EMPIRICAL STUDY OF CREDIT RATING AGENCIES: DO THE FINANCIAL CHARACTERISTICS OF COMPANIES HAVE AN IMPACT ON THE OCCURRENCE OF SPLIT RATINGS?

Jury:
Promoter:
Georges HÜBNER
Readers:
Julien HAMBUCKERS
Stéphanie HECK

Dissertation by
Laurence PICHEREAU
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Résumé

Depuis le début du 21ème siècle, la complexité de la plupart des instruments financiers n'a cessé d'augmenter. Par conséquent, les investisseurs n'ayant aucune connaissance ni expérience en finance éprouvent des difficultés à prendre de bonnes décisions. Afin de résoudre ce problème, les agences de notation évaluent la solvabilité (ou la capacité d'honorer ses obligations financières) d'émetteurs ou de titres en déterminant une notation sous la forme d'une lettre. Cependant, vu que chaque institution possède sa propre méthodologie, des divergences d'opinion (également appelées "notations fractionnées") peuvent survenir. Dès lors, le but poursuivi dans le cadre de ce mémoire est d'évaluer l'impact des caractéristiques financières et comptables d'entreprises notées sur la fréquence de ces divergences d'opinion.

Tout d'abord, ce rapport décrit le contexte dans lequel les agences de notation fonctionnent et définit les concepts s'y rapportant tels que le risque de crédit, la migration des notations (ou transition) etc. Egalement, les deux institutions relevées dans le cadre de cette étude (Standard & Poor's et Moody's) sont présentées en détails avec, plus particulièrement, les différences potentielles de méthodologie et d'interprétation de notations. Ensuite, une étude empirique est réalisée sur un échantillon composé de 134 entreprise de l'index STOXX® Europe 600 pour lequel les caractéristiques financières ainsi que les notations long terme des émetteurs sont disponibles. Des modèles économétriques sont par la suite utilisés et une comparaison est réalisée afin de répondre à la question de recherche de ce présent mémoire.

En conclusion, les résultats des différents modèles ont montré que la fréquence des notations fractionnées était impactée par des caractéristiques liées aux entreprises. En guise d'introduction, il a été découvert que Standard & Poor's était plus influencé par le ratio de levier tandis que Moody's prend davantage le revenu total en compte. Plus important encore, les résultats de l'étude ont prouvé que le revenu net, la totalité des actifs, les actifs courants, la capitalisation boursière ainsi que la liquidité affectaient tous la probabilité des notations fractionnées. Le constat le plus frappant était que la fréquence des notations fractionnées semblait être considérablement plus importante pour les banques que pour les autres entreprises. Cependant, la réalisation de cette étude a mis en évidence quelques limitations et incohérences qui nécessitent des recherches plus poussées.

Mots-clés: Instruments financiers – Agences de notation – Solvabilité – Notation – Notations Fractionnées – Caractéristiques financières – STOXX® Europe 600 – Econométrie

List of abbreviations

APE: Average Partial Effect

CRAs: Credit Rating Agencies

EAD: Exposure At Default

EDF: Expected Default Frequency

ESMA: European Securities and Market Authority

ESME: European Securities Markets Expert

IG: Investment Grade

LGD: Loss Given Default

LPM: Linear Probability Model

MLE: Maximum Likelihood Estimation

NIG: Non-Investment Grade

OLS: Ordinary Least Squares

PD: Probability of Default

PEA: Partial Effect at the Average

ROA: Return On Assets

ROE: Return On Equity

S&P: Standard & Poor's

SEC: Securities and Exchange Commission

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Introduction

Let's imagine that a random wealthy individual with no particular background in economics or finance wants to invest a part of their money in one way or another. Obviously, keeping it under a mattress or on a current account is a safe option but does not yield anything. Then, another possibility that comes to their mind is storing money in a bank through a savings account. The person in question considers seriously this option but, due to extremely low interest rates for deposits (close to 0%), that kind of investment does not seem attractive enough for them. Finally, the last possibility for the individual is to invest their money directly in companies by purchasing the related securities (shares or bonds). However, the investor has no knowledge in finance and wants to invest on his own without hiring a portfolio manager. How could they then get the necessary information to invest wisely?

The answer is: with the help of credit rating agencies (CRAs, for short). Indeed, these institutions have provided investors for years with useful pieces of advice that are necessary if they want to make sensible decisions about lending money to a company or not (Partnoy, 1999). Simultaneously, they have unquestionably played an important role in ensuring the function and the oversight of international financial markets (Gantenbein & Harasta, 2012).

As a matter of fact, CRAs assess the creditworthiness of issuers or securities. In other words, they use a certain methodology so as to evaluate these issuers' ability to meet financial obligations and express those assessments through letter grades (de Servigny & Renault, 2004). Nonetheless, ratings assigned by CRAs are only reflections of their opinion (by consequent very subjective) about the credit quality. In no case shall they be considered as inciting and definitive recommendations to hold, purchase or sell financial instruments. Yet, most investors do not take this into account and use to base their investment decisions only on the ratings provided. Unfortunately, at the beginning of the financial crisis in 2007, some of them lost a lot of money because of their lack of knowledge in finance and of carefulness.

Also, since the foundation of the first CRA in 1909 by John Moody's, the number of institutions on the market has kept increasing and so has the number of ratings they regularly issue (Caouette, Altman & Narayanan, 1998). It is thus important to note that this existence of so many CRAs on the financial market can lead to the fact that they assign a different rating for the same entity, whether it be an issuer or a given financial instrument. This is entirely due to the fact that they all use their own methodology defined on the basis of certain criteria. For example, Standard & Poor's evaluates only the creditworthiness taking the probability of default into account while Moody's considers the loss given default.

Therefore, it seems interesting to study the agencies' methodologies so as to be more aware of the rating process and its potential drawbacks. For the purposes of this dissertation, the causes of split ratings are analysed more in depth and put in parallel with financial and accounting characteristics of the companies rated. More particularly, the empirical study seeks to discover which of those characteristics have a significant influence on the occurrence of divergences in opinion related to ratings assigned. In order to do so, data is collected about the long-term issuer ratings of both Moody's and Standard & Poor's as well as financial and accounting information on a timespan ranging from 2000 to 2016. Actually, the focus of the study is on those two CRAs because of their dominant position on the market and the companies on which the analysis is realized belong to the STOXX® Europe 600 index. However, based on several criteria, the number of firms is reduced from 600 to 134. After a comparison and the use of econometrics models, the study will point out the factors that are more likely to make split rating occur. In brief, the aim of this paper is to detect a certain pattern and to get a better understanding of this phenomenon of split ratings.

The motivations behind this empirical study are of two kinds: academic and managerial. On one hand, this paper attempts to provide additional content to the existing literature about CRAs and the concept of ratings. Indeed, even if a lot of researchers addressed this issue, only a few of them focused especially on the link between rating differentials and long-term issuer ratings. In short, the subject has not been analysed in details yet and the literature found on that topic is neither concrete nor substantial. On the other hand, the final findings of this paper could provide investors with deeper knowledge about the phenomenon of split ratings, of which they might not even be aware. This can obviously be useful for individual, institutional as well as professional investors. They would thus be better informed about the companies in which they want to invest, reducing consequently the potential risks involved.

The structure of this paper will be composed of two main parts. To start with, the first chapter will review the existing literature about the whole subject of CRAs and the related concepts such as credit risk and migration will be explained. Then, the second chapter will describe in details the empirical study realized for the purposes of this paper, from data collection to final results. Finally, a conclusion will attempt to summarize the entire content of this paper, insisting on the findings of the statistical analysis.

1. Literature review

In order to understand the world of CRAs as a whole, it seems relevant to propose an explanation of all the factors that must be taken into account: namely credit risk, the concept of rating, the main rating agencies, their corresponding methodology and, above all, an explanation of the different ratings that exist with the possible differences in interpretation as well as the concept of transition.

This literature review will be thus subdivided into four main points. The first part will be dedicated to a brief description of the context in which the study is conducted, with a general explanation of the concept of credit risk as such, a definition of the notion of rating and credit scoring as well as a presentation of the different CRAs (mainly Moody’s and Standard & Poor’s). Then, the second section will focus on the variety of methodologies that exist among all agencies. The third part will explain the diverse existing ratings and will show the assortment of possible interpretations. Finally, the last section will discuss studies realized on the phenomena called “transition” (with the related matrices).

1.1. Brief description of the context

1.1.1. Concept of credit risk

As mentioned by Caouette et al. (1998), the most ancient form of risk in the financial markets is credit risk. It would have existed at least since 1800 B.C. as this type of risk is as old as the activity of lending itself. Yet, it was genuinely born as early as 1300 (just as the concept of insurance). Indeed, the merchant bank bore the risk back then by advancing funds against a bill of exchange (Kohn, 1999). Ever since, the concept has evolved a lot and managing credit risk has become the main concern of traditional banks. However, they were lately forced to head to relationship banking, being more focused on the relationship with the customer than on the profitability of loans. According to Caouette et al. (1998), this led to poor results in terms of management of credit risk and, when looking through the history of financial institutions, it can be shown that credit risk was the cause of the biggest banking failures.

Credit risk can be defined as “the risk of default or of reductions in market value caused by changes in the credit quality of issuers or counterparties” (Duffie & Singleton, 2003, p. 4). More simply, it is the possibility that a borrower will fail to meet their obligations in conformity with the terms agreed beforehand. This type of risk concerns all market players, whether it be banks or random individuals who borrow and/or lend. In other words, credit risk arises whenever an individual wants to get a product or a service without paying immediately for it (Caouette et al., 1998). The danger therefore is the default of any promised payments of interest and/or principal.

However, there are two categories of credit risk – issuer risk and counterparty risk. The former is the possibility that an issuer defaults and is then not capable of fulfilling payment obligations while the latter encompasses default, replacement and settlement risks (CRISIL Global Research & Analytics-Irevna, n.d).

Alongside market and operational risks, credit risk is a part of non-business risk while the business one is constituted by reputational, decisional and strategic risks (Hull, 2015). In addition, the banking industry has acknowledged the importance of market, operational and credit risks since the beginning of the last century. Also, credit risk could be put together with market and liquidity risks in order to represent the total financial risk a company bears. On one hand, market risk (also known as "systematic risk") relates to potential losses investors could experience because of adverse movements in macroeconomic factors (especially market prices), resulting in a poorer performance of financial markets. On the other hand, liquidity risk is linked to the risk that an institution is not able to convert its belongings into cash quickly enough without preventing from or minimizing the loss in the process (Reilly & Brown, 2012). The presence of non-business risk in a company is thus the reason why regulatory capital is needed. Hence, it makes sense for a company to have sufficient equity if credit risk has to be borne. Nonetheless, the amount of risk-based capital dedicated to credit risk must be a lot greater than that for market risk e.g. with regard to the banking system. All of this has been regulated mainly by the Basel Agreements since 1988. Appendix 1 summarizes the implementation evolution of the related regulations from 2011.

Identifying the major drivers of credit risk is a crucial step in the risk management process. If credit risk must be analysed and measured, the key drivers are the following ones: default, credit exposure, loss given default and maturity. A discrete state is used to represent the default driver, where the counterparty defaults or not and this happens of course with a certain probability of default (PD, for short). Credit exposure is the amount of money at which investors are exposed, equal to the market value of the claim of the counterparty (also called "exposure at default" or EAD). The loss given default (LGD, for short) represents the potential part of the amount that could be lost due to default (in percentage). The LGD can be obtained by computing $(1 - Recovery\ Rate)$. The maturity is the time that remains until the end of the agreement (Trueck & Rachev, 2009). As mentioned by Kern and Rudolph (2001), the following formula applies in general:

$$\begin{aligned} Expected\ Loss \\ &= Default\ Probability\ x\ \big(Outstanding\ Exposure\ x\ (1 \\ &- Recovery\ Rate)\big) \\ &= PD\ x\ EAD\ x\ LGD \end{aligned}$$

In order to measure credit risk and to compute regulatory capital, existing techniques can be classified under two categories (Basel II): the standardized and the internal ratings-based (IRB) approach. The former refers to banks using external credit ratings while the latter means that some institutions are allowed to make use of their own risk parameters and models (CRISIL Global Research & Analytics-Irevna, n.d). It is important to note that developing and owning a well-designed internal model is a real competitive advantage. On the other side, an additional classification can be made between the structural, intensity-based and survival approaches. The concept firm-value approach is used to appoint the structural one since a company's asset value is assumed to determine a firm's inability to meet its contractual obligations. Merton and first-passage time are two classic structural models (Zhang, 2009). Intensity-based approach is also called reduced-form and considers that the default event is unexpected and not correlated with the assets value, which is more realistic. With regard to the survival approach, it can be described as an analysis of time-to-failure data (Zhang, 2009). This model combines thus both the structural and the intensity-based approaches.

Furthermore, a distinction can be made between the several models that can be used. Firstly, JP Morgan's CreditMetrics applies to bond portfolio and relies on market values (Kern & Rudolph, 2001). The objective of this model is to provide a way to estimate the value distribution of a portfolio composed of assets that are exposed to changes in credit quality through the use of credit migration analysis (Hull, 2015). Then, the Merton model can be considered as the source of inspiration of the KMV's PortfolioManager approach as it aims to derive the actual probability of default without using statistical data. The main idea behind this model is that a firm defaults as soon as its market value falls under a certain predefined level. Nonetheless, PortfolioManager does not apply in a portfolio context but rather to stand-alone credit risk (Kern & Rudolph, 2001). Also, the actuarial model Credit Suisse Financial

Products' CreditRisk+ exists and only focuses on default risk – not on downgrade risk – with the assumption that it follows a Poisson process (random and not constant over time). Unlike KMV, the process of default here is not related to the capital structure of the firm. However, credit migration analysis is not considered in this approach (Crouhy, Galai & Mark, 2000). Finally, McKinsey's CreditPortfolioView can be considered as an econometric model between CreditRisk+ and CreditMetrics (Kern & Rudolph, 2001). In this case, it is assumed that the economy is linked to default and migration probabilities. Hence, a discrete time multi-period model is used where those probabilities are a function of macro-variables (Crouhy et al., 2000). See appendix 2 for a complete comparison of the four models.

As it has been shown here above, a lot of different models and approaches exist in order to compute credit risk. It is thus a challenge for risk managers and market regulators to agree on how to calculate this source of risk. For instance, even the two biggest CRAs do not agree on the procedure to employ in order to determine ratings. Indeed, Standard & Poor's uses an intensity-based model close to CreditMetrics whilst Moody's relies rather on a structural one similar to the KMV approach. Finding the perfect model that defines an optimal way to measure credit risk and evaluates the necessary regulatory capital is really difficult. Also, if banks are asked to keep more capital in reserve than needed, it could cause market distortion. According to Dionne (2003), the source of this disagreement actually resides in the fact that credit risk is not well understood because of its complexity.

1.1.2. Notion of rating

Another central concept that must be defined is the one of "rating". This part of the section will try to explain what a rating is and how this can be used to reflect the potential credit risk of a company or an obligation. The definition of credit rating could be the following: "an agency's opinion about the creditworthiness of an obligor with respect to a particular debt security or other financial obligation" (de Servigny & Renault, 2004, p. 24)[1]. It can also reflect the solvency of an issuer in general at a certain date, not only with reference to a specific security.

