend pay out to stockholders results in a high internal growth rate (Benos & Papanastasopoulos, 2007). Additionally, these variables allow us to estimate how much the company is responsive to the changes in the economic cycle. The model incorporating the firm's fixed effect looks as follows:

$$Rating_i = a_{ROAi} + a_{ROEi} + a_{D/Ci} + a_{D/Ei} + a_{Net\ Sales\ growth,i} + \beta_i + \gamma_{analyst} + \varepsilon_i \qquad (4)$$

5.2 Rating Agency Fixed Effects

The case of disagreements between the major CRAs was extensively studied in the past (Ederington, Yawitz, & Roberts, 1987). Initially, two major rating agencies were the absolute dominant force on the rating market, most of the research was focused on the rating differences between Moody's and S&P. The research suggested that the cases of rating disagreements between the CRAs occur the most often in the industries characterized by asset opaqueness and uncertainty of the financial services in particular (Livingston, Naranjo, & Zhou, 2007). Since the entrance of the third major player on the market (Fitch), the effects of competition on ratings became more evident. The difference in ratings can be explained by the difference in the current competitive positions of CRAs in the particular industry. In other words, the worse the competitive position of the CRA – the better would the ratings it tends to produce.

The most obvious reason for the difference in ratings between the CRAs is the different methodologies utilized by the CRAs. The quality of the underlying assumptions used in each CRA's model differs, therefore the discrepancies between the produced ratings occur. In order to represent the agency fixed effects, I used the dummy variable for each of the three major CRAs, the value of which can be either one or zero (depending on which CRA produced the rating). Therefore, the model equation looks as follows:

$$Rating_i = a_{ROAi} + a_{ROEi} + a_{\frac{D}{C}i} + a_{\frac{D}{E}i} + a_{Net\ Sales\ growth,i} + \beta_{S\&P} + \beta_{Moody's} + \beta_{Fitch} + \gamma_{analyst} + \varepsilon_i \qquad (5)$$

5.3 Analyst's Trait Variables

To represent the analyst in the model, instead of dummy variables I decided to use the set of variables describing the analyst's key traits. Using the hypotheses on the influence of analyst's traits which I outlined in the previous paragraphs, I selected the following variables:

1. Years of experience (full)

This variable is supposed to serve as a surrogate for the industry tenure of an analyst. The data on this variable was extracted from the Experience section of the analyst's public LinkedIn profiles. I estimated the total number of years of industry tenure by summing up the years of all industry-related (finance) previous and current job positions. The subtotals were rounded up to the whole years.

2. Years in the company (full)

This variable is represented by the number of whole years worked at the current CRA. My initial assumption, in this case, is, that the less the number of years with the CRA the more pessimistic would be the ratings he/she tends to produce.

3. MBA/No MBA

According to hypotheses, analyst's MBA diploma has an effect on the credit rating received by the company. The data on this variable was extracted from the Education section of the analyst's public LinkedIn profiles. As a result, one dummy variable was created: MBA.

4. CFA/No CFA

The hypotheses stated that analyst's CFA charter has an effect on the final published credit rating. The data on this variable was extracted from the Skills and Endorsements section of the analyst's public LinkedIn profiles and later was verified using the CFA Institute Members Directory. There were no discrepancies observed between the two sources. As a result, one dummy variable was created: CFA.

5. Gender

The hypotheses 5 relate to the analyst's gender. The data on this variable was extracted from the analyst's public LinkedIn profiles.

After including the variables representing the analysts' effects, the model equation looks as follows:

$$Rating_i = a_{ROAi} + a_{ROEi} + a_{\frac{D}{C}i} + a_{\frac{D}{E}i} + a_{Net\ Sales\ growth,i} + \beta_{S\&P} + \beta_{Moody's} + \beta_{Fitch} + \gamma_{years\ of\ experience} + \gamma_{years\ in\ company} + MBA + CFA + \varepsilon_i \quad (6)$$

5.4 RapidMiner

To analyse the data, I decided to use the software solution from the RapidMiner Gmbh. The simplicity of usage, the wide choice of prebuilt model and algorithms and powerful data visualization tools were the main factors why the RapidMiner was chosen. Using the University mail available to students of University of Ljubljana, I gained the access to the trial Educational Edition of the program (which contains the whole functionality of the software).

5.5 Sample

As it was mentioned in the previous paragraphs, the data on the rated bonds issued by the current and historical Dow Jones Average components were selected to the sample. In the process of data collection, 143 unique corporate credit ratings were collected using the Bloomberg terminal. 52 ratings were produced by S&P, 49 by Fitch, and 42 by Moody's. These ratings were matched to 64 unique credit analysts. Long-term senior unsecured corporate ratings represented 36 companies, as it is shown in Table 3:

Table 3: Dow Jones Average components included in the sample

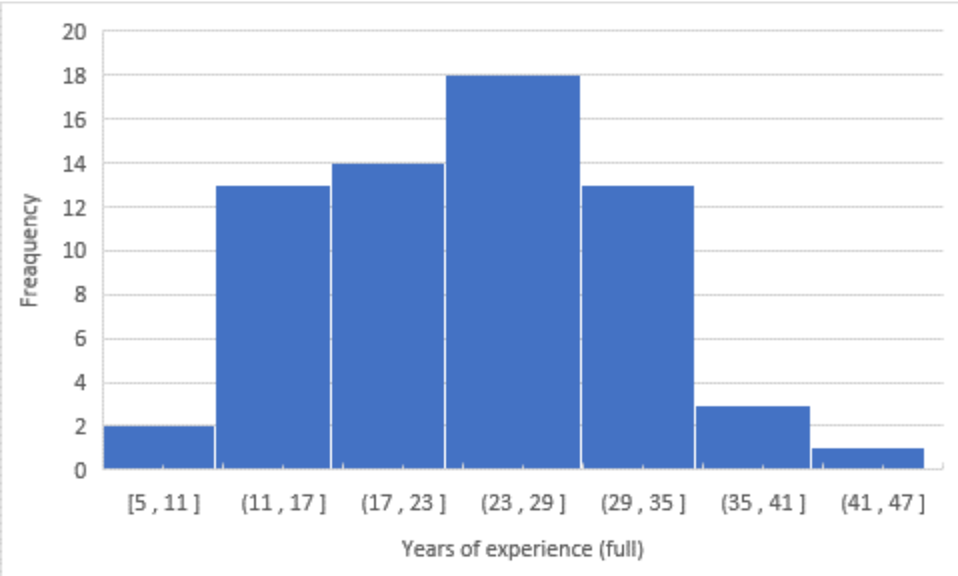
Name	*Ticker*		
Alcoa Corp.	AA	Johnson & Johnson	JNJ
Apple	AAPL	JPMorgan Chase	JPM
American International Group	AIG	Coca Cola	KO
American Express	AXP	McDonald's	MCD
Boeing	BA	3M	MMM
Bank of America	BAC	Altria Inc	MO
Citigroup	C	Merck	MRK
Caterpillar	CAT	Microsoft	MSFT
Chevron	CVX	Nike	NKE
Disney	DIS	Pfizer	PFE
Dow Chemical	DOW	AT&T	T
General eletric	GE	Travelers Companies Inc	TRV
Goldman Sacks	GS	United Health	UNH
Home Depot	HD	United Technologies	UTX
Honeywell International inc.	HON	Verizon	VZ
Hewlett-Packard	HPE	Walgreen	WBA
IBM	IBM	Walmart	WMT
Intel	INTC	Exxon Mobil	XOM

Source: Own work.