Moreover, ratings can be categorized into two types, corresponding to various financial instruments: long-term and short-term ones. They are both split into different categories and might use different scales following the timeframe (long or short). In addition, the difference

[1] There exists still no standard definition of credit rating that is generally agreed upon (Langohr, H. & Langohr, P., 2008).

of scale can be partly explained by the rating agency studied. According to de Servigny and Renault (2004), it may be interesting to put them all in parallel even if they are not totally comparable at first glance.

It is also important to note that the whole rating scale is divided into two wide categories: investment grade (IG, for short) and non-investment or speculative grade (NIG, for short). The former represents a category of securities that are more stable with limited risk while the latter comprises junk bonds that are way more likely to default (de Servigny & Renault, 2004). Furthermore, ordinary letters of the alphabet represent ratings and are classified in the alphabetical order: AAA is the best credit quality while D is considered as the worst. Also, additional pluses and minuses can be used to make the indication of risk subtler. Appendix 3 proposes an overview of the ordinal scales used by the main agencies. In the fourth part of this section, the concept of CRA will be discussed more in depth.

On top of that, it may be relevant to point out that ratings can be subject to changes no matter the time of the year and their level, sometimes without warning. Even the securities with the best credit quality can be downgraded to the lowest level (Securities and Exchange Commission, 2013). A lot of downgrades were observed, for example, in 2008 and the reason therefore was to reflect the impact of the financial crisis (May, 2010). However, a system of "watch" or "outlook" is used by the main agencies whenever possible in order to inform investors about a probable revision (up- or downgrade) of some of their ratings (Securities and Exchange Commission, 2013). This system of changing ratings is linked to the concept of transition that will be discussed in the fourth section of this literature review.

Besides, ratings are supplied by agencies if, and only if, sufficient and valuable information is available in order to be able to determine a satisfying credit opinion. This process is based on various analyses of which the content and computations depend on the agency chosen. In general, the evaluation of industrial companies is composed of business reviews and quantitative analyses most of the time (de Servigny & Renault, 2004). As mentioned previously, this will be discussed in the fourth part of the section regarding CRAs.

It is important to note that ratings can be obtained externally as well as internally. The first method consists in gathering information about creditworthiness coming from one or more different agencies while the second implies that financial institutions have to develop their own system and process to get their "home-made" ratings. Obviously, this second alternative is a lot more demanding and costly but represents a real competitive advantage if the model is built correctly.

Recently, the external method has been heavily criticised because of several shortcomings: horizon, dependence on business cycle and coherence of transition matrices across time and regions for example (de Servigny & Renault, 2004). This criticism led consequently to an increase in the number of internal models in banks over the past few years. According to Treacy and Carey (1998), internal credit ratings have become more and more important for risk management in big U.S. banks. As a matter of fact, those internal ratings are more or less similar to external ones "in that they summarize the risk of loss due to failure by a given borrower to pay as promised" (Treacy & Carey, 1998, p. 897). Nevertheless, those internal ratings are supposed to be kept internally, rather than revealed to the outside world. On top of that, the design and the configuration of the banks' systems differ from the ones of rating agencies (Treacy & Carey, 1998).

Nowadays, ratings are omnipresent and this ratings universe is a very busy place due to the incredible expansion of credit facilities. Indeed, according to Langohr H. and Langohr P. (2008), more than 42,000 issuers have seen their 745,000 securities rated by more than 150 different CRAs over approximately 100 countries. This can be explained by the increasing general demand for ratings in the financial world as those can bring value to market players, to capital markets as well as to the economy. Undoubtedly, the distance between investors and issuers can be reduced through the use of ratings, which facilitates optimal investment and issuing decisions. Costs on both sides are cut down; whether it be cost of information or of market access (Langohr, H. & Langohr, P., 2008).

As a matter of course, assigning ratings is not an exact science. It may happen that CRAs make mistakes in their assessments when loads of crucial events occur quickly and when the situation gets out of control. For instance, those institutions have been heavily criticised over the past 20 years since they did not manage to anticipate most of the recent crises. As stated by Host, Cvečićv and Zaninović (2012), they did not fulfil their main task, specifically evaluating correctly the obligors' capacity to repay their debt in due time. In any event, ratings accuracy relates to the interaction between ratings and defaults. This indicates if agencies assessed correctly the creditworthiness of issuers and securities as well as the related changes over time. There exists a multitude of ways to measure it but here, the focus will be on two: the Lorenz curve and the Gini coefficient.

On one hand, Lorenz curves were originally invented in the beginning of the 20th century to describe wealth disparities. In this case, they are used to illustrate the accuracy of ratings through inequalities of default rate dispersion among rating cohorts (Langohr, H. & Langohr, P., 2008). In general, Lorenz curves are drawn simultaneously with two extreme ones, namely the random and the ideal lines. Whereas the horizontal axis of the chart depicts the cumulative proportion of rated universe (from smallest to highest rating), the vertical one represents the cumulative share of defaults observed among them. According to Langohr H. and Langohr P. (2008), the Lorenz curve would be equal to the random line if ratings and default rates were uncorrelated, that is to say if the former did not discriminate the latter at all. All ratings would thus have the same default rate, which is depicted on the 45-degree line. On the contrary, if the discrimination were perfect, the ideal segment would represent the final Lorenz curve. In their book, Langohr H. and Langohr P. (2008) propose a typical representation of the Lorenz curve that applies in this case for S&P ratings performance:

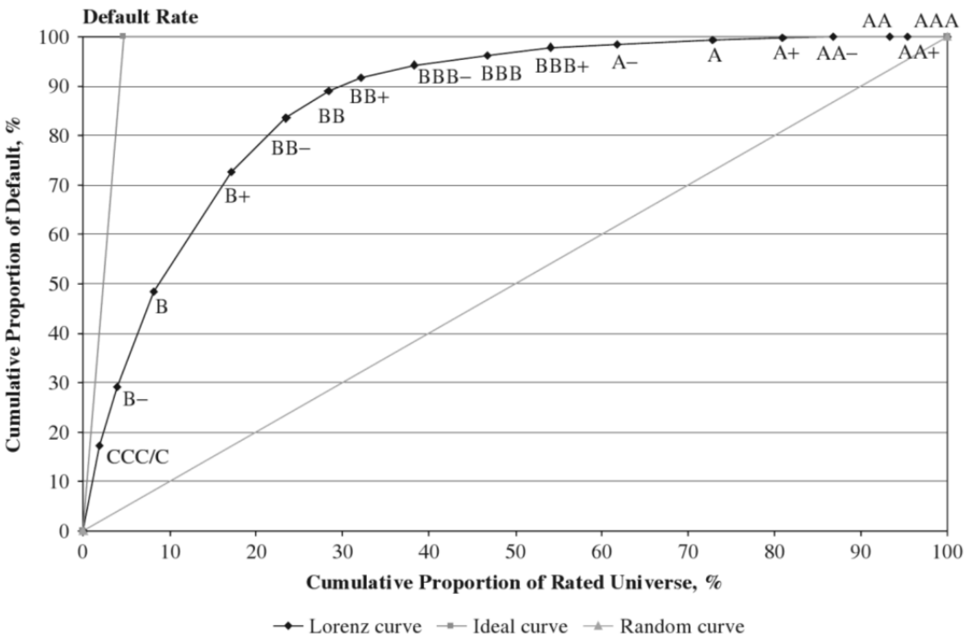


Figure 1: S&P three-year relative corporate ratings performance (1981-2006).
Source: Langohr & Langohr (2008)

On the other hand, the overall ratings exactness in predicting defaults can be straightforwardly measured with the accuracy ratio or Gini coefficient. Along with the Lorenz curve, it is a summary statistic that expresses through a digit how far the Lorenz and the ideal curves are from each other (Langohr, H. & Langohr, P., 2008). This figure is computed by dividing the surface between the random and Lorenz curves by the one between the ideal and random lines. In general, its spectrum goes from 0, if the Lorenz curve merges with the random curve, to 1, if it is equal to the so-called ideal line. Finally, evidence has shown that ratings accuracy is negatively correlated with the length of the horizon chosen, meaning that it gets better when the forecast period decreases. In short, ratings tend to be less precise over longer-term horizons.

In brief, as outlined above, ratings are helpful tools giving investors useful information in order to help them make sensible decisions (Partnoy, 1999). Nonetheless, even if the demand (and supply) has increased, the informational value of this assessment seems to have declined sharply over the last 50 years. As reported by Partnoy (1999), CRAs have gone from being proactive to reactive and their precise ratings are only due to a posteriori corrections. At last, it is important to make investors understand that credit ratings are subjective by nature. Also, the accuracy of those assessments might vary across time, sectors or geographical areas and can be measured with different methods. A rating is a reflection of credit risk only and not of other types of risk. Hence, investors should not take those pieces of advice as granted. In any event, a rating is thus not an exact science and does not guarantee at all that a security will be repaid with absolute certainty (Securities and Exchange Commission, 2013). The third section of this literature review will explain the differences between all the possible interpretations in that area.

1.1.3. Credit scoring

Along with rating, credit scoring is another method to evaluate creditworthiness and the ability to meet financial commitments. However, there is a slight difference between both concepts although investors tend to use them both interchangeably. Indeed, credit scoring is expressed through a digit (numerical form) and can only be applied to individuals whereas credit rating is represented by a letter grade and can be used for businesses or governments.

Originally, credit scoring was invented to assess the credit quality of smaller and private firms since previous models were solely based on equity information of listed companies (de Servigny & Renault, 2004). In the 1930s, Fitzpatrick and Fisher were the first researchers who contributed to the development of this numerical assessment, respectively with the correlation between the default probability and the credits characteristics as well as the technique of discriminant analysis. Later on, the 1960s saw a considerable improvement in the methodology and the use of credit scoring was extended to additional asset types. Consequently, the 1975 and 1976 Equal Opportunity Acts of the Fed officially recognized scoring as a valuable technique related to the credit granting activity. It is nowadays widely used, but principally by banks.

According to de Servigny & Renault (2004), all credit scoring-related models focus on the categorization of credit quality and on the prevision of default. Those techniques are especially appealing competitively speaking since their capacity to provide credit quality assessment in a defined time frame with limited costs permits productivity to increase. Yet, it is a challenge to find or elaborate an optimal scoring procedure. Five qualities are determinant and required in the choice process: accuracy, parsimony, nontriviality, feasibility, transparency and interpretability (Galindo & Tamayo, 2000, as cited in de Servigny & Renault, 2004). These days, the linear regression probability, the logit, the probit and the multiple discriminant analysis models are the most widespread multivariate scoring models. The distinction between these four will be clarified in the next chapter along with the empirical analysis.

Besides, Receiver Operating Characteristic (ROC) curves are used in order to evaluate the performance of scoring methods. It applies in the context of a model evaluating a population composed of N firms out of which D defaults. Each company is assigned a score (s_i) as well as a default probability (p_i) and the researcher decides of a certain level (T) such that if $p_i \leq T$, the firm is good and if $p_i > T$, it is bad (de Servigny & Renault, 2004). Depending on T, C_T and F_T represent the number of companies that are respectively correctly and wrongly categorized as bad. Then, the hit and false alarm rates are determined:

$$H_T = \frac{C_T}{D} \qquad F_T = \frac{W_T}{N - D}$$

H_T is thus plotted against F_T in a chart where the steeper the resulting ROC curve, the better. As stated by de Servigny & Renault (2004), the area located under the curve can be seen as a performance measure of credit scoring models despite its several pitfalls.

Finally, the Cumulative Accuracy Profile (CAP for short) is another measure of the prediction consistency of a scoring model (de Servigny & Renault, 2004). The methodology used to determine the performance is as follows. First, two rankings are made: with companies by decreasing order of probabilities of default through the scoring model and with actually observed defaults. This curve is then obtained in a chart where the horizontal axis displays the first ranking related to default probabilities and the vertical one illustrates the number of firms that have really gone into default. If the scoring model is perfectly designed and well thought, the D highest probabilities of default should be assigned to the D firms out of N that have indeed defaulted. As mentioned by de Servigny & Renault (2004), the CAP technique is useful as it supplies a rank-ordering accuracy assessment of a model but is greatly dependent on the sample chosen. By the way, under certain circumstances, the ROC and the CAP approaches might convey the same information even if the former is a more general measure than the latter.

1.1.4. Presentation of the main CRAs

As mentioned above, this last part of the section regarding the description of the context will review the rating industry and will discuss the related regulations and critics in this respect. To put it in a nutshell, the specialization of those entities lies in the fact that they evaluate independently the creditworthiness of various issuers in order to inform investors about the probability of receiving all principal and interest payments as scheduled for a given security (Caouette et al., 1998).

The birth of CRAs dates back to the 19th century. At that time, three types of institutions provided the functions supplied nowadays by CRAs: credit reporting agencies, the specialized business and financial press and investment bankers (Fernández & Vila, 2015). However, John Moody established the first real agency in 1909 by combining those three entities. Since then, a growing importance of the CRAs can be observed through the increasing number of ratings they issue (Caouette et al., 1998). This expanding use of ratings can be explained by the internationalization of financial markets, the increasing complexity of financial products and the growing usage of ratings in financial regulation and contracting (Frost, 2007, as cited in Bannier & Hirsch, 2010). An increase in the complexity of this piece of information has also been observed, jointly with the rising use of ratings (Bannier & Hirsch, 2010).

Overall around 160 local and international CRAs including the three major global players – namely Fitch IBCA, Moody's Investor Services and Standard & Poor's (S&P for short) – compose the credit rating industry (Langohr, H. & Langohr, P., 2008). The independent "Big Three" represent these days between 90% and 95% of the market share in the rating sector where the two biggest ones (Moody's and S&P) have in their hands approximately 80% of it (White, 2010, as cited in Fernández & Vila, 2015). This small group of global players form a sort of oligopoly. Besides, according to de Haan and Amtenbrink (2011), most of other minor CRAs are either national, regional, local or focus on a certain product-type.

Originally designed to inform nonprofessional investors, CRAs have gained greater importance on the financial market and have been increasingly used by regulators and institutions (Cantor & Packer, 1994). Hence, it is often argued that the whole marketplace is over-reliant on those ratings issued. Indeed, as referred to earlier, more than 745,000 securities were rated in 2008 and all future investors tend to rely only on this piece of information when making a decision. At the same time, a lot of criticism has been made over the oligopoly formed by the Big Three.

As previously stated, agencies are in general able to supply ratings when they have enough public and private information at their disposal. The process starts when a corporation requests an assessment of its creditworthiness. From that moment, the agency puts a team in place in order to collect data and analyse the situation (May, 2010). The final rating assigned is communicated to the issuer who will review the draft version of the press release. Afterwards, the agency disclosed the newly decided rating to the market (Langohr, H. & Langohr, P., 2008). For more details, appendix 4 outlines the typical scheme of a request for rating, which is composed of eight steps and appendix 5 describes the whole process going from asking for a rating to reviewing it. As a matter of course, some other agencies assign also ratings to approximately all publicly traded corporations without any prior request. The different methodologies used by the main entities will be described in details in section 2.

Furthermore, the rating process can be categorized into two different business models: solicited or unsolicited. In brief, solicited ratings are assigned upon request of a particular issuer while unsolicited ones are not (Ceelen, 2012). On one hand, the “issuer pays” model exists thanks to which investors can get all the available ratings on issuers on CRAs’ websites free of charge as the issuer paid beforehand to get rated. The Big Three are generally referred to when this model is evoked. On the other hand, there is the “investor pays” model where ratings are disclosed only to those who subscribed to the service (European Securities Markets Expert, 2008).

CRAs have been heavily criticised over the last few years for several reasons and the financial crisis of 2008 has led to further increasing criticism (Haspolat, 2015). First of all, according to Garcia (2012, as cited in Boehm, 2013), the lack of transparency behind the decisions made about ratings is one of the main issues. Indeed, a lot of market players agree on the fact that there is not enough disclosure of assumptions, documents reviewed, ratings processes etc. (Langohr, H. & Langohr, P., 2008). Then, the problem of conflicts of interest arises mainly in the context of the “issuer pays” model where the attribution of a rating (inflated) becomes nearly an ambiguous matter of power and heavy negotiation (Boehm, 2013). This happens as both the agency and the corporation have an interest in ensuring that the rating process is carried out in their favour, which leads to subjectivity instead of the guaranteed objectivity and independence (Stolper, 2009). On top of that, as previously stated, CRAs are accused of being more reactive than proactive (Partnoy, 1999). They only adjust their recommendations and opinions afterwards rather than making use of their predictive power. For example, CRA were subject to intense criticism when ENRON collapsed in 2001. As affirmed by McVea (2010, as cited in Boehm, 2013), the biggest pre-crisis failure of those agencies was to downgrade ENRON only a few days before bankruptcy although its financial issues were globally well known. Finally, as aforementioned, the “natural” oligopoly formed by the Big Three represents one of the biggest reproaches with respect to the rating industry. Unquestionably, it is really complicated for new CRAs to succeed and for existing minor ones to conquer more share due to the nature of the market. Also, according to Partnoy (2006), this importance of the big agencies is “reinforced by regulations that depend exclusively on credit ratings issued by Nationally Recognized Statistical Rating Organizations (NRSROs)” (p. 60). This all thus leads to a lack of competition (Garcia, 2013, as cited in Boehm, 2013).

Into the bargain, some market players criticize the fact that ratings are used a lot in regulation but not much regulated. In the same vein, researchers and policymakers have confirmed their accentuating role in the recent financial crisis (Host et al., 2012). Hence, regulating the rating industry has become a necessary priority in all policy decisions worldwide. CRAs have been regulated lately, mainly through recent Basel Agreements with regard to the computation of the regulatory capital. In addition, Regulation (EC) No 1060/2009 of the European Parliament and of the Council urges CRAs to avoid potential conflicts of interest and to provide high quality and sufficiently transparent rating processes.

1.2. Comparison of the different methodologies

In order to take advantage of the growing access to financial and market data and to benefit from the increased computing power, agencies regularly try to enhance their methodologies (Bielecki, Brigo & Patras, 2011). So, this section of the literature review will describe the differences between the current models used by major CRAs in order to deliver the service for which they were originally designed, specifically assigning a rating.

1.2.1. Scope of the paper

In the rest of this paper, the focus will only be on two of the three main CRAs – namely Moody's and Standard & Poor's (S&P for short). This choice has been made considering the fact that Fitch has generally a smaller share than its two main competitors on the rating market. This could be explained by the fact that Fitch rates a limited number of issuers compared to the two others (Cantor & Packer, 1997) even though they all issue the same types of ratings (see appendix 6). Indeed, as stated by the European Securities and Market Authority (European Securities and Market Authority, 2014), S&P is the leading agency of the rating industry with 39.69% of market share in Europe, followed rather closely by Moody's with 34.53% while Fitch lags behind those two with only 16.22% in 2014. See Appendix 7 for a detailed chart of CRAs' market share computation for Europe. As a matter of fact, Appendix 8 depicts the same situation, but on the U.S. market as of date of 2011. Obviously, the final general ranking is similar but the figures relating to the market share differ slightly. Moreover, Fitch discloses less information about its rating processes whereas the "Big Two" puts a lot of it at their customers' disposal. Therefore, it seems more relevant to study the behaviour of these last two rather than of the whole Big Three. This still represents an analysis of approximately 75% of the rating industry.

1.2.2. Services offered by CRAs

According to de Servigny and Renault (2004), it is important to understand that agencies do not offer exactly the same information via their ratings. In order to provide investors and issuers with accurate creditworthiness assessments, CRAs make use of diverse methods and models. The main difference in methodology is about assigning ratings either on the basis of the probability of default or the expected loss (Boehm, 2013). The default probability is the likelihood that a debtor will not be able to make the promised payments as scheduled and the expected loss is the amount of money a lender can expect to lose if the borrower defaults (default probability multiplied by the loss severity). This difference of methodology can be problematic in the non-investment grade – or junk – part of the rated universe by commonly creating big split ratings (Caouette et al., 1998). An explanation of the potential differences between the interpretations of ratings will be proposed in the third section of this literature review.

In this case, Standard & Poor's is the agency that considers its ratings rather as judgements about the probability of default of issuers. On the other side, Moody's goes one step further and assigns ratings that reflect the agency's point of view on the expected loss of securities (de Servigny & Renault, 2004). On their websites, Moody's and Standard & Poor's offer a similar general definition of the concept of rating. In short, they define it as being a forward-looking independent assessment of the creditworthiness and relative credit risks of issuers. Appendix 9 and 10 summarize the ideas of the Big Three about the notion of rating. Nevertheless, the definitions diverge at one point in the reference documents:

> *"[Moody's] Long-term ratings are assigned to issuers or obligations with an original maturity of one year or more and reflect both on the likelihood of a default on contractually promised payments and the expected financial loss suffered in the event of default"* (Moody's Investors Service (2016). *Rating Symbols and Definitions*, p. 4)

> *"The opinion reflects Standard & Poor's view of the obligor's capacity and willingness to meet its financial commitments as they come due, and may assess terms, such as collateral security and subordination, which could affect ultimate payment in the event of default"* (Standard & Poor's Ratings Services (2014). *Standard & Poor's Ratings Definitions*, p. 4)

The main difference between those definitions clearly confirms the divergence in methodologies used by Moody's and Standard & Poor's. While the former mentions the concept of expected loss (involving simultaneously the likelihood of default and the loss severity), the latter only addresses the subject of default probability. In short, subtle differences can be observed in what their assessments measure. This is one of the reasons why market players should remain careful while comparing ratings from various CRAs despite the fact that resulting rating grades seem to be equivalent at first glance (Ghosh, 2013).

However, there is one thing both agencies totally agree on: the disclaimers. Indeed, in their terms and conditions of use, they remind investors that their ratings are only opinions (subjective by nature) and not inciting recommendations to make investment decisions, whether it be holding, purchasing or selling securities. Also, they warn investors not to rely exclusively on ratings when making a decision, as they do guarantee neither on-going updates nor verification of the information received at the beginning of the rating process. Finally, the Big Two signals that ratings may be changed, suspended or withdrawn at any time[2].

[2] See Moody's terms of use (https://www.moodys.com/termsofuseinfo.aspx) and S&P file "Standard & Poor's ratings definitions" (http://www.spratings.com/en_US/understanding-ratings?rd=understandingratings.com)

As mentioned earlier, common features used by Moody's and Standard & Poor's are rating outlooks and rating reviews in order to notify investors of a potential revision that may arise (Securities and Exchange Commission, 2013). On one hand, rating outlooks can be useful to draw attention to a probable direction of a rating over the mid-term in reaction to changing financial and/or economic business conditions (Langohr, H. & Langohr, P., 2008). They are not necessarily followed up by an up- or downgrade but still maintain the stability and improve the precision of long-term ratings. An outlook can be positive (raised rating), negative (lowered), stable (not likely to change) or developing (raised or lowered). On the other hand, according to Langohr H. and Langohr P. (2008), a stronger indication of potential rate changes is proposed through rating reviews. They signify that the issuer rating will change with a very high probability but without always knowing precisely the direction. Rating Alerts, CreditWatches and Watchlists are used to list and summarize the reviews announced. Nonetheless, it might happen that some rating actions are not preceded by any of this kind of alert (Securities and Exchange Commission, 2013).

1.2.3. Critics and flaws

Besides, CRAs have been heavily criticised with regard to the timeliness of their ratings and to their conservative migrations. This criticism is based on the evidence given by the period of 2001-2002 where financial condition and liquidity prospects of issuers had a greater volatility and deteriorated more rapidly (Langohr, H. & Langohr, P., 2008). In terms of methodology, Altman and Rijken (2005) link this phenomenon to the "through-the-cycle" component of ratings dynamics. This method is designed in such a way that equilibrium between rating stability and timeliness is achieved. In order to reach a balance, agencies decide to ignore momentary changes in credit quality and to employ a prudent migration policy. With that kind of method, agencies avoid disproportionate rating reversals. Nevertheless, through-the-cycle methodology does not fit investors' needs, as they look for short-lived point-in-time assessments of credit quality. In other words, they seek measurements of credit quality that are both sensitive to permanent and transitory changes (Altman & Rijken, 2005).

Even though CRAs have tried hard to enhance their methodologies, they have been subject to a lot of criticism as aforementioned. In particular, Bielecki et al. (2011) have pinpointed the irony that "the rating agencies' worst failures relate to credit products that were, by design, built on credit ratings such as collateralized debt obligations of mezzanine asset-backed securities" (p. 9). Into the bargain, some rating timing differences have been raised by a certain number of researchers. For example, according to Bissoondoyal-Bheenick (2004), S&P was way more optimistic than Moody's about Mexico during the Mexican crisis in 1994. The former had given a BB+ rating with a positive outlook whereas the latter had assigned a Ba. In that matter, the Securities and Exchange Commission has been strictly prohibited via the Reform Act from regulating rating methods and models despite its comments and objections in the U.S. Still, the EU regulation has required CRAs' methodologies to be continuous, systematic, rigorous and potentially subject to validation (ESMA, 2010, as cited in Hemraj, 2015). Therefore, agencies have a long way to go and a lot of research to make in order to further improve their methodologies.

Hence, this thesis aims to reveal if different ratings could be assigned by the two main CRAs because of this divergence in terms of methodology and because of financial characteristics of the companies analysed. The study realized for the purposes of this paper will seek to discover if agencies disagree on the importance given to one or another accounting factor in the rating process and if this could influence the final assessment, which would result in a split rating. The conditions of realization and the sample of the analysis in question will be introduced more in depth throughout the third chapter of this thesis.

1.3. Differences in interpretation of ratings

From the outset, market players (investors, issuers, regulators…) have not benefited from the same access to financial data, which results in information asymmetry. Consequently, they all use ratings issued by various CRAs to help them make investment decisions although they sometimes have misleading expectations of what those ratings really mean (Langohr, H. & Langohr, P., 2008). That kind of misconception can occur either when talking about ratings in general or while comparing the fundamental scales of the Big Two. This third section of the literature review will thus try to outline the typical misunderstandings and the scale differences between Moody's and Standard & Poor's.

1.3.1. General misinterpretations

Originally, ratings were invented to resolve the problem of information asymmetry and to create value for all investors and issuers. Yet, as most of them are either nonprofessional or badly informed, they can have a wrong comprehension of the concept of rating. In their book, Langohr H. and Langohr P. (2008) insist on five correct interpretations so as to avoid many recurrent misunderstandings about ratings and to propose at the same time a relevant explanation for each of them.

Firstly, ratings are often considered as pure probabilities of default although they are not. Default probabilities measure the degree of likelihood that the counterparty will default (default risk) on a continuous scale ranging from 0 to 1 while ratings address reference measures of it. Indeed, they propose a subjective assessment of the frequency of default of any instrument at a certain point in time, statistically based on past observations. However, some securities with the same rating might have default probabilities that differ slightly. Therefore, CRAs use the concept of expected default frequency (EDF) that proposes an average of these observations. They represent thus an unbiased and efficient default probability over the long-term for securities belonging to the same rating category (Langohr, H. & Langohr, P., 2008). Still, it is important to note that investors must interpret carefully this piece of information. It is not as objective as it may seem at first glance and it quickly becomes very arbitrary and indeterminate.

Besides, the time perspective of ratings is preserved through the business cycle for as long as the maturity of the security at least. According to Langohr H. and Langohr P. (2008), CRAs analyse creditworthiness and its financial drivers over the long-term, which implies that assigned ratings propose an assessment of the credit risk until maturity. In doing so, agencies want to cover both the issuer and its financial condition over a certain number of years and to elude transitory oddities simultaneously. In their analysis, they include a broad range of business-driven data: R&D, technology, strategy, legal status… In other words, ratings assess the structural company characteristics and are not adjusted in function of the business cycle. They are thus cycle-neutral and long-lived.

Furthermore, ratings can be considered as being descriptive rather than prescriptive of a debt situation (Langohr, H. & Langohr, P., 2008). The company's shareholders are empowered to adjust the amount of debt and to find an optimal quantity in order to maximize their value. In that sense, they could be tempted to increase the firm's capacity to reimburse its bills due to the limits and consequently to prefer a lower credit rating. Nonetheless, the creditworthiness assessment assigned to an enterprise does not entirely depend on its amount of debt at a given time. The rating may range from the lowest (speculative) to the highest (safest) and be as optimal no matter the importance of its liabilities. So, ratings are useful when making financial choices but do not inform precisely on the debt in a company.

Moreover, investors tend to believe that ratings price credit risk while they only measure it. Indeed, agencies are not able to value it precisely, since default risk is the only component that matters in the analysis. There is still another type of risk that could play a role even if CRAs do not have much to say about it: market risk (or credit exposure). In their book, Langohr H. and Langohr P. (2008) compare bond ratings with bond yields. They affirm that the former moves in a discrete way whereas the latter changes continuously. Those two financial features either follow the market or move against it. In order to illustrate this phenomenon, the example of France Telecom Eurobonds is referred to. From May 1999 to April 2000, yields and rates followed each other closely. Things changed afterwards: yields started to move independently from the general rate trend until November 2001. After this period of ups and downs, the relationship that prevailed before May 2000 could be observed again on the market. In brief, "credit ratings grade credit risk" (Langohr, H. & Langohr, P., 2008, p. 82).

Finally, credit ratings are not totally comparable to equity ratings although analysts from these two domains usually employ similar analytical tools. As stated by Langohr H. and Langohr P. (2008), the main difference between those two concepts lies in the fact that ratings consider the downside risk while equity analysts focus more on the upside potential of a firm. For example, this contrast is clearly visible with the case of a highly leveraged transaction. It may augment the share price, which is a good thing for equity holders but on the other side it may reduce cash flows due to the additional debt taken. In extreme cases, it can even cause bankruptcy or insolvency. Also, they could be differentiated according to the time window used when studying them. On one hand, credit ratings are forward-looking with usually a 2-year period before and after. This timespan can be sometimes reduced to the maturity of the security being rated at the very least. On the other hand, equity analysts look more deeply into the expected performance of a stock or on current earnings announcements over the last 6 to 12 months. In short, credit ratings are more long-lived than equity ratings.

1.3.2. Scale differences and misconceptions

In 1997, Cantor, Packer and Cole affirmed that the two leading agencies (Moody's and S&P) used to attribute lesser credit ratings on average compared to their main competitors. Yet, evidence showed a few years later that the correlation between Moody's and S&P ratings was positive. In other words, they both issued higher creditworthiness assessments in average due to increased competition (Bielecki et al., 2011). But what does this exactly mean? How could this be collated and understood? As aforementioned, this paper will focus on the two dominant CRAs – namely Moody's and Standard & Poor's. Even though they seem to provide exactly the same service, there are some particular differences in scale and in interpretation that must be pinpointed. This part of the section will thus compare and determine the exact meaning of ratings assigned by both agencies through their respective scales.