As it is shown in Figure 3, the years of experience are normally distributed. The average (mean) analyst's industry tenure is 24.056, with a standard deviation of 6.835. The maximum industry tenure in the sample is 47, and the minimum is 5. Such high average years of experience can be explained with the sample selection: since the companies in the sample are among the largest customers for the CRAs, they are usually covered by the most experienced analysts. The rated entities operate globally and sometimes in several industries simultaneously, therefore, the higher rating process complexity can be viewed as another reason for selecting the most senior analysts for the position.

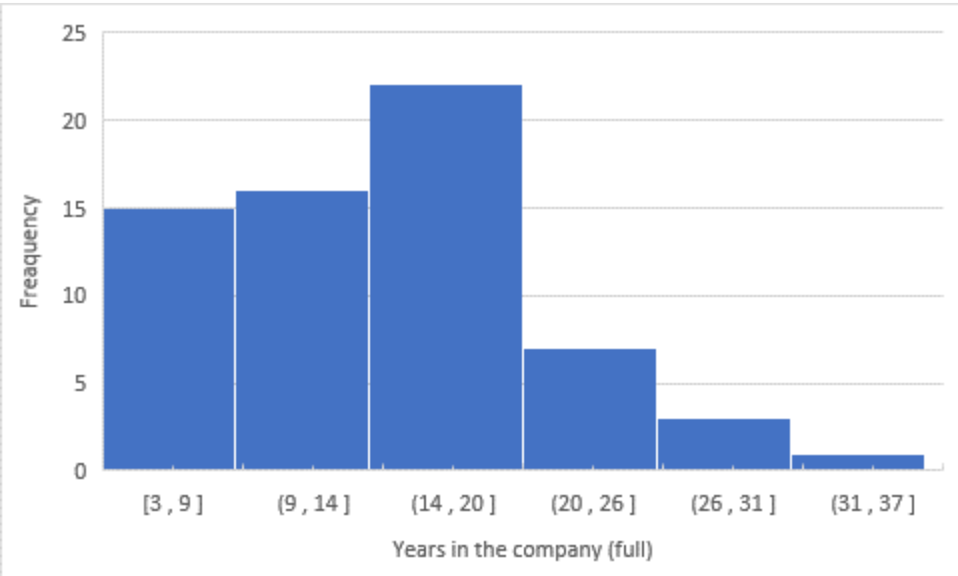
Years in the company distribution is skewed to the right, as it can be observed from Figure 4. The mean years worked at the current CRA are 14.629, whereas the minimum and maximum are 3 and 37 respectively. The standard deviation was equal to 6.883. 97 analysts in the sample accomplished an MBA program and 62 analysts possessed a CFA charter. The sample comprised of 19 female and 124 male analysts.

Figure 3: Years of experience frequency distribution



Source: Own work.

Figure 4: Years in the company



Source: Own work.

6 DATA ANALYSIS

In this chapter, I will describe the methodology used in the process of the analysis of the collected sample. Most of the data analysis was done using the tools of the RapidMiner software package. In the last part of this section, I will present the model design which was utilized in this thesis.

6.1 Logistic Regression

The initial method for the data analysis was the logistic regression, however, the RapidMiner software functionality was unable to run the algorithm with the selected sample. The core issue is that the sample data included the polynomial fields, which are not suitable for the calculation. Using an operator named Nominal to Numerical is the best solution according to the RapidMiner technical manual. This operator is usually utilized to transform the text into the numbers. Unfortunately, the use of the operator did not allow us to transform the data efficiently to analyse the sample. Because of that, the Random Forest algorithm was selected as a measure of substitution.

6.2 Random Forest

The decision tree methodology developed by Brieman, Friedman, Olshen, and Stone (1984) lies as a basis for the Random Forest technique. The decision tree is a classification algorithm. Classification algorithms allow us to gain an insight into the predictive structure of the data, by understanding the interactions between variables and its' scale. It produces simple characterizations of the conditions that establish when an observed object is in one class rather than another.

According to Brieman, Friedman, Olshen, and Stone (1984) the shortcomings of the pre-existing models were:

"Many of the presently available statistical techniques were designed for small data sets having a standard structure will all variables of the same type; the underlying assumption was that the phenomenon is homogeneous, that is, that the same relationship between variables held over all of the measurement space. This led to models where only a few parameters were necessary to reduce the effects of the various factors involved."

In other words, the pre-existing models by design will not be efficient with the datasets which include variables of different types. Another issue arises when the data proves to be high-dimensional. The data in our sample includes both categorical and continuous explanatory variables. The variables included representing the different dimensions as a financial, individual analyst, and CRA. There two key processes in the classification tree algorithm: recursive partitioning and pruning.

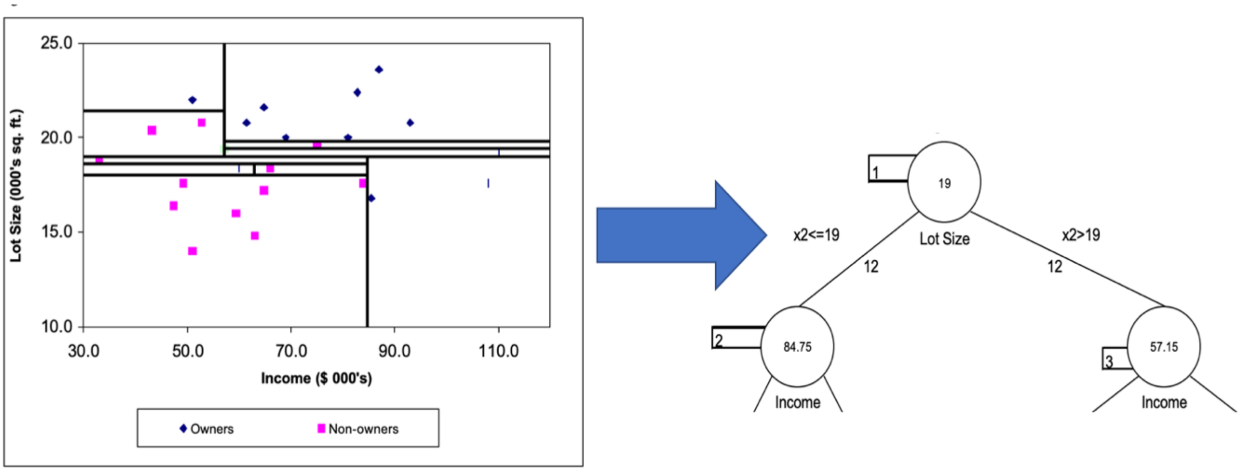
During the partitioning process, the p dimensional space of explanatory variables is recursively divided. The goal of any partitioning algorithms is to divide the data set into subsets until each one of them is either "pure" in terms of target class or sufficiently small. According to Rosaria Silipo and Kathrin Melcher (2019), a pure subset is a subset that contains only samples of one class. First, variable x_1 with the value of s_1 is selected. After that, the p dimensional space is split in two rectangles: one contains all points with $x_1 > s_1$, second contain s all points with $x_1 \leq s_1$. After that, one of the rectangles is split again by choosing the new variable and dividing the space of the rectangle at the point of the chosen variable's value. This procedure is repeated continuously until each of the rectangles will be containing the most homogenous values possible. In other words, the partitioning is occurring until each rectangle contains the points which belong to only one class.

In the context of the Random Forest algorithm, entropy is a measure of the "purity" of the dataset. Mathematically entropy can be calculated as the sum over all classes of the probability of each class multiplied by the logarithm of it. For a binary classification problem, thus, the range of the entropy falls between 0 and 1 (Silipo & Melcher, 2019). The target split leads to the subsets' lowest value of entropy possible, 0.0. However, this value is hardly achievable in practice: usually, it is sufficient enough if a split creates subsets with lower entropy than the original dataset. Knowing the entropy before and after the split, it is possible to capture also the Information Gain, which is calculated as a difference between the entropy before the split and the sum of the output entropies weighted by the size of the subsets. The positive value of the Information Gain signals us that the resulting split subsets are purer than the original dataset.

Another important measure of purity is the Gini Index. In order to get the Gini index, it is necessary to calculate the Gini impurity. Gini impurity can be mathematically defined as 1 minus the sum of the squares of the class probabilities in a dataset. The Gini index is then calculated as the weighted sum of the Gini impurity of the different subsets after a split, where each portion is weighted by the ratio of the size of the subset with respect to the size of the parent dataset (Silipo & Melcher, 2019).

As it can be observed from Figure 5, the value split of the p dimensional space can be illustrated as a node splitting into the two successive nodes. The first splitting node is usually called the root node. The node splits together to form a flowchart-structure, called a decision tree. If we would need to classify a new observation with only values of explanatory variables known, we would follow the nodes according to the splitting values until we would reach a branch with no further splits, also called the leaf node.

Figure 5: Value split as a node split illustration.



Source:Massachusetts Institute of Technology (2003).

After the recursive partitioning, the procedure of pruning takes place. The issue arising after dividing the space into rectangles is that the rectangles containing only a few points may occur. One of the potential outcomes is the tree can be over-fitting the training data. In other words, if the decision tree is too complex and deep it can lead to the construction of models that are too detailed and unable to efficiently generalize on new data. The last splits do not represent patterns that are likely to occur in the succeeding classifications.

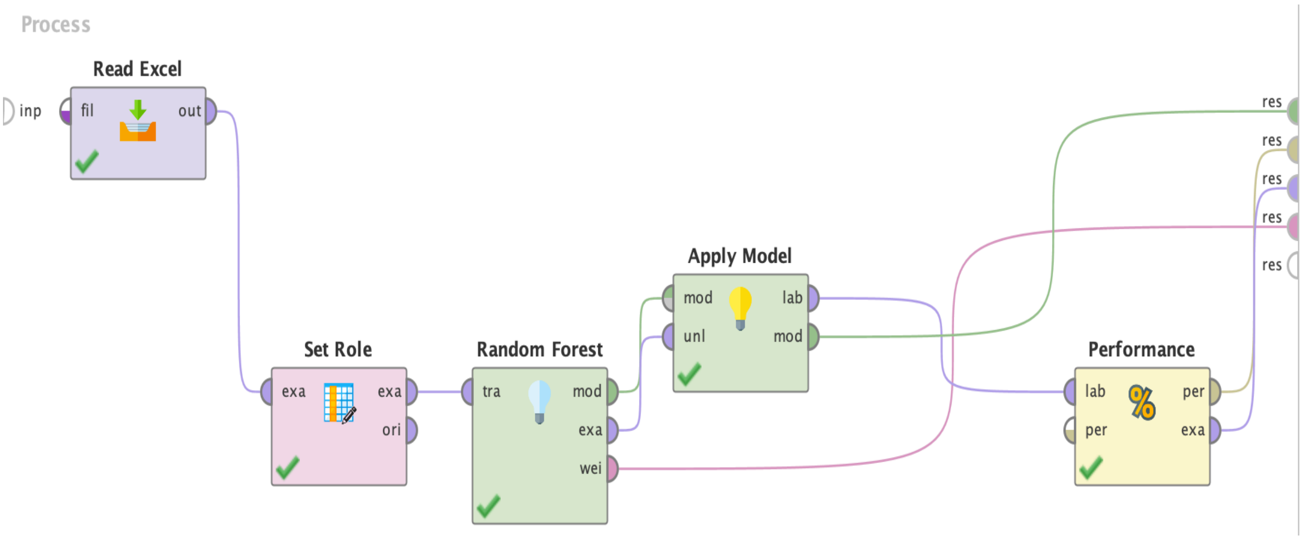
The pruning procedure selects the decision node and transforms it into the leaf node, thereby erasing all the successive branches extending from that decision node. By repeating this procedure, the size of the decision tree is reduced to better fit the data. The pruning utilizes the method of the smallest misclassification error (Massachusetts Institute of Technology, 2003):

"…process trades off misclassification error in the validation data set against the number of decision nodes in the pruned tree to arrive at a tree that captures the patterns but not the noise in the training data. It uses a criterion called the "cost complexity" of a tree to generate a sequence of trees which are successively smaller to the point of having a tree with just the root node. We then pick as our best tree the one tree in the sequence that gives the smallest misclassification error in the validation data."

The algorithm of Random Forest is generally based on the idea that several decision trees are keen to lead to more accurate forecasts than just a single decision tree. Therefore, random forest constructs n unique decision trees, which lead to different predictions, and then merge them, together to capture the aggregate prediction, which is more accurate than the predictions produced by the individual decision trees. All of the decision trees produced by the algorithm are taken into consideration for the final prediction. The most common rule applied when selecting the final prediction is the majority rule. In other words, the prediction which was produced by the majority of n decision trees is selected.

RapidMiner software allows us to run the algorithm using the Random Forest operator. In order, to run the algorithm on the collected sample, I utilized the following design in the application:

Figure 6: Random Forest model design.



Source: Own work based on Rapidminer.

Operator Read Excel extracts the sample data from the attached excel file, whereas operator Set Role selects the dependent value of interest (the final published credit rating score). The operators Apply Model and Performance are utilised in order to provide classificatio error and, consequenlty, accuracy values: the average absolute error between the label and prediction (RapidMiner, 2020).

The main disadvantage of Random Forest in the context of this research is that it does produce the attribute weights but it does not produce the coefficients. The significance, sign, and the value of the coefficient were the key to either rejecting or accepting the hypotheses outlined in the previous chapters.

6.3 Results

The Random Forest operator produces a series of individual decision trees. The decision pass is dependent on the explanatory variables. In the decision tree illustrated below the Years in the company (full) variable was selected as the first splitting value with a value of 28.

According to the technical manual of RapidMiner (RapidMiner, 2020), the class weights are:

“An ExampleSet containing Attributes and weight values, where each weight represents the feature importance for the given Attribute. A weight is given by the sum of improvements the selection of a given Attribute provided at a node. The amount of improvement is dependent on the chosen criterion."