In his article, Ederington (1986) proposes three possible reasons for the existence of split ratings. Indeed, even if Moody's and S&P are supposed to assign an equivalent assessment to the same security or issuer, it is not rare that agencies' final ratings reflect a slight divergence in opinion. Firstly, this phenomenon could occur in cases where CRAs have a totally different understanding and dissimilar standards for each rating despite the fact that they agree on the general concept of creditworthiness. Then, split ratings could be due to systematic discrepancies in their rating methods. For example, CRAs could consider exactly the same factors in their procedures but with a different importance or they could even use totally distinct criteria when assigning a rating. Finally, the task of assessing creditworthiness is difficult and subjective, especially when it lies at the limit between two ratings. Consequently, there may be a divergence in opinion although the procedures are exactly similar (Ederington, 1986).

Whether it be solicited or not, ratings describe the agencies' opinion about the credit strength of issuers or securities using symbols made of letters such as AAA, BB- or Caa. Notably, this scale distinguishes itself with its fundamental "ordinality", which allows a comparison of all ratings scattered along it (Langohr, H. & Langohr, P., 2008). Each combination of letters designates a group of obligors and/or financial instruments sharing approximately the same credit risk characteristics. When assigning ratings, CRAs make thus use of their own system of letter grades along with a spectrum of credit quality that ranges from the very highest (AAA or Aaa) to the very lowest (D or C) as illustrated in Appendix 3 (Caouette et al., 1998). Moody's firstly used this system in 1909. There are many ways to adapt this method and each agency possesses its own assortment of ratings structures. Most of them even make a distinction between issue- and issuer-ratings (in addition to the classic long-term/short-term classification). The former assesses the performance of a particular debt instrument while the latter considers the issuer as a whole, without referring to a certain security. It is important to notify that those two types of ratings are different in meaning but are still dependent on each other.

In this paper, the study will be based on the majority of the companies belonging to the STOXX® Europe 600 index. The data used in this analysis will be of two kinds: the related long-term issuer ratings (or senior unsecured if necessary) from Moody's and the Standard & Poor's long-term issuer ratings, expressed both in local (or domestic) currency. They will be studied more in depth and compared simultaneously with the financial and accounting characteristics of the companies involved. More details about the methodology of the analysis can be found in the next chapter. Hence, the focus in the remaining part of the section will be on the general scales of both agencies with regard to the long-term issuer credit ratings.

Appendix 11 shows the different definitions proposed by Moody's to its different letter grades. In this case, the agency uses the same global long-term rating scale for issuers and securities. This spectrum goes from Aaa for securities/issuers with the lowest risk and highest credit quality to C for obligations/obligors that are very likely to default. Moody's offers also a broad range of other scales: short-term, national, linked to the probability of default etc. On the other side, appendix 12 summarizes the letter grades of Standard & Poor's. If the rating assigned is AAA, it means that the issuer's capacity to meet its financial commitments is very strong while D (or SD) reveals a general default situation. Just as its main concurrent, S&P uses other scales that are issue-related, short-term, linked to a product-type, to recovery rates etc. In addition, the main difference between both spectra could lie in the definitions of the ratings themselves: Moody's rather mentions credit risk and quality while S&P insists on the capacity to meet financial obligations. It goes without saying that in general the lower the rating, the lower the recovery rate since creditworthiness deteriorates.

To sum it up, both agencies can draw a line in their scales between investment-grade (IG) and speculative-grade (SG or NIG) securities. The former relates to the securities and issuers rated BBB- by S&P or Baa3 by Moody's and above whereas the latter refers to obligations and obligors respectively rated BB+ or Ba1 and below (Cantor et al., 1997). Also, pluses and minuses can be added to letter grades in order to nuance them a little bit more. Finally, the biggest (and most important) difference in interpretation between both agencies lies in the heart of the definition of rating. As mentioned earlier, Moody's assesses through its ratings the probability of default and the expected loss of a particular security or issuer when Standard & Poor's focuses only on default probabilities. That is often considered as the main reason why split ratings occur.

1.4. Rating transitions or migrations

As aforesaid, CRAs' main task is to attribute ratings to many issuers and securities, whether it be upon request or not. As a matter of fact, they evaluate creditworthiness with their own procedures and provide useful information to sophisticated as well as nonprofessional investors (Cantor & Packer, 1994). This credit ratings assignment process occurs mainly when the obligation is newly issued, when the issuer pays for it or when agencies decide spontaneously to rate new entities. Investors and regulators tend to rely importantly on these opinions as those institutions – especially the Big Three – became especially powerful in the financial market (Boehm, 2013). Hence, CRAs try to update their creditworthiness assessments on a regular basis so as to offer ratings that are as accurate as possible. This last section of the literature review will outline the concept of transition with the related matrices and will compare the point of views of both Moody's and S&P in that area.

1.4.1. Concept of transition and related matrices

Typically, agencies rate financial instruments when they are newly issued or obligors when they request it. Financial condition and liquidity prospects at a certain point in time are thus reflected through the resulting letter grade and this opinion is only valid at the moment of the rating process. In subsequent years, CRAs try to review periodically their assessments in order to provide rigorous and up-to-date information continuously, no matter when investors desire to consult it (Caouette et al., 1998). For example, if the creditworthiness of a company in particular changes, ratings should evolve accordingly. This significant change in credit quality is generally followed by an up- or downgrade, which normally results in a variation (positive or negative) of the price of the security. Yet, according to Caouette et al. (1998), it may happen that the market has already taken the improvement or deterioration into account and that the price has changed before the effective rating review. In brief, value is often affected by this system of rating follow-up.

In general, when referring to the phenomenon of transition, authors and researchers also employ the term "migration". As illustrated with the following definitions, there is a very subtle difference between those two concepts. Semantically, migration means going somewhere and coming back while transition refers to a shifting from one point to another without any promise of return. In this case, ratings can obviously be up- or downgraded and then go back freely to their initial letter grades if necessary. There is a continuous movement along the scale defined by the agencies concerned. For the rest of this section, we will consider that transition and migration mean the same, namely a change in rating due to an improvement or worsening of credit quality over time.

CRAs do not change their ratings overnight. Indeed, investors must be informed beforehand through one way or another. Therefore, since most issuers and securities do not usually keep a fixed and steady credit quality over time, agencies made up a system of rating outlooks and reviews. Those two indicators serve to preserve stability with regard to long-term ratings, although they can jeopardize their accuracy (Langohr, H. & Langohr, P., 2008). Rating outlooks and reviews are used to warn investors and to reflect variations in the financial condition of issuers and securities before a potential change in rating. A transition can thus occur at any moment over their lifetime (or maturity). Through such migrations, agencies acknowledge that the credit quality has changed significantly and that the previous rating did not fully mirror the current creditworthiness anymore.

Moreover, the rating transitions scheme is impacted by the business cycle. For example, as stated by Langohr H. and Langohr P. (2008), a very high D-U ratio (number of downgrades divided by the amount of upgrades) can be observed in 1990, which reveals an extremely poor credit climate during that year. On the contrary, the low D-U ratio of 2004 reflects a benign credit environment. Into the bargain, the schema of migrations can be influenced by the rating category as well. Studies show that the number of transitions grows with the age of a rating group and that changes in credit quality assessments are more frequently observed among lower rated cohorts than higher rated.

As aforementioned, this rating follow-up affects investors (both sophisticated and non-professional) and the value of their financial instruments in a number of ways. Firstly, when credit ratings vary, the price of the securities in question fluctuates and this results either in a loss or in a gain for the owner. If an entire portfolio is impacted by those migrations, the repercussion is absolutely non-negligible in case of a negative trend. In that matter, there are several techniques to measure concretely the effect a rating change. Furthermore, this change in creditworthiness assessments may be a problem for institutions that have explicitly defined some of their investment policies beforehand (Caouette et al., 1998). Indeed, if they can only hold a certain number of securities with a particular credit quality in total, the defined limits may be exceeded due to those transitions. Finally, this concept of migration has incited market players to use the method of crossover investing. According to Caouette et al. (1998), investors will then try to have a portfolio composed of financial instruments that have the following characteristics: very likely to be upgraded and less likely to be downgraded. Neither a status quo (stable rating) nor a downgrade is thus a desirable result.

The notion of migration has recently ridden high and has been studied in great detail by many researchers and authors. The major finding is the related concept of transition (or migration) matrices that report probabilities of rating changes across categories over a chosen timespan (Langohr, H. & Langohr, P., 2008). In other words, as mentioned by Nickell, Perraudin and Varotto (2000), they outline probabilities for securities of a given rating moving to some other over a certain period of time. For example, appendix 13 shows a typical Standard & Poor's transition matrix providing an indication of the probable path of financial instruments. On the vertical axis, initial ratings can be found and the horizontal one proposes the resulting letter grade after migration. Diagonal figures represent measures of stability since they are probabilities of ratings remaining unchanged. Elements above the diagonal refer thus to probabilities of downgrades and the numbers below it rather to upgrades. As highlighted, ratings tend to be more stable in higher rating cohorts since they have higher transition probabilities (Langohr, H. & Langohr, P., 2008).

In order to build migration matrices, more and more financial practitioners have used the Markov chain model since it is a relatively easy probability representation (Kiefer & Larson, 2004). The pioneers and the first researchers to make use of this concept when modelling default and transition were Jarrow et al. in 1997. As a matter of fact, this process assumes to have stationary probabilities and estimates the likelihood of a modification in rating by summing up all the changes that occur over a certain period of time. According to Trueck and Rachev (2009), that kind of model can be considered as a special form of the intensity-based approach to credit risk. In the case of a discrete-time Markov model, there is a measurable and finite amount K of states that a stochastic process X_t can have. If $X_t = i,$ the transition probability is written p_{ij} and represents the likelihood of X_t going from the state i to j. This shows that both the initial and the final states influence the resulting p_{ij} (Kiefer & Larson, 2004). As soon as all those probabilities are computed, they commonly form a transition matrix such as:

$$P = \begin{bmatrix} p_{11} & p_{12} & \vdots & p_{1K} \\ p_{21} & p_{22} & \vdots & p_{2K} \\ \cdots & \cdots & \vdots & \cdots \\ p_{K1} & p_{K2} & \vdots & p_{KK} \end{bmatrix}$$

It is important to note that the sum of the probabilities of each row must be equal to 1 as ratings must either stay stable (unchanged with a chance p_{ii}) or change for an alternative state. Then, if a vector X summarizes all the possible states for the Markov process, the probabilistic evolution can be described with the following equation:

$$X_{t+1} = X_t \, P$$

The Markov chain model has been a great success among financial practitioners thanks to the simplicity of this last equation. This made the concept especially attractive to those who wanted to analyse the ratings transition behaviour of credit (Kiefer & Larson, 2004).

Those matrices can thus be of two types: either discrete-time or continuous-time. The main difference between those two categories is that the former computes probabilities for a defined amount of dates while the latter proposes a way to obtain probabilities for all horizons (de Servigny & Renault, 2004). Generally, CRAs put at their investors' disposal transition matrices that are in discrete time, usually with a fixed horizon of one year. In this respect, appendix 13 is a matrix provided by Standard & Poor's with a 1-year and a 3-year timespan.

However, Nickell et al. (2000) found out in their study that transition matrices are not time-stationary unlike the hypothesis of the Markov model. In other words, they tend to vary across time resulting consequently in time-heterogeneity (Bielecki et al., 2011). Also, the pattern of rating migrations depends on the economic cycle. The number of downgrades and the default probabilities are more likely to increase significantly in periods of recession. On the contrary, a larger amount of upgrades and lower probabilities of default can be observed in expansions.

Besides, transition matrices are influenced by loads of other factors that were not taken into account in the standard Markov setup (Güttler, 2006). Firstly, the so-called "downward momentum" is the most broadly analysed as it plays an important role. Evidence has shown that downgrades are more likely to be followed by downgrades again and defaults than by upgrades. Then, the issuers' domicile seems to be a relevant factor: Japanese companies tend to be downgraded more often than non-Japanese ones (Nickel et al., 2000, as cited in Güttler, 2006). Also, when comparing the different sectors on the market, banks appear to have a higher volatility of rating transitions despite the fact that industrial sectors suffer more frequently from larger movements. Finally, migrations seem to be influenced by the time since issuance too. In this regard, Altman and Kao (1992, as cited in Güttler, 2006) proved that older financial instruments use to be up- or downgraded more easily than newly issued ones.

1.4.2. Transition matrices of the main CRAs

As aforementioned, the Big Two makes use of distinct methodologies to assess the credit quality of issuers and financial instruments. While Standard & Poor's only focuses on the default probability, Moody's evaluates rather the loss given default. What about their transition models? Are they also that much dissimilar? This last part of the section will attempt to compare the two main agencies concerned by the study with regard to the concept of transition.

Moody's Credit Transition Model is employed to predict default probabilities, up- and downgrades in order to reflect the potential future path of any issuer or security. This issuer-based procedure is of the discrete-time type and does not depend on the timespan chosen. It is thus a model used to forecast all transitions no matter the horizon, which can be applied to any portfolio. Moreover, this technique includes various factors in the analysis: current rating, transition history of the obligor (or obligation) and also macroeconomic drivers such as unemployment rates and high yield credit spreads (Moody's Credit Policy, 2007). The most interesting feature of this model is that it focuses on the current economic state and on the future path of those business-related drivers simultaneously. This characteristic appears to be especially important, as evidence has shown that rating performance is influenced by economic cycles (Moody's Analytics, 2010).

Each year, Standard & Poor's releases studies about default rates and transitions at a broad range of assets so as to evaluate its own ratings performance. In those reports, migration is defined as being a measure of how much a rating has been up- or downgraded over a chosen horizon. In that sense, the agency wants to provide investors and financial practitioners with helpful indicators of volatility and relative stability of its credit ratings (Standard & Poor's Ratings Services, 2014). In order to do so, they compute one-year transition rates with a particular method called "static pools": they take each security or issuer at the beginning of a certain year as well as at the end of the same year and then compare the ratings collected to determine if there has been a change (Standard & Poor's Ratings Services, 2015). It is important to note that if a borrower has kept the same rating for more than one year, it is counted in the computation as many times as the number of years.

In brief, the Big Two seems to have a similar understanding of the concept of transition as well as comparable computation methods. Nonetheless, they sometimes record ratings migrations at different periods of the year. In his study, Güttler (2006) analyses whether ratings transitions by one agency can influence the probability of observing ratings change by the second. In this respect, he has presented evidence that previous downgrades by one of both institutions have a great positive impact on the default and rating downgrade probabilities of the other. Consequently, it may happen that one of two CRAs lags behind and just reacts to follow its competitor's opinion later on.

2. Empirical analysis

As mentioned previously, the statistical study undertaken for the purposes of this paper will focus on two of the three main CRAs in the rating industry (Moody's and Standard & Poor's). This research design reflects both the situation in the market and access to data. Indeed, the third agency belonging to the Big Three, namely Fitch IBCA, has a way smaller market share than its two main competitors. Also, Fitch keeps its methodology and general information slightly more confidential and secret, which would have jeopardized the data collection process if the focus had been on the three agencies at the same time.