In other words, the class weight can be treated as an indicator of comparative importance and relevance. The algorithm of weight calculation is a novelty approach, which was implemented following the idea from "A comparison of random forest and its gini importance with standard chemometric methods for the feature selection and classification of spectral data" by Menze, Masuch, Kelm and Himmelreich (2009). The Random Forest operator by RapidMiner used in this research, however, extends the criterias for calculating the benefit creaded from tehadditional split: in addition tothe Gini Index, mentioned in the original paper, it also supports the Information Gain and Information Gain Ratio. The latter two are seen as the more reliable criterions (RapidMiner, 2020).

Table 4: Attribute weights.

Attribute:	Weight:
Debt to total Capital	0.151
ROA	0.139
ROE	0.112
Net sales (or Operational revenue) growth	0.099
Debt/Equity	0.087
Years of experience (full)	0.085
Years in the company (full)	0.084
S&P	0.038
Fitch	0.038
Gender	0.035
MBA	0.029
CFA	0.029
No MBA	0.026
Moodys	0.023
No CFA	0.023

Source: Own work based on Rapidminer.

As it is shown in Table 4, the KPIs retrieved from the companies' financial statements proved to bear the highest importance among the selected variables: Debt to total Capital, ROA, ROE, Net sales growth, and Debt/equity received the highest calculated weights. This result goes in line with the logic of credit rating, where the indicators of the company's financial performance are the main determinants of the appointed credit rating. Debt to Total Capital achieved the highest weight score, representing the most important criterion. Interestingly, but CRA's fixed effects achieved lower weights that the Years of experience (full) and Years in the company (full). S&P and Fitch's fixed effects proved to have a higher influence on the appointed credit rating than Moody's.

Among the analysts' effects, industry, and company tenure, which are surrogate variables for experience, were the most relevant attributes; whereas, the MBA and CFA charters were among the least important factors.

Figure 7: Model *performance accuracy.*

accuracy: 95.80%

	true 4	true 5	true 3	true 6	true 7	true 8	true 2	true 9	true 1	true 11	class preci...
pred. 4	8	0	0	0	0	0	0	0	0	0	100.00%
pred. 5	0	17	0	0	0	0	0	0	0	0	100.00%
pred. 3	0	0	7	0	0	0	0	0	0	0	100.00%
pred. 6	1	5	0	32	0	0	0	0	0	0	84.21%
pred. 7	0	0	0	0	22	0	0	0	0	0	100.00%
pred. 8	0	0	0	0	0	23	0	0	0	0	100.00%
pred. 2	0	0	0	0	0	0	7	0	0	0	100.00%
pred. 9	0	0	0	0	0	0	0	14	0	0	100.00%
pred. 1	0	0	0	0	0	0	0	0	5	0	100.00%
pred. 11	0	0	0	0	0	0	0	0	0	2	100.00%
class recall	88.89%	77.27%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	

Source: Own work based on Rapidminer.

The model achieved high accuracy scores of 95.80% as can be seen from Figure 7. The classification error was 4.20%. Such a high achieved accuracy score can be partially explained with small sample size.

7 RESEARCH LIMITATIONS AND FUTURE RESEARCH PROPOSITIONS

In 2005, in addition to studying the main financial determinants of credit ratings Emawtee Bissoondoyal-Bheenick (2005) also included other varibles to the model:

“There are other factors which play a significant role in the ratings, which include industry structure, a company’s role in the sector, business risk, the regulatory environment, capital structure and covenant protection in a company’s financing structure.”

In other words, apart of agency’ and firm’s fixed effects, industry, legislative and macroeconomic effects have a great influence on the final published credit rating. In order to simplify the data collection process, I excluded these factors from the model. However, I believe that including the variables representing these factors in the potential future research can improve the quality of the results and the overall explanatory power of the model.

The model incorporating the proposed changes should look as follows:

$$Rating_i = a_i + \beta_i + \gamma_{analyst} + \lambda_{industry} + \lambda_{macro} + \lambda_{legislative} + + \varepsilon_i \qquad (7)$$

As equation (7) shows, $Rating_i$ represented the long-term issuer rating for the firm i, a_i was a firm's yearly fixed effect, β_i is a rating agency fixed effect and ε_i was an error term. $\gamma_{analyst}$ is represented by multiple variables of analyst's key traits. Additional three variables were added to the model: $\lambda_{industry}$, which is intended to represent the industry fixed effect (affected by the industry overall environment and growth, comapany's role in its main industry sector); λ_{macro} representing the macroeconomic fixed effect; and $\lambda_{legislative}$, representing the regulatory environment in which company operates, including the industry-specific regulatory risks.

Changing the firm-years as a base period to the firm-quarters in the variable can bring another potential improvement to the model. Firm-quarters, representing the company-specific quarterly accounting data, allows the model to capture the effects of events that occurred after the issuance of the latest yearly financial statement. I propose to use Compustat as a resource for quarterly data since it is available if using the Bloomberg Terminal. The composition of the variable should also be modified in order to include the stock price data. Despite the fact, that the direct effect of rating changes can be observed on the stock price in the absolute majority of cases, it is important to investigate the reverse side of this relationship; moreover, since the previously used model includes only the companies' book values and coefficients adding the measures of market risk may significantly improve the explanatory power of the model. To take into account the effects of the stock market, I propose to include the following variables:

1. Equity Beta
2. Equity Volatility
3. Market-to-Book

Equity Beta is a coefficient of daily stock returns relative to the value-weighted market portfolio for the previous fiscal year (Fracassi, Petry, & Tate, 2013). The beta coefficient measures the volatility of the stock relative to the market. I propose to use data on average daily stock returns over the last fiscal year as a measure of Equity Volatility. Market-to-Book value represents the market valuation of the company's equity.

I think, that the inclusion of solvency and liquidity ratios to the variable, has a great potential to further improve the model. Variables like working capital ratio, quick ratio, and current ratio provide a good assessment of the company's ability to meet its currently outstanding obligations. Liquidity ratios, like current liabilities service ratio and interest coverage ratio, in turn, indicate whether a company can service its debt.

Another significant challenge I faced throughout my research was the effects of the extreme heterogeneity of industries: due to the fact that sample comprised of components of Dow Jones Industrial Average, consequently, companies included in the sample were operating in the different industries; the direct comparison of the financial performance appeared to be hardly possible. For example, companies operating in the banking and finance industry have different capital structure requirements as companies operating in the aerospace industry. Therefore, I believe that separating the sampled companies by industry can improve the model and improve the explanatory power of the a_{jt}variable.

In 2013, Borensztein, Cowan and Valenzuela (2013) were studying the effects of the sovereign ceiling on the corporate credit ratings: for years, the policy of never rating a corporation above the sovereign rating was widely accepted by the major CRAs. The research results suggested the following (Borensztein, Cowan, & Valenzuela, 2013):

"A powerful set of analyses suggests the presence of a sovereign ceiling lite policy that is not an absolute constraint, but a limitation that tends to reduce corporate ratings, when these ratings are above the sovereign rating. The results also suggest that the influence of a sovereign ceiling on corporate ratings remains particularly significant in countries where capital account restrictions are still in place and in countries with high political risk."