This thesis will attempt to reveal split ratings among companies that are rated by both Moody's and S&P. Then, those rating differentials will be studied more in depth in order to determine whether they are caused by divergences in terms of methodology with regard to financial and accounting characteristics of the companies analysed. In other words, the statistical analysis seeks to discover if Moody's and S&P disagree on the importance given to one (or another) business-related factor in the rating process and if this could influence the resulting occurrence of such split ratings.

Therefore, this third chapter will be subdivided into four main sections. First, the research design will be described in details. All criteria of differentiation will be introduced along with the index concerned by the study. Then, the second section will explain the methodology developed and used as part of this empirical analysis. Thirdly, the main results of the study will be presented. Finally, concluding remarks and recommendations will be expressed as well as reflexions, potential drawbacks and critics.

2.1. Research design

In order to understand correctly the *raison d'être* of this quantitative study, it is important to precisely outline the process of sample selection. Indeed, the methodology and the main results can only be comprehended and appreciated if the data collection technique is clearly presented. This section describes how data has been collected and managed so as to answer the research question of this paper.

2.1.1. Sample selection and data collection

First of all, the sample selection method was based on the index called STOXX® Europe 600. The choice fell on a European index due seemingly to poor interest and a lack of previous studies in that area. For example, Shimizu, Lee and Takei (2013) analysed the determinants of split ratings through a comparison of American and Japanese companies. However, little research can be found with regard to the European situation.

In a few words, the STOXX® Europe 600 index comes from the STOXX Europe Total Market Index (TMI) and is a part of the STOXX Global 1800 Index. The index concerned by the study comprises a steady number of 600 constituents and is represented by small, mid and large capitalization enterprises from 18 countries of Europe: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom[3].

Due to data scarcity, only a reasonable part of the STOXX® Europe 600 index could be studied for the purposes of this paper. The mechanism used to determine the sample and the relevant firms was designed as described subsequently. The 600 companies composing the index were ranked in function of their market capitalization (weights) from highest to lowest. By the way, it is worth mentioning that the weighting scheme of the STOXX® Europe 600 index was established according to free-float market capitalization (STOXX® Index Methodology Guide, 2016). Also, weights were computed on the basis of gross returns (GR) as it permits to look at all the factors, even those outside control unlike net returns (NR). Then, the currency used to express those gross returns is the Euro since STOXX® Europe 600 is a European index of which most firms employ the Euro as main legal tender.

From that ranking, the first half was chosen for the sample, which means 300 firms with the highest weights or 87.86% of the index (based on the data released in April). Undoubtedly, studying the full spectrum of the STOXX® Europe 600 index would have been more accurate and relevant but a limited access to data made this impossible. Nevertheless, this still represents a significant part, in weights, of the initially listed companies. Appendix 14 lists all the 300 enterprises included in the sample at first. The data collected formed thus a homogeneous pool within a similar geographic area (Europe). This homogeneity is an especially important rule when building a sample to analyse.

[3] Retrieved from https://www.stoxx.com/index-details?symbol=SXXP

As stated many times before, the study focused on data coming from the two biggest CRAs on the market, i.e. Moody’s and Standard & Poor’s. The reasons for this choice have been expressed here above (market share and access to data). Then, the following ratings from those two institutions were necessary in order to conduct the analysis: the related long-term issuer ratings (or the senior unsecured debt if necessary) from Moody’s and the Standard & Poor’s long-term issuer credit ratings, expressed both in domestic (or local) currency.

In this case, issuer-related ratings of the 300 companies belonging to the sample were considered as the principal data of the study. Indeed, since the research question of this paper was linked to the creditworthiness assessment of firms in terms of debt issuers as such, it made more sense to focus on the ratings of the companies themselves rather than on a certain type of security. However, it might happen that this kind of data is not available on any of the agencies’ websites either because institutions have decided not to rate the firm in question or because they only assess the credit quality of a few securities. Obviously, both Moody’s and S&P do not assign ratings to all companies that exist worldwide and one of the two might rate an enterprise that the other does not and vice versa.

As far as Standard & Poor’s is concerned, the website of the institution only provides investors with the latest ratings of companies, and not with the respective historical evolution. However, the ratings needed to conduct the study could, most of the time, be collected with the help of the software called “S&P Capital IQ”. With regard to Moody’s, long-term issuer ratings of certain firms were sometimes missing on the website. Instead, the credit quality assessment of the so-called “senior unsecured debt” was used if necessary. The reason behind this choice is that Moody’s considers issuer ratings as expressions of its own opinion about the ability of firms to repay senior unsecured debt and obligations (Moody’s Investors Service, 2016). This partly explains why senior unsecured and long-term issuer ratings are usually equal when companies possess both of them. From now on, we’ll thus view these two concepts as equivalent.

Also, in addition to the classic ones, Moody’s website offers a very broad range of additional credit quality assessments. Among those, the BACKED and MTN types can be found, most of the time in relation with senior unsecured debt. On one hand, the former represents ratings of securities that are supported by specific vehicles issued by financial institutions, e.g. liquidity facilities or external letters of credit (Moody’s Investors Service, 2016). On the other hand, Moody’s can make use of medium-term note (MTN) programs in order to assign provisional ratings that are neither of the typical short- nor long-term type. This is usually designated through a *(P)* in front of the letter grade (Moody's Investors Service, 2016). Both those BACKED and MTN ratings are computed using a different methodology compared to the classic method. However, the sample used in this study was standardised as much as possible to make it as representative as possible. In other words, ratings were chosen if and only if they were pure long-term issuer-related assessments and any other type of rating (such as BACKED or MTN) was definitely ignored.

As mentioned earlier, the STOXX® Europe 600 index could not be analysed entirely due to data scarcity with regard to Standard & Poor's ratings, although Moody's provided for free the ratings needed on its website (current one as well as the historical evolution). Consequently, the poor access to S&P data and the need for external help to obtain it resulted in the initial sample being only composed of 300 companies instead of 600. Also, the empirical study of this paper solely focused on issuer-related ratings retrieved from both CRAs, which made the number of firms even smaller. However, this reduction of sample did not affect the significance of the analysis.

Starting from those 300 firms, the number of companies in the sample was reduced as described subsequently. First, Standard & Poor's rated only 220 of them and data related to the 80 remaining ones was missing. This can be explained by the fact that the institution does not assess the credit quality of all existing firms in the world but rather of a limited number. Then, among the 220 enterprises, the S&P long-term issuer rating expressed in local currency could be found for 207 of them while 13 were unrated or did not have the required credit quality assessment. Moreover, the empirical study of this paper focused on companies that were simultaneously rated by Moody's as well as by S&P. The 207 remaining ones had thus to be sorted once again into two groups in function of their possession of a Moody's rating or not. As a result, 134 firms out of 207 had a long-term issuer or senior unsecured rating expressed in domestic currency while the 73 others were not rated or did not possess the required rating. Obviously, Moody's does not evaluate either the creditworthiness of every single firm in the world, just as Standard & Poor's.

The figure 2 here below summarizes the results of the selection process. In brief, the sample concerned by the study is composed of 134 companies out of the initial 300, which represented 45% (or 61% if we consider the data of the 220 firms effectively available from the outset). This allowed the analysis to be significant enough with a weighted total of

52.51% of the whole STOXX® Europe 600 index studied. The 134 firms that belong to the sample are exhaustively listed in appendix 15 with their respective sectors, countries and weights.

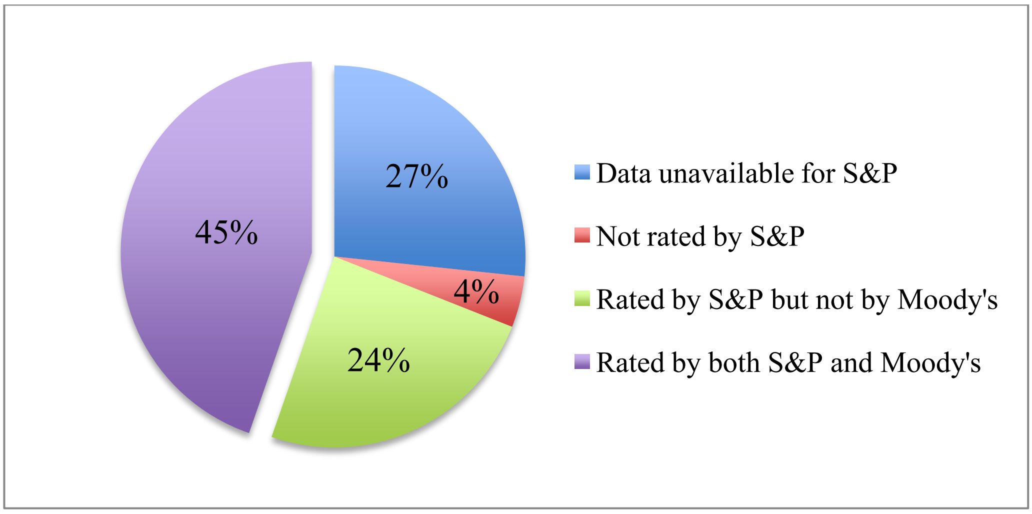


Figure 2: Results of the sample selection

Finally, the 134 companies chosen for the study can be classified according to their country of origin as well as the sector they operate in. On one hand, it can be observed on the first chart hereunder that the United Kingdom and France account for almost half of the sample with respectively 36 and 21 firms, or a total of 57 companies out of 134 initially (more or less 43%). Countries such as Switzerland, Germany, Spain, Italy, Holland and Sweden have all a fairly reasonable number of firms belonging to the sample while Austria, Belgium, Denmark, Finland, Ireland, Luxemburg, Norway and Portugal are slightly under-represented.

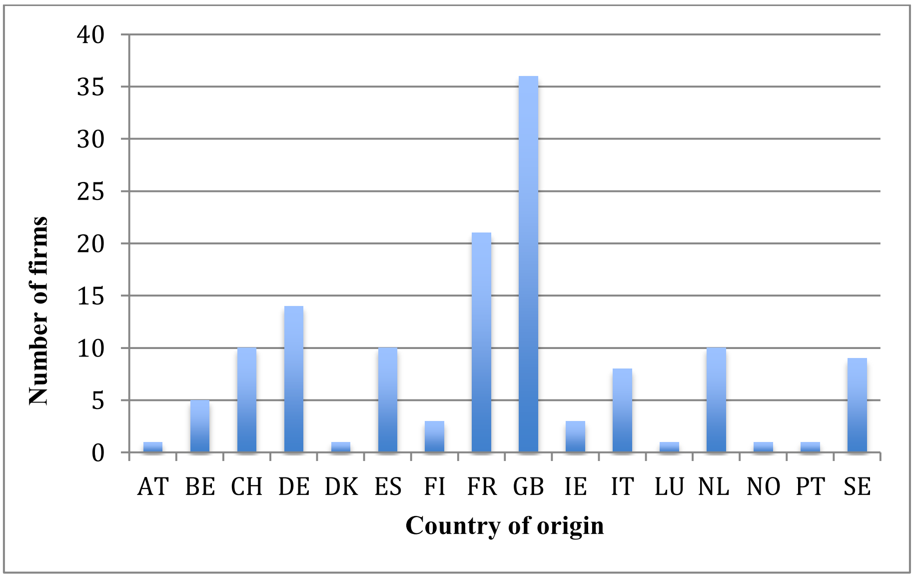


Figure 3: Repartition of the sample in the EU

On the other hand, the following chart depicts the repartition of the 134 firms that belong to the sample in function of the different sectors they operate in. It is important to note that the banking sector is the one that is the most represented (with 26 enterprises out of 134), followed by Utilities and Industrial Goods & Services with respectively 15 and 14 companies. Then, the number of enterprises in the sectors of Insurance and Automobile & Parts is rather high whereas all other ones are poorly portrayed in the sample.

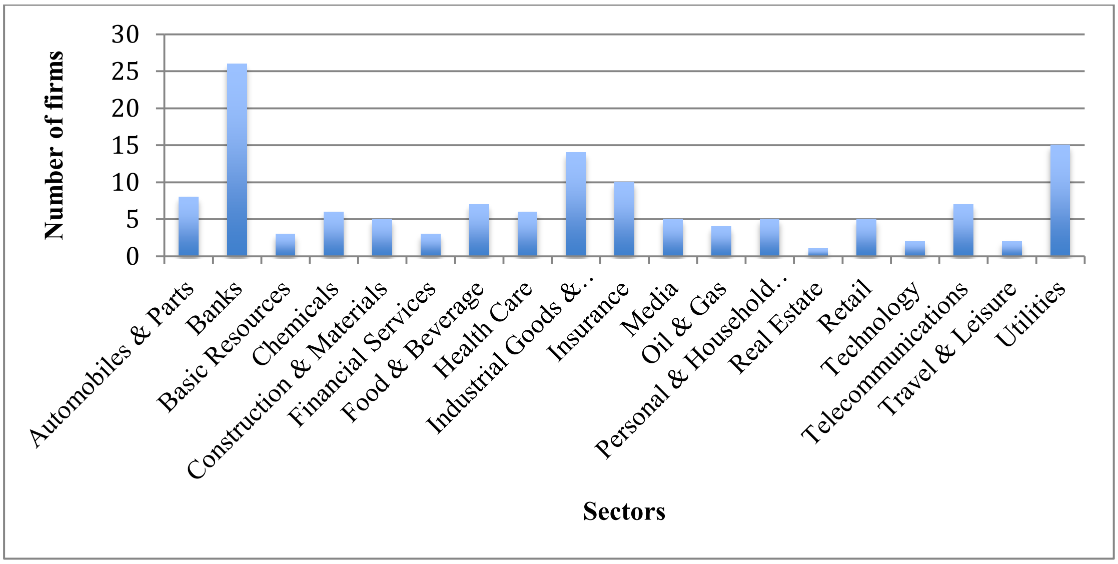


Figure 4: Repartition of the sample among sectors

2.1.2. Financial and accounting characteristics

As highlighted in the literature review, Ederington (1986) affirms that the phenomenon of split ratings can occur in three different cases: if CRAs have dissimilar understandings and standards with regard to their rating scales, if they use distinct methodologies (with discrepant weights assigned to company characteristics) or due to the subjectivity and difficulty linked to the rating task. Therefore, Ederington (1986) attempted to find in his paper what the possible reason could be (out of these three abovementioned) for the existence of split ratings in the matter of corporate bonds. The sample studied was composed of 493 industrial bonds with the following properties: issued in the period 1975-1980, rated B or higher by both Moody's and Standard & Poor's and with a duration of more than 10 years. Out of these 493 securities, 63 (or 13%) of them appeared to have split ratings. Ederington (1986) chose then to use various financial features in link with coverage, profitability and leverage in order to conduct his study. Finally, he concluded that the phenomenon of split ratings occurred mainly due to random divergences in opinion, especially when credit quality assessments were close to the cutoff point. In short, only the subjectivity and the difficulty of the creditworthiness evaluation task led to rating differentials (third hypothesis here above). On the contrary, Cantor (1994, as cited in Dandapani & Lawrence, 2007) found out that rating differentials were rather due to the use of distinct methodologies by the main CRAs as well as the presence of judgemental elements.

Moreover, Dandapani and Lawrence (2007) compared university grades with bond ratings and the following results came out: approximately one-third of split bond ratings can be explained by differences in ratings scales whereas the other two-thirds are most of the time caused by randomness, information asymmetry or judgemental differences. In the same vein, Jewell and Livingston (1998) studied a large sample of more than 1,200 industrial bonds and found out that none of the two CRAs (neither Moody's nor S&P) have a tendency to assign higher ratings than the other. Yet, if it still happens, this is due to insignificant random differences.

Also, in their article, Livingston, Naranjo and Zhou (2007) called Ederington's finding the "random error hypothesis of split ratings". This means thus that there is no reason beforehand to expect that the Big Two will assign divergent ratings to the same financial instrument. However, if it does happen, it can only be due to unsystematic differences in judgment (Billingsley, Lamy, Marr & Thompson, 1985). On the contrary, it has been shown that split ratings tend to occur more regularly for banks than for companies from other sectors because of their typical opaque assets (Morgan, 2002, as cited in Livingston et al., 2007). This phenomenon is called "the asset opaqueness hypothesis of split ratings". In this respect, Livingston et al. (2007) tried to discover whether this asset opaqueness hypothesis could equally be applied to firms from the non-banking sector. In order to do so, they used an initial sample composed of 3,213 domestic bonds issued in a period ranging from 1983 to 2000. To put it in a nutshell, the study provided the following results: issues that are related to asset opaqueness partly give a reason for the split ratings of non-banking companies. In other words, enterprises that own more opaque assets are much more likely to experience such divergences in opinion (Livingston et al., 2007). This finding brings thus evidence that split ratings are not only caused by random errors, unlike what Ederington (1986) affirmed in in his paper.

In a more recent study, Bowe and Larik (2014) analysed a sample composed of American dual-rated (by S&P and Moody's) firms. Their main finding was that big and lucrative companies with better interest coverage and more independent directors as well as institutional investment usually experience less rating differentials. In addition, Bowe and Larik (2014) affirmed that Moody's tends to be more conservative than its principal concurrent, which confirms what Morgan (2002, as cited in Bowe & Larik, 2014) and Livingston et al. (2010) stated. In other words, Moody's assigns inferior ratings to smaller, less beneficial enterprises in the event of a split rating.

With regard to split rating trust, Livingston, Wei and Zhou (2010) analysed the impact of split ratings on bond yields. In order to do so, they used a sample composed of more than 6,500 newly issued corporate bonds for a period ranging from 1983 to 2008. They asserted that investors make a real difference between S&P's and Moody's ratings and reputations: in the case of a split rating, lower yields are required when the latter assigns superior creditworthiness assessments compared to the competitor's opinion. It seems thus that Moody's reputation is held in higher regard than Standard & Poor's and that its ratings are taken more seriously.

Concerning the international context, researchers such as Shimizu et al. (2013) attempted to compare split bond ratings through a sample composed of companies rated both by Japanese and American CRAs. They found out that such institutions in Japan tend to be less conservative as they put more weight than their American competitors on financial indicators like return on assets (ROA), assets, leverage and liquidity.

Along the same lines, a lot of researchers used samples composed of bonds (and solely bonds). They designed their studies in such a way that financial characteristics of the companies concerned could explain split bond ratings. Nevertheless, only a limited number of them concentrated on more general divergences in opinion, such as those related to the issuer types, just as Bowe and Larik did in 2014. Therefore, in this paper, the analysis focused on rating differentials with regard to long-term issuer-related (or senior unsecured) ratings expressed in domestic (or local) currency and attempted to justify these divergences in opinion through business-related factors. This decision has thus been made due to poor interest and a lack of previous studies in that area.

When the ratings of the 134 different companies were pooled together after collection, they were studied more in depth and compared simultaneously with the financial and accounting traits of the firms. In that matter, Ederington (1986) mentions a certain number of factors that both agencies consider as especially important when assigning ratings. Although Standard &

Poor's asserts that they take a lot of different financial statistics into account, they have recognized that four of them were the most primordial in the rating process:

- *"pretax fixed charge coverage,*
- *the ratio of cash flow to long-term debt,*
- *pretax return on long-term capital, and*
- *leverage measured as the ratio of long-term debt to total capitalization"* (Standard and Poor's Corporation (1979). *Standard and Poor's Rating Guide*, p. 42, as cited in Ederington, 1986)

On the contrary, Moody's has not made an official identification of the factors considered as the most important. Nonetheless, several studies have shown that indicators of leverage, coverage and profitability can play the role of key determinants during the rating process. In the same vein, a significant correlation has been discovered between measures of size of issuing companies and ratings assigned by Moody's (Ederington, 1986).

Given the general obsolete character of all the studies mentioned in this paper, the timespan chosen for the analysis ranged from January 2000 to July 2016, clearly along with the aim of making more up-to-date findings. In order to collect monthly data in link with financial and accounting characteristics of the companies belonging to the sample between 2000 and 2016, the software called "S&P Capital IQ" was used. However, due to data scarcity and a limited access to computer rooms with the powerful software, only a few could be exploited for this sample period. Hence, on the basis of the literature, table 1 displays the firm-specific financial (and accounting) features and ratios chosen for a potential inclusion in X.

In general, most of the basic business-related traits presented here above were collected thanks to the software "S&P Capital IQ" and were expressed in million euros. Yet, it goes without saying that ratios such as Return on Equity (ROE) as well as the four ones computed (in the second column) were rather formulated through a simple digit. Also, this information provided by the software and the ratios calculated are all commonly used and easily understandable. Nevertheless, there is only one slight difference in definition that should be highlighted with regard to the terms unlevered and levered cash flows. Indeed, the former represents the amount of cash that a company has at its disposal before meeting all its financial obligations while the latter is the firm's cash flow after paying them. In brief, the only difference between those two concepts is the expenses that have already been withdrawn or not.

Provided by Capital IQ	To be computed
Net income	Return on Assets
Total debt	Leverage
Total equity	Liquidity
Firm size measured with total assets	Cash-flows/Long-term debt
Total liabilities	
Current assets	
Current liability	
Total revenue	
Gross profit	
Return on equity	
Market capitalization	
Total enterprise value	
Unlevered cash-flows	
Levered cash-flows	
Long-term debt	

Table 1: Financial and accounting characteristics

Concerning the four ratios to be computed on the basis of the data collected, it seems relevant to mention the formulas used in order to generate results. First, the Return on Assets (ROA) ratio was calculated by dividing the net income by the total assets. This digit proposes an estimation of the profit made by the firm for every dollar of its assets. Then, leverage can be evaluated by computing the following ratio: total debt to total equity. This reflects the amount of capital a company owns coming purely in the form of debt. Furthermore, dividing the current assets by the current liabilities (also called the "current ratio") assesses the liquidity position of an enterprise or, in other words, the firm's capacity to reimburse its current liabilities with its current assets (both short-lived). Undoubtedly, the higher the ratio, the better the liquidity position. Finally, the ratio recommended by Ederington (1986), i.e. cash flows divided by long-term debt, was calculated. This digit mirrors the company's ability to pay off its long-term debt with the cash flows it generates yearly.

In addition, it is important to note that, unlike Bowe and Larik (2014), no indicator of corporate governance quality was chosen since the focus of this empirical study was mainly on accounting and financial characteristics per se. This means that, for example, the number of independent directors was not considered as relevant for the analysis among others. Yet, it could be interesting to include that kind of additional features in further studies.

2.2. Methodology

This part of the third chapter is linked to the general methods developed so as to answer the research question of this paper. However, elaborating an accurate and proper methodology is only made possible on the basis of some literature and previous studies read beforehand. This section will thus be divided into two parts. Firstly, the theoretical context in link with the models to use will be outlined. Then, the second subdivision will present the one effectively developed and put in practice for the purposes of this paper.

2.2.1. Theoretical background

As mentioned earlier, the empirical study of this paper will attempt to detect split ratings for companies rated by both Moody's and S&P and then determine whether this phenomenon could possibly be caused by divergences in terms of methodology with regard to financial and accounting factors. In other words, the results of this analysis is supposed to help to find out if both CRAs do not agree on the importance to give to those business-related traits in the rating process and if this could influence the occurrence of such divergences in opinion. In order to do so, a dual-rated sample was composed to avoid potential selection biases due to the number of ratings a firm possesses (Jewell and Livingston, 1998). Obviously, since the statistical analysis addressed both CRAs, only the companies that were both rated by the two institutions during the same period of time could be considered.

According to Livingston et al. (2010), most academic researchers consider in their studies that ratings assigned by both CRAs are equivalent although those institutions frequently have divergent opinions. Along the same lines, Cantor et al. (1997) affirm that if models do not rely on both pieces of information, then they will face greater biases and more inefficient forecasts. That is why making this statistical analysis can be interesting so as to additionally pinpoint the necessity to take both ratings into account and, above all, the differences between Moody's and Standard & Poor's when appropriate.

In this analysis, ratings as well as financial characteristics for a certain number of companies were collected and compared across time. Hence, for the purposes of this empirical study and due to the form taken by the input, panel data econometrics had to be used. Indeed, panel data (also called "longitudinal") combines two dimensions: cross-sectional and time series (Wooldridge, 2013). The cross-sectional dimension is referred to when researchers study multiple characteristics on a certain number of individuals at a defined point in time. Those factors analysed can be wages, hours, and education for example. In this paper, the variables studied are the ratings of both CRAs, the differences in ratings, the financial ratios etc. Then, time series can be mentioned when factors are analysed across time instead of only at one determined moment. In brief, panel data results of the mix of those two dimensions. This term is thus mentioned when researchers study the behaviour of exactly the same individuals, whether it be companies, people, towns or anything else, across time (Wooldridge, 2013).

When panel data is analysed, the hypothesis that observations are independently distributed across time cannot be made. This is mainly due to the fact that there exist some unobserved heterogeneity effects that cannot be measured and, therefore, some special models have been found to take this information into account (Wooldridge, 2013). In particular, two methods are available in panel data analysis so as to deal with those unobserved and immeasurable elements: fixed effects and random effects transformations.

Let's consider a model with different explanatory variables:

$$y_{it} = \beta_0 + \beta_1 x_{it1} + \cdots + \beta_k x_{itk} + a_i + u_{it} \qquad t = 1,2,\dots,T$$

In this equation, β_k represents the coefficient attributed to the independent variable x_{itk}, where the combination of both terms determines the real impact of the exogenous factor in question on the dependent variable. More importantly, $a_i + u_{it}$ is the composite error term v_{it}. In particular, a_i represents the unobserved characteristics of the individuals mentioned here above that are constant over time but differ for each individual. Those immeasurable heterogeneity effects result in a problem of endogeneity and of biased coefficients if they are indeed correlated with the exogenous factors. In the case of a fixed effects transformation (also called "within transformation"), it is assumed that a_i is correlated with one or more of the explanatory variables x_{itk} and the goal is to make the term a_i disappear from the equation by subtracting all terms their own mean so as to get time-demeaned data (Wooldridge, 2013). With random effects transformation, it is assumed on the contrary that a_i is not correlated with any of the exogenous variables x_{itk}. The term a_i will thus be kept and left like it is since the process of fixed effects that consists in eliminating a_i is considered as leading to inefficient estimators. However, this solution results in making a strong hypothesis about the uncorrelated terms in the equation and might not be careful enough. In short, random effects do not permit arbitrary correlation between the unobserved effects called a_i and the explanatory variables x_{itk} whereas fixed effects do.

In his book, Wooldridge (2013) states that most researchers believe that fixed effects are more useful in order to estimate *ceteris paribus* effects but there still exist certain situations in which random effects can be applied preferably. Most undoubtedly, it makes no sense to use fixed effects for equations where key explanatory variables are fixed over time so as to determine the impact on y_{it}. Nonetheless, applying both random and fixed effects and comparing the coefficients obtained is fairly in common use.

As previously explained, the goal of this paper is to evaluate the potential impact of financial characteristics on the occurrence of split ratings. So, the general model used for this empirical study will be composed of a binary dependent variable $E(y|\boldsymbol{x})$ (also called "limited dependent variable") that can solely take the value of either 0 or 1. The 0-state means that the event did not occur while the 1-state designates the opposite case, where the event in question is the presence of a split rating in this case. This endogenous variable $E(y|\boldsymbol{x})$ is impacted by multiple exogenous factors x_{it}, namely accounting ratios in the present study. Nevertheless, when such a discrete dependent variable can only take a limited number of values, typical linear regressions are not especially appropriate to model it because of several flaws although they are easy to estimate and interpret. For example, if a certain set of values is given to the independent variables, out-of-the-range predictions can be obtained (less than 0 or greater than 1). In the case of functions that predict probabilities, this can be very problematic, as they must be comprised between 0 and 1. In brief, the linear model can be useful for forecasting probabilities but only for a limited part of the values taken by the exogenous variables, and especially not for the extreme ones. Hence, instead of treating y_{it} as a pseudo continuous variable through linear regressions, both logit and probit models can be used in spite of the difficulty of interpretation (Wooldridge, 2013).

Logit and probit models (also called "binary response models") are most of the time used when the dependent variable is a dummy one or when the fitted probabilities of the model chosen can only range from 0 to 1. According to Wooldridge (2013), this kind of theory can be interesting because of its response probability that is expressed as follows, where x represents the set of explanatory variables:

$$\mathrm{P}(\mathrm{y} = 1|\mathbf{x}) = \mathrm{P}(\mathrm{y} = 1|\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_\mathrm{k})$$

In the classical linear probability model (LPM), that type of response probability is considered as a linear function of the parameters. Yet, in order to limit the drawbacks linked to the LPM that were mentioned here above, the following form of equation is considered (Wooldridge, 2013):

$$\mathrm{P}(\mathrm{y}=1|\mathbf{x}) = \mathrm{G}(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k) = G(\beta_0 + \boldsymbol{x\beta})$$

In this equation, G is usually represented by a function whose values range strictly from 0 to 1 in order to make sure that the response probabilities are effectively between 0 and 1 only. The denomination logit or probit will then depend on the function assigned to G. On one hand, the logit model is typically defined with the logistic function for G:

$$\mathrm{G}(\mathrm{z}) = \frac{\exp(\mathrm{z})}{[1+\exp(\mathrm{z})]} = \Lambda\,(\mathrm{z}).$$

For all real numbers z, the cumulative distribution function for a standard logistic random variable is used as G. On the other hand, the probit model assigns the standard normal cumulative distribution function to G and is usually formulated as an integral:

$$G(z) = \Phi(z) = \int_{-\infty}^{z} \phi(v)dv,$$

where $\phi(v)$ designates the standard normal density. Both functions are obviously increasing (Wooldridge, 2013). In order to estimate those binary response models, the maximum likelihood estimation (MLE) is used in which the heteroskedasticity is automatically taken into account.

Despite the usefulness and the easy manipulation of the logit and probit models, there is one major difficulty: interpreting the resulting coefficients. Indeed, the results provided by most software products can give an idea of the sign (positive or negative) for the partial effects of each explanatory variable on the response probability as well as their statistical significance. However, they cannot be interpreted directly like those of linear regressions. In order to be able to do so, two methods can be used: the partial effect at the average (PEA) or the average partial effect (APE). On one hand, the *PEA* method consists in replacing each x_j in the equation by its sample average. The partial effect of each exogenous variable is thus assessed for the average individual in the sample (Wooldridge, 2013). Though, problems may arise with this *PEA* in two situations: if some of the x_j are discrete or represented by a nonlinear function, the results might make no sense. On the other hand, the *APE* method computes the mean of the individual partial effects all across the sample. After using one or the other approach, the new coefficients of the logit or probit models can be interpreted such as in linear regressions with the typical reasoning “if x increases by 1, then y increases by so much” (Wooldridge, 2013).