The results were later supported by more recent research (Almeida, Cunha, Ferreira, & Restrepo, 2017). Therefore, I believe, that inclusion of the country's sovereign rating effect to the model can improve the explanatory power of the model. In the context of current research, where the sample comprised of exclusively US-based companies, the potential effect of the sovereign rating ceiling can be regarded as neglectable. However, in case that companies based outside of the U.S. are included in the sample, the addition of the sovereign rating ceiling effect to the model can prove to be beneficial. Another potential credit rating determinant which can further improve the model is the variable representing the competition in the rating industry in the country. The model used in this research did not include the state of the competition in the particular industry (CRA's competitive position) as a separate variable, instead of the Rating Agency, fixed effects variable was supposed to cover it. As it was described in the previous chapters, researchers identified that higher competition among the CRAs in the country/industry increase the probability of inflated ratings occurring (Bolton, Freixas, & Shapiro, 2012).

The composition of the $\gamma_{analyst}$ variable set can be modified by adding the variables representing the analyst's age and University rating. The inclusion of the analyst's age variable to the model allows us to test the hypotheses regarding the development of analyst's optimism/pessimism throughout the life-cycle. Because the information on the analyst's age is unavailable from the public LinkedIn profile, simple estimation used by Fracassi, Petry and Tate (2013) in their research can be utilized:

"To construct the age variable, we estimate the birth year by taking the minimum between the first year of employment minus 22 years and the first year of college minus 18 years."

The data on the analyst's university education is usually included in the public LinkedIn profile. Grading the universities according to the World University Rating allows us to study the potential correlation between the final published credit rating and the university ranking. One of the potential drawbacks of such an approach is the discrepancy between the period when the university was rated and the period when the analyst was studying there.

8 CONCLUSION

In this thesis, I attempted to test the influence of the analysts' traits on the final published credit rating. Due to the research limitations described in the previous section, I was unable to use the regression, however, using the classification model I was able to retrieve the attribute weights; which indicate the relevance and the importance of the explanatory variables. The results proved that the financial effects, which were represented with the KPIs, bear the highest importance in the credit rating process of the corporate senior unsecured debt obligations. The CRAs' fixed effects appeared to be less important than the analyst's industry and CRA-specific tenure. Gender, CFA charter, and MBA diploma were assigned comparatively low weights, bearing less importance. The crucial drawback of the collected sample was that it was not divided according to the industries, hence the KPI requirements differ significantly across industries, such as capitalization and liquidity requirements. In this thesis, LinkedIn was used as a primary source for retrieving the individual analyst traits. Due to the nature of the LinkedIn network, only the limited amount of personal information was available, mostly connected to the analyst's professional experience. By including other sources of information on the individuals, such as Facebook, it is possible to link individual analyst traits to the analyst's effects on ratings more efficiently.

I think, that the analyst rotation mechanism, similar to the one mandatory among the company auditors, is an efficient way to mitigate the analyst effects. Preventing the long-term relationships between the firms and their credit analysts has a great potential to discourage analysts from appointing the inflated ratings to the companies.

I strongly believe that further research on the topic using the more capable and precise data analysis tools is necessary. To better understand the criterion influencing the appointed credit ratings, we need to better understand the people responsible for these ratings. ESMA as well as SEC are focusing their regulative efforts on the CRAs, practically ignoring the individuals possessing the right of the final say in the credit rating process. By shifting the focus from the companies to the people, I reckon it will be possible to significantly improve the rating quality.

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APPENDICES

Appendix 1: Summary in Slovene language.

Dandanes je glavni namen bonitetnih ocen zagotavljanje informacij o kreditni sposobnosti posojilojemalcev. Vlagatelji in drugi udeleženci na trgu, si želijo, da bi jih uporabili kot pokazatelj verjetnosti neplačila v primeru izdaje novega dolga. Zato imajo bonitetne ocene velik vpliv na možnosti podjetij za dostop do novega kapitala in na pogoje, pod katerimi si ga lahko izposodijo. Ker so bonitetne ocene splošno priznane, predstavljajo "vstopnico" na finančne trge za podjetja, ki iščejo sredstva.

Kljub velikemu pomenu za vse udeležence na trgu so bile bonitetne ocene v središču sporov od svetovne finančne krize leta 2008 naprej, njihova verodostojnost pa je vprašljiva še danes. V času porasta strukturiranih finančnih produktov so bonitetne agencije hitro razširile svoje poslovanje, zaradi česar njihovo ocenjevanje ni bilo več tako natančno, kar izhaja iz dejstva, da so najvišje bonitetne ocene prejela podjetja, ki so bila tik pred propadom (Bar-Isaac & Shapiro, 2011). Nestrokovnost vlagateljev (Skreta & Veldkamp, 2009), regulativna arbitraža (White, 2010) in različni konflikti interesov in težave, s katerimi so se srečevale bonitetne agencije (Bolton, Freixas, & Shapiro, 2012), so bile med številnimi potencialnimi vzroki nastanka krize. Pred, med in po finančni krizi so se kritiki CRA osredotočali na tri glavna vprašanja v zvezi z integriteto dejavnosti bonitetnih agencij (McVea, 2010):

1. konflikt interesov;
2. zgrešeni modeli in nepravočasni popravki;
3. pomanjkanje odgovornosti.

Če primerjamo dolgoročne bonitetne ocene iste družbe, ki se izdajajo istočasno v različnih agencijah, opazimo razlike v ocenah. Te razlike lahko v delu pripišemo metodološkim razlikam in asimetriji informacij, s katerimi bonitetne agencije razpolagajo, kar predstavlja fiksni učinek bonitetne agencije. Po podatkih Fracassija, Petryja in Tatea (2013) obstajajo fiksni učinki analitikov in predstavljajo 30% razlike v ocenah. Z drugimi besedami, njihova raziskava je pokazala, da bonitetna pristranskost analitikov močno vpliva na kreditni razmik na dolg ocenjenih podjetij in posledično na pogoje, ki jih ponujajo med izdajo novega javnega dolga. Poleg tega so raziskovalci opazili, da podjetja, ki jih ocenjujejo bolj pesimistični analitiki, navadno izdajo manj dolga, se bolj opirajo na gotovinsko in lastniško financiranje ter rastejo počasneje kot ostala podjetja z bolj optimističnimi analitiki (Fracassi, Petry, & Tate, 2013).

Kljub visokem vplivu analitika na ocene in s tem na ceno dolga na splošno, so njihovi vzroki in dejavniki še vedno premalo raziskani, medtem ko so v prejšnjih treh desetletjih poglobljeno raziskali vplive različnih hevristik in pristranskosti na presoje analitikov kapitala. Narava bonitetne ocene je močno odvisna od posameznikovih analitičnih in napovedovalnih veščin, podobno kot pri dnevnih dejavnostih analitikov kapitala. Primer »revolving doors« med investicijskimi bankami in bonitetnimi agencijami samo še dodatno prikaže podobnosti med zahtevanim naborom kvalifikacij in naravo dela. V tem magistrskem delu sem poskušal preizkusiti, ali se lahko v primeru analitikov bonitetnih ocen uporabijo enake vedenjske težnje in hevristike, ki jih opažamo pri vedenju kapitalskih analitikov. Domneval sem, da je mogoče z razvrščanjem nekaterih opaznih lastnosti analitika in preučevanjem njihovih vplivov na analitikovo presojo predvideti kakovost analitikovega ocenjevanja in njegov vpliv na bonitetno oceno.