With regard to probit and logit models, there exists a pseudo R-squared so as to evaluate the total explanatory power of the exogenous factors chosen for inclusion in the equation. According to Wooldridge (2013), this measure is closely related to the typical R-squared coefficient determined by the linear probability model. Thus, just as with linear regressions, the pseudo R-squared in question can be interpreted in this way: it is close to 0 if the variables x_j present a poor explanatory power or close to 1 in the opposite case.

2.2.2. Methodology effectively used

In this second part, the methodology developed and effectively put into practice in order to generate results will be presented. At first, the management of data after collection will be further discussed. Then, the real manipulations and the models used in the software Stata will be outlined in details.

Concerning the monthly data related to financial characteristics, the software Capital IQ was asked to report their values on the first trading day of every month for each year as well as to express them in million euros when a currency had to be chosen. This decision was made since most countries of the companies that belong to the sample used the Euro as main currency. With regard to ratings data, the change in letter grades can occur at any time in the month of the year whenever CRAs consider that a transition is necessary to reflect as good as possible the reality on the market. Therefore, changes in ratings were considered as if they had occurred at the beginning of the month, even if they did it a few days later. For example, if the LT issuer rating of a company was downgraded on 18 December, this information was reported on 1 December in the Excel sheet as long as 1 December was effectively the first trading day of the month. The purpose was to match the data related to the financial characteristics with the credit quality assessments of both Moody’s and Standard & Poor’s.

On the basis of the study realized by Livingston et al. (2010), letter grades provided for the whole sample period (2000-2016) by both CRAs were transformed into numerical rating variables with the help of a scale ranging from 1 (for a C of Moody’s or a D of S&P) to 19 (for Aaa or AAA). This method can somehow be compared with the concept of credit scoring that is another way to evaluate creditworthiness and the ability to meet financial commitments through a digit. However, as mentioned in the literature review, credit rating and scoring have different scopes and apply to different entities. The following table was used in order to translate the creditworthiness assessments into the corresponding digit:

Moody's	Standard & Poor's	Numerical variable rating
Aaa	AAA	19
Aa1	AA+	18
Aa2	AA	17
Aa3	AA-	16
A1	A+	15
A2	A	14
A3	A-	13
Baa1	BBB+	12
Baa2	BBB	11
Baa3	BBB-	10
Ba1	BB+	9
Ba2	BB	8
Ba3	BB-	7
B1	B+	6
B2	B	5
B3	B-	4
Caa	CCC	3
Ca	CC/C	2
C	D	1

Table 2: Transformation of rating scales into numerical variables

Such a method to convert letter grades into numerical variables was handy so as to transform that initial information into more quantitative data. This permitted to compute a lot of parameters such the average rating assigned by Moody's or Standard & Poor's, the mean of split ratings and so on, which would not have been possible with the original qualitative character of the input provided by both institutions.

According to Bowe and Larik (2014), Moody's and S&P split ratings can be compared at two different levels: in function of the category or the notch. In a few words, Standard & Poor's adds pluses and minuses and Moody's category numbers such as 1, 2, and 3 to their initial letter grades in order to differentiate notch-rating categories and to make assessments subtler. A category-level split considers divergences in opinion without taking the additional information mentioned here above into account. For example, it compares issuers or securities rated AA by S&P and Aa by Moody's with others evaluated AAA/Aaa but does not examine e.g. in more details those assigned the ratings AA+/Aa1 with AA-/Aa3. This notch-related feature was introduced by Moody's and Standard & Poor's in 1982 and 1974 respectively (Bowe & Larik, 2014). As it can be observed in the numerical scale, both notch-level and category-level splits were considered in this analysis. The reason behind this choice was that considering sub-ratings in addition to split ratings between letter grades permitted to have more precise estimations. Also, as the sample period ranged from 2000 to 2016, data was available for both institutions with the related notches, which would not have been possible if the timespan studied had been before 1982. Nonetheless, it is not clear yet whether differences in split ratings between subratings are as important and influential as the ones between letter grades (Jewell & Livingston, 1998).

Then, the Excel sheet initially constituted of all the data concerning financial characteristics (19 in total) as well as ratings for both CRAs ($RatingM$ and $RatingSP$) solely was completed with additional useful information. Indeed, the file necessary to run the Stata software included the following indications: date, number of the month in the period ($Numbermonth$), day, month, year, name of the company, assigned number to the firm ($Numbercomp$), sector. It is important to note that numbers had to be assigned to variables such as the name of the company or the month of the period since Stata does not recognize chains of characters such as letters but well digits.

When all the final data was totally ready for use, several computations were performed in order to interpret it more concretely. First, dummy variables were created to have supplementary precisions with regard to the sector or the time of the year. On one hand, a binary variable called $Dummybank$ indicated whether the company was a bank or not. On the other hand, two others named $Crisis2008$ and $Crisis2011$ pointed out whether it was in a period of financial crisis or not (either for 2008-2009 or 2011-2012).

Also, since letter grades had been transformed into numerical variables, the rating difference between both ratings could be computed for all enterprises and months if and only if they were made available by the two institutions simultaneously. This new variable called $Ratingdiff$ was calculated as follows:

$$Ratingdiff = RatingSP - RatingM$$

In most studies, the opposite has been done, i.e. subtracting S&P ratings to Moody's ones. However, since evidence has shown that Moody's tends to be more conservative and to assign lower ratings than its principal concurrent, it made more sense to operate the subtraction in this way. Then, when all rating differences were computed, the simple mean of the variable was determined to be equal to -0.068 approximately. This meant that, based on the sample selected, S&P ratings were on average 0.068 notch below Moody's ones when a split rating occurred. This finding is yet not consistent with what Morgan (2002, as cited in Livingston et al., 2007) and Livingston et al. (2007) suggested. Hypothetically, this difference in results could be partly explained by two factors: the lower number of individuals in the sample as well as the limited means at disposal to conduct this study. Still, it might be interesting to study this problematic a bit more in depth so as to ensure there is a real tendency from Moody's to assign lower ratings or to discover that this theory could be possibly disproved with such counter examples.

Afterwards, an additional binary variable was created in order to indicate the presence of split ratings no matter the sign of the rating difference. In short, $Dummyrtgdifgen$ was equal to 1 if ratings differed (whether it be because of higher ratings from Standard & Poor's or the opposite) or to 0 if they were equal. In addition, the cells in Excel were just left empty in the case of missing data. As 134 enterprises were analysed on a period of 199 months, there were 26,666 possibilities of split ratings with, most obviously, possible redundancies (due to some of them lasting more than just one month). From that new binary variable, additional general information could be obtained. In the total sample, 9,541 occurrences out of 26,666 (or 35.78%) presented a split rating while 8,844 (or 33.17%) did not and 8,281 (or 31.05%) could not be evaluated as data was missing for one or the other agency. The following pie chart depicts the situation more clearly:

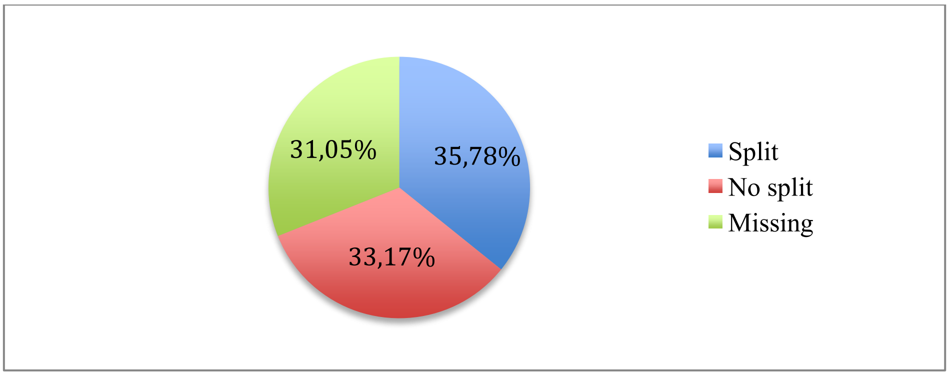


Figure 5: Repartition of split ratings

If the cases where data is missing were not considered, the number of split ratings and non-split remained the same but the percentages went from 35.78% to 51.90% (9,541 out of 18,385) for the split rated part and from 33.17% to 48.90% for non-split rated (8,844). Then, by studying more in depth the split rated sample composed of 9,541 occurrences in total, it could be observed that in 49.07% (4,682) of the cases, the rating difference was positive while the remaining 50.93% (4,859) concerned a negative one. This contradicted again the findings of most researchers in that field since they asserted that Moody's used to assign lower ratings. Yet, in this analysis, resulting statistics showed that in the majority of cases, Moody's letter grades tend to be higher than the ones given by S&P. This could be again partly due to the small sample and limited means. As mentioned earlier, the conduction of a deeper and greater analysis could be useful so as to discover if Moody's is effectively more conservative or if it is rather the opposite case in reality. Appendix 16 summarizes the situation by displaying cross-tabulations of issuer ratings.

Moreover, the number of occurrences of every result related to the $Ratingdiff$ variable could be analysed more closely in order to determine whether split ratings were in general of great amplitude when they occurred or not. The discrete variable ranged from -8 (for issuers that were rated eight notches lower by S&P than Moody's) to 4 (in the event of a rating assigned by S&P that is four notches higher in comparison with Moody's). On the chart below, it can clearly be observed that difference in notches equal to -1 or +1 were the most common as they tended to occur in 75% of the cases. It was followed by the -2/+2 results, which meant that split ratings with an amplitude of 2 in absolute value represented 20% of the occurrences. In addition, it can be affirmed that all other possible differences in notches were rather insignificant.

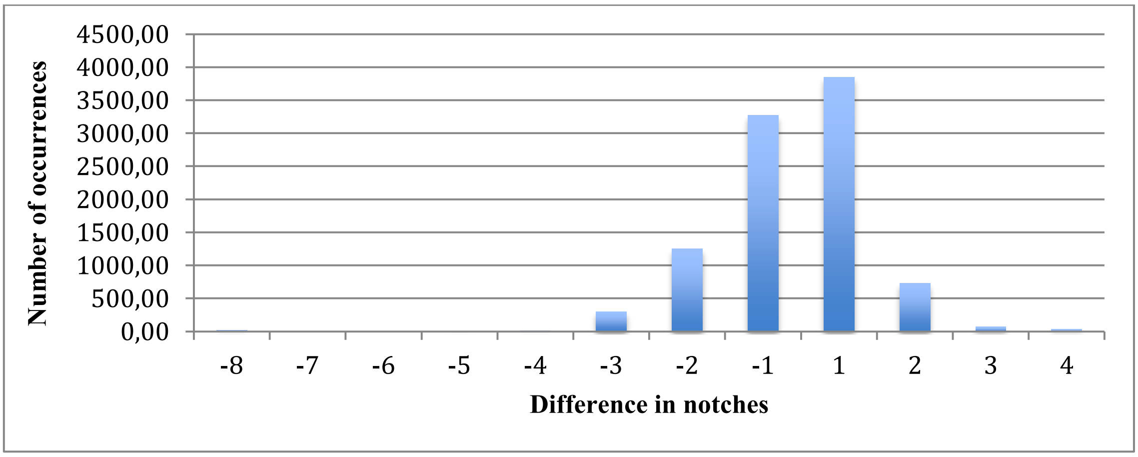


Figure 6: Repartition of occurrences in function of the results of the variable Ratingdiff

Furthermore, thanks to the simple variables $RatingM$ and $RatingSP$, the average rating assigned by both institutions could be computed. In the case of the non-split rated part of the sample, Moody's and Standard & Poor's tended to give unsurprisingly a similar average rating equal to 13.014. This digit is located very slightly above A3 or A- on the numerical scale developed for the purposes of this paper. With regard to the split rated subsample, it presented an average rating of 13.86 for Moody's and 13.73 for S&P, which was again above A3 or A- but closer to A2 or A. Unlike Livingston et al. (2010), the average rating computed appeared to be lower for non-split rated issuers than for the other ones. Also, even if no differentiation was made in the sample between the states split/non-split, the average rating assigned by Moody's would still be higher than the one of S&P (13.77 vs. 13.44). In this study, statistics kept thus showing that Moody's assigned higher ratings than its main competitor, which contradicted once again all previous findings. As stated here above, further studies could be necessary to shed light on this inconsistency.

In the Excel file, a last limited dependent variable $Dummyrtgdif3$ was computed so as to highlight the real nature of split ratings. This variable was not really binary but still took a restricted set of values, namely +1, 0 or -1. If S&P ratings were higher than Moody's, resulting in a strictly positive rating difference, then it was equal to +1 whereas in the opposite case (consequently with a strictly negative difference), it took the value of -1. It goes without saying that the value 0 was assigned if ratings were equal.

All those variables being finally assembled in a unique Excel file, the concrete computation part of this empirical analysis could start with the help of Stata. After having imported the data in the software, the process was composed of several phases in order to generate relevant results. First, introductory linear regressions were run on both $RatingM$ and $RatingSP$ in order to get a first idea about the general financial characteristics that could possibly influence ratings assigned by one or the other CRA separately. Then, the variable $Ratingdiff$ that measured split rating through a digit was studied by means of an additional linear regression. The aim was to determine the impact of the exogenous factors on the amplitude of the split ratings observed. In brief, $Ratingdiff$ was analysed so as to discover whether some accounting and financial characteristics of the companies belonging to the sample could tend to provoke split ratings of greater amplitude. In those two cases, the dependent variables were discrete but lying within a less limited set of values (either from 1 to 19 or from -8 to 4) than in presence of a dummy one (1/0). That is why linear regressions were employed instead of binary response models.

Furthermore, the logit model was applied to the binary variable called $Dummyrtgdifgen$ that was equal to 1 in the event of a split rating or 0 in the opposite case. This analysis was rather symmetric as no differentiation was made between the cases of positive and negative rating differences. Still, it was interesting to define which financial characteristics could influence the probability of having split ratings in general. The logit model was preferred over the probit one since both random and fixed effects transformations could be used. Indeed, when a probit model is employed, only the coefficients in link with random effects can be computed whereas both can be determined if a logit model is applied. As stated by Wooldridge (2013), a lot of researchers usually calculate both random and fixed effects coefficients and compare them afterwards. However, using probit or logit would have generated approximately the same results.

Finally, the approximate effect of the exogenous variables on $Dummyrtgdif3$ (+1/0/-1) was estimated with the use of a last linear regression. This decision was made considering that a logit model would not fit properly in this case since the dependent variable was not a real binary one (because of the additional state -1). Adding this third state called "-1" aimed to reveal the real nature of the split ratings that occurred: either because $RatingM > RatingSP$ or the contrary. Yet, it is important to note that the approximation determined by the linear regression was far more accurate within the range [-1;1] than for extreme values.