Predpostavil sem, da lahko identiteta analitika v zadostni meri vpliva na bonitetni postopek. Bonitetno oceno lahko namreč štejemo kot sestavljeno vrednost, ki jo dosežemo z obdelavo različnih podatkov o uspešnosti in obetih podjetja, zato lahko analitiki te podatke različno zaznajo in analizirajo. S pomočjo profesionalne mreže LinkedIn, v kombinaciji s spletnimi stranmi za objavo bonitetnih ocen večjih bonitetnih agencij mi je uspelo zbrati vzorec ocenjenih dolgoročnih poslovnih obveznosti s podatki o analitikih, ki so bili odgovorni za bonitetne ocene. LinkedIn je bil uporabljen kot primarni vir za pridobivanje posameznih lastnosti analitika. Zaradi narave mreže LinkedIn je bila na voljo le omejena količina osebnih podatkov, ki so večinoma povezani s poklicnimi izkušnjami analitika. Vzorec vsebuje ključni kazalniki poslovanja podjetij, fiksni učinek bonitetne agencije in osebnostni karakteristike analitikov, vnaprej imenovani kot atributi.

V tej nalogi sem poskusil preizkusiti vpliv lastnosti analitikov na končno objavljeno bonitetno oceno. Zaradi tehničnih omejitev, ki sem jih imel pri raziskavi, nisem mogel uporabiti regresijskega modela, vendar sem s klasifikacijskim modelom lahko dobil relativno »utezi« atributov; ki kažejo na pomembnost in pomen pojasnjevalnih spremenljivk. Rezultati so pokazali, da so finančni učinki, ki so bili zastopani s ključnimi kazalniki uspešnosti, najbolj pomembni. Fiksni učinki bonitetnih agencij se niso izkazali za tako pomembne, kot izkušnje analitika v panogi. Spol, listina CFA in diploma MBA pa imajo relativno najmanjši pomen. Ključna pomanjkljivost zbranega vzorca je bila, da ni bil razdeljen glede na panoge, zato se zahteve ključnih kazalnikov uspešnosti bistveno razlikujejo po panogah, kot na primer zahteve po kapitalizaciji in likvidnosti.

Menim, da je mehanizem rotacije analitika, ki je podoben tistemu, ki je obvezen pri revizorjih, učinkovit način za ublažitev učinkov analitika. Onemogočanje dolgoročnih odnosov med podjetji in njihovimi kreditnimi analitiki lahko odvrne analitike od izdajanja previsokih bonitetnih ocen podjetjem.

Trdno verjamem, da so potrebne nadaljnje raziskave o tej temi z uporabo naprednejših in natančnejših orodij za analizo podatkov. Za boljše razumevanje dejavnikov, ki vplivajo na bonitetne ocene, moramo bolje razumeti ljudi, odgovorne za izdajanje le-teh. ESMA in tudi SEC svoje regulativne napore osredotočajo na bonitetne agencije, tako da praktično ne upoštevajo posameznikov, ki imajo zadnjo besedo v postopku bonitetnega ocenjevanja. S preusmeritvijo pozornosti iz podjetij na ljudi menim, da bo mogoče bistveno izboljšati kakovost ocenjevanja.

Appendix 2: List of analysts with the key traits.

Name	School (MS, in case of MBA - BBA)	Gender	MBA/no:	No of comp.in the sample	Company	Years in the company (full)	Years of experience (full)	CFA/No:
Alen Lin	University of Illinois at Urbana-Champaign	m	Northwestern University - Kellogg School of Management	2	Fitch	3	25	No
Ana Arsov	Boston University	f	No	4	Moody's	6	19	No
Andrew Chang	University of California, Berkeley	m	University of Chicago Booth School of Business	4	S&P	10	17	No
Andy Sookram	Fordham University	m	No	2	S&P	13	24	No
Arthur Wong	Rutgers University	m	NYU Stern School of Business	1	S&P	21	26	No
Brendan Browne	Miami University	m	No	1	S&P	10	15	No
Bruce Clark	Yale University	m	No	1	Moody's	37	37	No
Carin Dehne-Kiley	Carleton College (BA)	f	NYU Stern School of Business	1	S&P	9	15	CFA
Carissa LaTorre	Colgate University (BA)	f	NYU Stern School of Business	3	S&P	13	13	No
Charles O'Shea	University of Rochester	m	No	1	Moody's	17	34	No
Chris Johnson	Claremont McKenna College	m	No	1	S&P	14	15	CFA
Christopher Denicolo	Georgia Institute of Technology	m	NYU Stern School of Business	2	S&P	18	18	CFA
Craig D Fraser	The Wharton School	m	Columbia Business School	1	Fitch	18	29	No
David E Peterson	DePaul University’s Kellstadt Graduate School of Business	m	DePaul University’s Kellstadt Graduate School of Business	1	Fitch	19	31	No
David Kaplan	York University	m	Bernard M. Baruch College, Zicklin School of Business	1	S&P	14	14	CFA
David Silverman	Tulane University	m	No	3	Fitch	4	19	CFA
David Tsui	University of California, Los Angeles	m	Cornell University	6	S&P	13	21	CFA
Diya Iyer	University of Virginia	f	Columbia Business School	2	S&P	8	16	No
Donald Marleau	Laurentian University	m	No	1	S&P	22	25	CFA
Doug Pawlowski	University of Illinois at Urbana-Champaign	m	University of Chicago Booth School of Business	5	Fitch	24	25	CFA
Edwin Wiest	Columbia Business School	m	Columbia Business School	1	Moody's	17	47	No
Eric Ause	St. Olaf College	m	University of Minnsota - Carlson School of Management	4	Fitch	19	31	CFA

Gerald Granovsky	Rensselaer Polytechnic Institute	m	Columbia Business School	2	Moody's	14	28	No
James Sung	NYU Stern School of Business	m	No	3	S&P	17	17	No
Jason Grohotolski	Drexel University	m	No	1	Moody's	16	20	No
Jason Pompeii	Brown University	m	NYU Stern School of Business	5	Fitch	17	23	No
Johannes Moller	Stellenbosch University	m	Columbia Business School	1	Fitch	4	11	CFA
John Iten	University of Virginia	m	Fuqua School of Business at Duke University	2	S&P	27	27	No
John Rogers	Manhattan College	m	NYU Stern School of Business	1	Moody's	22	37	CFA
Jonathan Root	State University of New York at Buffalo	m	NYU Stern School of Business	1	Moody's	14	31	CFA
Linda Montag	Grove City College	f	No	1	Moody's	10	23	No
Marc R. Pinto	Trinity College Hartford	m	Columbia Business School	2	Moody's	7	27	CFA
Mariola Borysiak	Bernard M. Baruch College, Zicklin School of Business	f	No	1	S&P	18	18	No
Mark Narron	NYU Stern School of Business	m	No	1	Fitch	6	25	No
Michael Levesque	Cornell University	m	No	5	Moody's	22	24	CFA
Michael Taiano	Pace University	m	University of Florida	2	Fitch	4	25	CFA
Monica Bonnar	Manhattanvill e College	f	NYU Stern School of Business	1	Fitch	16	31	No
Naveen Sarma	Boston University	m	NYU Stern School of Business	3	S&P	14	30	No
Neil Mack	Fordham University	m	Columbia Business School	2	Moody's	3	31	CFA
Nikola Swann	London School of Economics and Political Science	m	No	1	S&P	18	22	CFA
Patrick Hughes	University of Notre Dame	m	No	1	Fitch	3	5	No
Paul Harvey	Connecticut College	m	Pace University - Lubin School of Business	1	S&P	26	26	No
Paul Kurias	University of Chicago - Booth School of Business	m	University of Chicago Booth School of Business	1	S&P	16	16	No
Peter Nerby	Ivey Business School	m	No	2	Moody's	21	21	CFA
Peter Speer	University of Michigan - Stephan M. Ross School of Business	m	No	2	Moody's	16	28	No
Rene Lipsch	Erasmus University Rotterdam	m	London Business School	6	Moody's	6	25	No
Rian Pressman	Fordham University	m	Case Western Reserve University - Weatherhead School of Management	5	S&P	14	19	CFA

Robert Kirby	University of Illinois at Chicago	m	University of Chicago Booth School of Business	5	Fitch	15	34	CFA
Rumohr Bain	Hope College	m	No	3	Fitch	7	13	CFA
Samantha Stone	Baruch College	f	Columbia Business School	1	S&P	16	18	No
Scott Tuhy	University of Pennsylvania	m	No	1	Moody's	13	30	No
Stuart Plesser	University of Michigan - Stephan M. Ross School of Business	m	NYU Stern School of Business	1	S&P	13	29	No
Svetlana Olsha	Pace University	f	Columbia Business School	2	S&P	8	13	CFA
Warren Kornfeld	The Wharton School	m	No	2	Moody's	18	37	No
William Densmore	University of Illinois at Urbana-Champaign	m	DePaul University’s Kellstadt Graduate School of Business	4	Fitch	20	30	No
Bruce Ballentine	Harward College	m	Columbia Business School	3	Moody's	19	29	No
Tracy Dolin	Brandeis University	f	No	2	S&P	14	16	No
Jim Auden	University of Illinois at Chicago	m	University of Rochester	3	Fitch	31	31	No
Brennan Clark	Fairfield University	m	University of Notre Dame	1	S&P	5	14	No
Nancy Meadows	NYU Stern School of Business	f	NYU Stern School of Business	1	Moody's	4	25	No
David Berge	United States Merchant Marince Academy	m	Columbia Business School	1	Moody's	17	33	CFA
James Siahaan	The University of Connecticut	m	Cornell University	1	S&P	15	20	CFA
Neil Begley	St. Jones University	m	No	2	Moody's	25	34	No
Allyn Arden	Trinity College Hartford	m	No	1	S&P	15	20	CFA

Source: Own work based on LinkedIn.

Appendix 3: Rated Long-Term Senior Unsecured Debt.

Company	Rating period/year	Announcement date	Analyst/Head-analyst	Rating agency	Rating
3M	2016	14.09.2016	Carissa LaTorre	S&P	AA-
3M	2016	14.09.2016	Rene Lipsch	Moody's	A1
3M	2014	29.05.2014	Carissa LaTorre	S&P	AA-
3M	2015	13.05.2015	Carissa LaTorre	S&P	AA-
3M	2014	29.05.2014	Edwin Wiest	Moody's	Aa2
3M	2015	13.05.2015	Rene Lipsch	Moody's	Aa3
AXP	2019	19.08.2019	Michael Taiano	Fitch	A/F1
AXP	2019	21.05.2019	Warren Kornfeld	Moody's	A3
AXP	2019	16.05.2019	Rian Pressman	S&P	BBB+
AXP	2017	08.11.2017	Warren Kornfeld	Moody's	A3
AXP	2017	26.10.2017	Rian Pressman	S&P	BBB+
AXP	2017	08.09.2017	Michael Taiano	Fitch	A
AAPL	2017	02.02.2017	Gerald Granovsky	Moody's	Aa1
AAPL	2017	04.05.2017	Andrew Chang	S&P	AA+
AAPL	2016	28.07.2016	Andrew Chang	S&P	AA+
AAPL	2016	28.07.2016	Gerald Granovsky	Moody's	Aa1
BA	2019	18.12.2019	Jonathan Root	Moody's	A3
BA	2019	17.12.2019	Craig D Fraser	Fitch	A/F1
BA	2019	19.12.2019	Christopher Denicolo	S&P	A-
CAT	2019	25.11.2019	Eric Ause	Fitch	A/F1
CAT	2019	12.09.2019	Bruce Clark	Moody's	A3
CAT	2019	16.09.2019	Svetlana Olsha	S&P	A
CVX	2019	15.01.2019	Peter Speer	Moody's	Aa2
CVX	2019	15.04.2019	Paul Harvey	S&P	AA

KO	2018	22.02.2018	William Densmore	Fitch	A
KO	2018	30.03.2018	Linda Montag	Moody's	Aa3
KO	2018	26.04.2018	Chris Johnson	S&P	A+
DIS	2019	16.04.2019	David E Peterson	Fitch	A
DIS	2019	12.03.2019	Naveen Sarma	S&P	A
DOW	2018	08.11.2018	Patrick Hughes	Fitch	BBB+
DOW	2018	06.11.2018	John Rogers	Moody's	Baa2
DOW	2018	28.11.2018	Paul Kurias	S&P	BBB
XOM	2019	13.08.2019	Carin Dehne-Kiley	S&P	AA+
XOM	2019	19.11.2019	Peter Speer	Moody's	Aaa
GS	2019	29.08.2019	Stuart Plesser	S&P	BBB+
GS	2019	16.05.2019	Ana Arsov	Moody's	A3
GS	2019	12.06.2019	Johannes Moller	Fitch	A-
HD	2019	14.05.2019	David Silverman	Fitch	A
HD	2019	03.06.2019	Samantha Stone	S&P	A
HD	2018	27.11.2018	Andy Sookram	S&P	A
HD	2018	31.10.2018	David Silverman	Fitch	A
IBM	2018	29.10.2018	David Tsui	S&P	A
IBM	2019	29.10.2018	Jason Grohotolski	Moody's	A1
INTC	2015	22.07.2015	Andrew Chang	S&P	A+
INTC	2015	01.06.2015	Jason Pompeii	Fitch	A+
INTC	2019	18.11.2019	Andrew Chang	S&P	A+
INTC	2019	01.06.2015	Jason Pompeii	Fitch	A+
JNJ	2019	04.09.2019	Robert Kirby	Fitch	AAA
JNJ	2019	28.08.2019	Michael Levesque	Moody's	Aaa
JPM	2018	21.06.2018	Rumohr Bain	Fitch	AA-
JPM	2018	25.10.2018	Peter Nerby	Moody's	A2
JPM	2018	09.11.2018	Brendan Browne	S&P	A-
MCD	2019	08.10.2019	William Densmore	Fitch	BBB

MCD	2019	07.08.2019	Diya Iyer	S&P	BBB+
MRK	2015	08.12.2015	Michael Levesque	Moody's	A1
MRK	2015	05.02.2015	Arthur Wong	S&P	AA
MRK	2015	08.10.2015	Robert Kirby	Fitch	A
MSFT	2016	01.08.2016	David Tsui	S&P	AAA
MSFT	2016	15.06.2016	Alen Lin	Fitch	AA+
MSFT	2015	09.02.2015	David Tsui	S&P	AAA
MSFT	2015	21.04.2015	Alen Lin	Fitch	AA+
NKE	2015	26.10.2015	Scott Tuhy	Moody's	A1
NKE	2015	26.10.2015	Mariola Borysiak	S&P	AA-
PFE	2019	29.07.2019	David Kaplan	S&P	AA-
PFE	2019	01.08.2019	Robert Kirby	Fitch	A
PFE	2019	29.07.2019	Michael Levesque	Moody's	A1
PFE	2016	28.09.2016	Robert Kirby	Fitch	A+
PFE	2016	26.09.2016	Michael Levesque	Moody's	A1
PFE	2015	23.11.2015	Robert Kirby	Fitch	A+
PFE	2015	23.11.2015	Michael Levesque	Moody's	A1
TRV	2019	20.05.2019	Doug Pawlowski	Fitch	A+
TRV	2019	01.11.2019	Marc R. Pinto	Moody's	A2
TRV	2019	27.02.2019	John Iten	S&P	A
TRV	2017	15.05.2017	John Iten	S&P	A
TRV	2017	13.07.2017	Marc R. Pinto	Moody's	A2
TRV	2017	19.06.2017	Doug Pawlowski	Fitch	A+
UTX	2018	09.08.2018	Rene Lipsch	Moody's	Baa1
UTX	2018	13.09.2018	Christopher Denicolo	S&P	BBB+
UNH	2019	23.07.2019	James Sung	S&P	A+
UNH	2019	04.03.2019	Doug Pawlowski	Fitch	A
UNH	2018	13.03.2018	Doug Pawlowski	Fitch	A
UNH	2018	14.06.2018	James Sung	S&P	A+
UNH	2017	18.10.2017	James Sung	S&P	A+
UNH	2017	18.10.2017	Doug Pawlowski	Fitch	A
VZ	2019	16.04.2019	William Densmore	Fitch	A-

VZ	2019	04.03.2019	Naveen Sarma	S&P	BBB+
VZ	2019	08.04.2019	Neil Mack	Moody's	Baa1
VZ	2015	06.02.2015	William Densmore	Fitch	A-
VZ	2015	11.02.2015	Naveen Sarma	S&P	BBB+
VZ	2015	05.02.2015	Neil Mack	Moody's	Baa1
WMT	2018	09.05.2018	David Silverman	Fitch	AA
WMT	2018	09.05.2018	Charles O'Shea	Moody's	Aa2
WMT	2018	20.06.2018	Diya Iyer	S&P	AA
WBA	2018	19.01.2018	Andy Sookram	S&P	BBB
WBA	2018	12.10.2018	David Silverman	Fitch	BBB
WBA	2016	26.05.2016	Andy Sookram	S&P	BBB
WBA	2018	26.09.2016	David Silverman	Fitch	BBB
GE	2018	02.10.2018	Svetlana Olsha	S&P	BBB+
GE	2018	02.10.2018	Rene Lipsch	Moody's	A2
GE	2018	01.10.2018	Eric Ause	Fitch	A
GE	2017	16.11.2017	Rene Lipsch	Moody's	A2
GE	2017	28.11.2017	Eric Ause	Fitch	A+
GE	2016	31.10.2016	Rene Lipsch	Moody's	A1
GE	2016	31.10.2016	Eric Ause	Fitch	AA-
HPE	2017	11.09.2017	David Tsui	S&P	BBB
HPE	2017	20.10.2017	Jason Pompeii	Fitch	BBB+
HPE	2018	10.09.2018	David Tsui	S&P	BBB
HPE	2018	18.10.2018	Jason Pompeii	Fitch	BBB+
HPE	2015	30.09.2015	Jason Pompeii	Fitch	A-
HPE	2015	01.10.2015	David Tsui	S&P	BBB
AA	2018	02.05.2018	Monica Bonnar	Fitch	BB+
AA	2018	14.05.2018	Donald Marleau	S&P	BB+
BAC	2019	06.03.2019	Ana Arsov	Moody's	A2
BAC	2019	08.03.2019	Rian Pressman	S&P	A-
BAC	2019	12.06.2019	Rumohr Bain	Fitch	A+
BAC	2017	12.09.2017	Ana Arsov	Moody's	Baa1

BAC	2017	22.11.2017	Rian Pressman	S&P	A-
BAC	2017	28.09.2017	Rumohr Bain	Fitch	A
BAC	2018	26.12.2018	Rian Pressman	S&P	A-
BAC	2018	05.12.2018	Ana Arsov	Moody's	A3
C	2019	16.05.2019	Peter Nerby	Moody's	A3
C	2019	12.06.2019	Mark Narron	Fitch	A
C	2019	30.04.2019	Nikola Swann	S&P	BBB+
AIG	2017	15/01/2017	Bruce Ballentine	Moody's	Baa1
AIG	2017	31/01/2017	Tracy Dolin	S&P	BBB+
AIG	2017	14/02/2017	Jim Auden	Fitch	A-
AIG	2018	22/01/2018	Bruce Ballentine	Moody's	Baa1
AIG	2018	22/01/2018	Jim Auden	Fitch	A-
AIG	2018	19/03/2018	Tracy Dolin	S&P	BBB+
AIG	2016	26/01/2016	Jim Auden	Fitch	A-
AIG	2016	26/01/2016	Bruce Ballentine	Moody's	Baa1
MO	2018	20/12/2018	Brennan Clark	S&P	BBB
MO	2018	22/12/2018	William Densmore	Fitch	BBB
MO	2016	09/03/2016	Nancy Meadows	Moody's	A3
MO	2016	18/04/2016	William Densmore	Fitch	BBB+
HON	2017	10/11/2017	David Berge	Moody's	A2
HON	2017	23/11/2017	James Siahaan	S&P	A
HON	2017	16/11/2017	Eric Ause	Fitch	A
T	2018	15/06/2018	Neil Begley	Moody's	Baa2
T	2018	15/06/2018	Allyn Arden	S&P	BBB
T	2018	18/06/2018	William Densmore	Fitch	A-
T	2016	24/10/2016	Neil Begley	Moody's	Baa1
T	2016	24/10/2016	William Densmore	Fitch	A-

Source: Own work based on Moody's, S&P, Fitch Investors service and LinkedIn.

Appendix 4: KPI summary statistics.

KPI:	Min.	Average	Max.
ROA	-0,074	0,055	0,253
ROE	-5,922	0,006	1,03
Debt to Total Capital	0,34	0,714	1,173
Debt/Equity	-24,431	2,949	12,711
Net sales (or Operational Revenue) growth	-0,164	0,02	0,344

Source: Own work based on RapidMiner.