Also, as two dependent variables could take here a limited set of values only (two for $Dummyrtgdifgen$ or three in total for $Dummyrtgdif3$), the heteroskedasticity implied by the model must absolutely be corrected with the use of the function "robust" in Stata. As a small reminder, homoskedasticity is generally referred to when the variance of the unobserved error term u in a linear regression equation is considered as constant. Nevertheless, this assumption cannot be made in all cases, especially not when data presents a temporal dimension. Then, in presence of heteroskedasticity, ordinary least squares (OLS) methods usually fail to estimate unbiased or consistent coefficients (Wooldridge, 2013). Since OLS models are still useful and easy to manipulate, they cannot be totally abandoned. Thus, econometricians developed helpful ways to adjust standard errors and other statistics so as to make them consistent even in case of heteroskedasticity. Those procedures are called "heteroskedasticity-robust" and permit to report statistics no matter the potential constant character or not of the error term related to the population. In brief, it was pretty sensible to use those methods for every regression developed in this study.

2.3. Main results

This third part of the third chapter aims to present the main outcomes coming from the study realized for the purposes of this paper. It is important to note that Stata was the software used in order to generate those results. This section will thus be divided into four main points in function of the dependent variable chosen for the model. First, the findings related to both $RatingM$ and $RatingSP$ will be outlined. Then, the second point will present the impact of the financial and accounting characteristics on the numerical variable $Ratingdiff$. Besides and most importantly, the results in link with the logit model used for $Dummyrtgdifgen$ will be described in details. Finally, the last point will display the conclusions that can be drawn from the linear regression applied to the pseudo-dummy variable $Dummyrtgdif3$. Appendix 17 will report the codes and commands introduced in the software for each of the steps mentioned here above.

2.3.1. Linear regressions for $RatingM$ and $RatingSP$

By way of introduction, linear regressions (with the robust function) were applied to both variables RatingM and RatingSP in order to evaluate the general impact of accounting and financial characteristics on ratings assigned by the two CRAs. The results generated by Stata can be found in appendix 18 with the different coefficients, standard errors as well as levels of confidence.

About Moody's creditworthiness assessments, it can be observed with the random effects transformation feature that multiple variables are significant at least at a 90% confidence level: totassets, totrev, mtkcap, levCF, unlevCF, ROA, dummybank, crisis2008 and crisis2011. On one hand, the market capitalization is in this case only impactful at 90% as its p-value is lower than 10% but higher than 5%. The impact of this financial variable on Moody's ratings is positive although low (coefficient equal to 0.0000106 with a standard error of 0.00000611). This means that companies with higher market capitalization are supposed to get higher credit quality assessments from Moody's. However, with such a small standard error resulting from low variations, it can be concluded that the variable market capitalization has a rather limited effect on $RatingM$. On the other hand, the dummy variable created to determine whether it is a period of financial crisis (2011-2012) is also significant at 90% solely. Its impact on Moody's ratings is not surprising since the coefficient computed -0.148 tends to suggest that the CRA lowers its letter grades in time of crisis because of potential financial difficulties experienced by companies.

From the abovementioned significant components, only a few are still statistically different from 0 at a level of 95% thanks to a p-value lower than 5%: totassets, levCF, unlevCF, ROA, crisis2008. The significance of the variable totassets goes in line with what Ederington (1986) affirmed with regard to the characteristics that Moody's consider when assigning ratings since this is supposed to reflect the size of a company. The results of the linear regression performed in this study show that the amount of assets impact rather negatively the letter grades (coefficient of -0.000000289). In other words, if a company increases its total assets, it is supposed to get a lower rating. This can sound surprising and may require further investigation, as an increase in the total assets should boost a firm's ability to meet its financial obligations. Concerning the levered (-0.000102) and unlevered cash flows (0.000100), they impact ratings in opposite directions: while the former makes the ratings decrease when it increases, the latter does the contrary. As Ederington (1986) affirmed, Moody's consider profitability variables in its rating process and this explains the significance of levered and unlevered cash flows at 95%. Then, the return on assets with a coefficient equal to 5.302 is the variable with the biggest impact on Moody's ratings: when the ROA is increased with one unit, then the company is supposed to increase by 5 notches. This is valid as profitability plays a big role in the rating computation (Ederington, 1986). Finally, the variable that indicates the crisis of 2008 influences letter grade in a strange way. Indeed, its coefficient is equal to 0.218 and this would mean that the CRA upgrades companies in period of crisis. This may require again further investigation.

Then, if the confidence level is raised to reach 99%, only totrev and dummybank remain significant at all levels. The total revenue seems to have a negative impact on the ratings assigned (-0.0000177) but this does not really make sense since total revenue is a measure of profitability and should boost letter grades. Indeed, better revenues should increase the firm's ability to meet financial obligations. Then, the dummy variable created to point out the sector companies operate in has a coefficient of 3.103. In other words, if the firm in question is a bank, then its rating should be higher of 3 notches approximately.

With regard to Moody's ratings with the fixed effects transformation, the results obtained are a bit different. In this case, the same multiple variables are significant at least at a 90% confidence level (totassets, totrev, levCF, unlevCF, ROA, crisis2008 and crisis2011) apart from dummybank and mktcap that disappeared. At 90% in this case, the total amount of assets is impactful while this variable was considered at 95% with the random effects. This means that its p-value lies now between 10 and 5% rather than below 5%. The coefficient is rather close to the previous and is now equal to -0.000000268 (vs. -0.000000289), which provides the same interpretation as earlier. Also, both binary variables related to the crisis period have an impact on Moody's ratings at 90%. In short, in period of crisis 2008-2009, credit quality assessments were impacted positively with a coefficient of 0.211 while it is the opposite for the crisis of 2011-2012 (-0.147). It makes more sense to have a negative coefficient than positive one and these contradictory results may require further investigation.

At a 95% confidence level, levCF, unlevCF and ROA are still significant just as it was the case with the random effects estimation. Their coefficients have very slightly changed with respectively -0.000107, 0.000105 and 5.323 but still keep the influence, whether it be positive or negative. It provides thus the same interpretations as earlier. Yet, the fact that levered and unlevered cash flows impact the ratings in opposite direction could seem surprising as they are both indicators of profitability and should present positive coefficients. Also, along the same line, ROA has a great influence on ratings assigned by Moody's with a coefficient equal to 5.323, which means that if the ratio return on assets increases by one unit, then letter grades are supposed to be 5 notches higher.

Then, for a 99% confidence level, only totrev remains and is significant simultaneously at all levels. With the random effects, its coefficient was equal to -0.0000177 while it is now -0.0000186. The same question arises with the sign of the result since higher total revenues should influence Moody's to assign better ratings due to an improved capacity to meet financial obligations.

At the same time, the impact of financial characteristics on Standard & Poor's ratings was analysed and it can be observed that, with the random effects transformation, the following variables are significant at least at a 90% confidence level: totassets, mktcap, levCF, unlCF, ROA, leverage, dummybank, crisis2011. The financial characteristic linked to leverage is statistically different from 0 at a 90% confidence level. Its coefficient is equal to 0.000778, which means that the higher the leverage the higher the rating assigned by S&P. This goes in line with the findings of Ederington (1986) about the main influential characteristics in link with S&P rating process.

With regard to the 95% confidence level, no financial characteristic in particular is revealed in the table in appendix 18. Yet, all of them that were mentioned here above are significant at 99% (and thus also at 95% and 90%) apart from leverage. The variable of total assets has a coefficient equal to 0.000000396, which means that an increase in assets in the balance sheet has a positive impact on the rating assigned by Standard & Poor’s. Such a positive coefficient seems to be more logical than the negative one obtained with Moody’s. Then, market capitalization influences positively the credit quality assessments (0.0000172) and the same interpretation can be made: the higher the market capitalization, the higher the letter grade. Concerning levered and unlevered cash flows, they are here perfectly symmetric with respectively -0.000125 and 0.000125. Again, their influence on ratings goes in the opposite direction. As a quick reminder, levered cash flows are equal to unlevered cash flows where expenses for financial obligations were subtracted. Also, the return on assets ratio presents a fairly high coefficient equal to 3.948 that reveals its great positive influence on the letter grades . Finally, the dummy variables linked to the bank sector and period of crisis 2011-2012 present opposite sign: while the former has a resulting coefficient equal to 2.217, the latter has a negative one (-0.378). This means that the fact that a company is operating in the bank sector has a positive influence of two notches on letter grades. On the contrary, being in the period of crisis 2011-2012 ensures that ratings decrease.

If the fixed effects transformation is used instead, the results obtained are almost the same with only one variable (dummybank) that has disappeared. In brief, the following factors are significant for the 90% confidence level at least: totassets, mktcap, levCF, unlCF, ROA, leverage, crisis2011. At 90% only, the variable leverage is still impactful with a coefficient equal to 0.000775, which means that companies with a higher leverage ratio are more likely to receive higher ratings from S&P. This confirms the findings made with the random effects transformation as well as Ederington’s (1986) again.

At the 95% confidence level, the table in appendix 18 does not display any new significant variable of the model. However, the ones mentioned in the previous paragraph are statistically different from 0 at 99%, 95% and 90% apart from leverage. The coefficient of the financial characteristic total assets is worth in this case 0.000000392 and reflects a positive impact of the amount of assets on letter grades, just as with the random effects feature. Then, market capitalization influences positively the ratings with a coefficient equal to 0.0000170. This seems logical, as a company with a higher market capitalization should see its ability to meet financial obligations increase and thus its rating as well. Also, levered and unlevered cash flows impact the letter grades in an opposite way but kind of symmetrically with respectively -0.000131 and 0.000131. This trend seems to be present in the whole model although it is surprising. With regard to the return on assets variable, it presents a high coefficient of 3.968 that shows an important positive influence on the ratings assigned by S&P. Lastly, the binary variable in link with financial crisis of 2011-2012 affects the creditworthiness assessments in the following way: during the financial crisis of 2011-2012, ratings tend to be 0.376 lower than during the other years of the timespan.

In general, concerning Moody's, it seems pretty surprising that the variable leverage is not significant at all, neither in the random effects nor in the fixed effects transformation. This contradicts slightly what Ederington (1986) stated in his paper by affirming that the institution's rating process is mainly impacted by measures of size, leverage and profit. Still, indicators of size like total assets and profitability such as total revenue are most of the time significant in the model. On the contrary, Standard & Poor's ratings are influenced by leverage both with the fixed and random effects transformations. Yet, Ederington (1986) affirmed also that the ratio cash flows on long-term debt was rather impactful for S&P but this variable has never been included in the significant ones.

In summary, it is important to note that all coefficients are pretty small but this could be explained with the scale used in this study. Indeed, ratings ranged here from 1 to 19 on the numerical scale and an increase for that kind of variable is usually rather small but still significant in comparison with factors like wages e.g. In brief, the main difference between the two CRAs with regard to the influential financial characteristics is that S&P is more impacted by measures of leverage at a 90% confidence level while Moody's is not, but well by total revenue.

2.3.2. Linear regression for $Ratingdiff$

After having realized linear regressions on Moody's and S&P ratings and compared the results as an introduction, the numerical variable $Ratingdiff$ was treated the same way (also with the robust function) in order to assess the general impact of accounting and financial characteristics on the amplitude (expressed through a digit) of split ratings. The results obtained with the help of Stata can be found in appendix 19 in the first two columns with the different coefficients, standard errors and levels of confidence.

Concerning the dependent variable $Ratingdiff$, it can be observed with the random effects transformation feature that multiple variables are significant at least at a 90% confidence level: totdebt, totequity, totassets, totliab, ROE, TEV, leverage, CFLTdebt, dummybank, and crisis2011. In this list, none of the factors were solely statistically different from 0 at 90% but well also at other confidence levels. If the one of 95% is considered, five of them are especially relevant. First, the variable total debt was attributed a positive coefficient equal to

0.00000387. This can be interpreted by the fact that an increase in total debt from companies will augment the amplitude of the split rating (expressed in number of notches). Then, the impact of total equity on the numerical rating difference is negative with a coefficient equal to -0.00000594. It seems thus that total debt and total equity have a contradictory influence on the dependent variable of this model. Also, the return on equity ratio (ROE) presents a coefficient that is worth -0.000120, implying thus that if companies rated by both CRAs have a high ROE, the rating difference will be weaker. This finding is in fact consistent with what Bowe and Larik (2014) affirmed in their paper: profitable firms experience less and smaller split ratings. Moreover, leverage seems to play a significant role as well: the higher the leverage in a firm, the higher the amplitude of the split rating (0.000246). Finally, the binary variable linked to the crisis of 2011 has a coefficient of -0.101. In fact, when the rating difference is observed in period of crisis, especially the one of 2011-2012, it makes the amplitude decrease by 0.101. It could be supposed here that CRAs adjust their methodologies during the years of a financial crisis, which makes their ratings more aligned and the split less important.

At the 99% confidence level, the five remaining variables from the ten listed in the previous paragraph are significant. Firstly, the total amount of assets seems to have a positive impact on the difference in number of notches between both ratings, namely with a coefficient equal to 0.000000569. Thus, if a firm experiences an increase of its assets, the gap between both ratings is likely to be higher as well. On the contrary, the variable total liabilities influences negatively the dependent variable studied here since its coefficient is worth -0.00000191. An increase in the total liabilities could result in a reduction of the split rating. This could mean that Moody's and Standard & Poor's have a kind of similar understanding and reaction to a worsening of the creditworthiness due to additional liabilities, making their ratings converge. Still, it goes in the opposite direction in comparison with the factor total debt. Then, the negative effect of the total enterprise value (TEV) on the rating difference is proved to be statistically different from 0 at the 99% confidence level. Indeed, this variable has a coefficient that is worth -0.00000255. In other words, if the value of enterprise is raised, then the rating difference is likely to decrease. Concerning the factor cash flows to long-term debt, it was valued at -0.0469 by the software. Since the coefficient is again negative, the impact can be interpreted that way: the higher the ratio, the smaller the gap between the ratings assigned by the Big Two. Lastly, the binary variable linked to the sector of banks was attribued a coefficient equal to -1.153. This means that the rating difference is lower if the company studied is a financial institution. That kind of finding can seem abnormal, as assigning a rating to a bank is more difficult than to a random company. Indeed, its risk structure is more complicated and it leaves more space for subjectivity and differences in methodology. In that sense, Morgan (2002, as cited in Livingston et al., 2007) found out that banks are more likely to experience split ratings, among others because of their typical asset opaqueness.

With regard to rating difference with the fixed effects transformation, the results obtained differ slightly. In this case, more or less the same multiple variables are significant at least at a 95% confidence level (totdebt, totequity, totassets, totliab, ROE, TEV, leverage, CFLTdebt and crisis2011). The main difference between the results of the fixed and random effects features is the following: the binary factor for banks is not statistically different from 0 anymore. For the 95% confidence level, six variables out of nine are significant. The total debt is proven to have a coefficient 0.00000396, meaning that the amplitude of the split rating is raised if the total amount of debt increases. Then, the total amount of equity has anew a negative impact on the rating difference expressed in number of notches (-0.00000595). This contradictory influence that was already mentioned with the random effects transformation is thus confirmed. As far as the return on equity (ROE) ratio is concerned, its influence on the numerical rating difference between ratings is rather negative (-0.000120) and has not varied even if a new transformation was used (fixed effects). In the same vein, the variable linked to leverage remained constant with the same positive coefficient (0.000246) and standard error. Moreover, the software assigned exactly the same impact to the binary variable crisis2011 on the rating difference than with the fixed effects, namely -0.101. However, the only difference here is that the ratio cash flows on long-term debt is not significant at a 99% confidence interval anymore. The coefficient is equal to -0.0455, which means that an increase of this ratio makes the split rating lower.

At the 99% confidence level, there are three significant variables instead of four previously as CFLTdebt is not statistically different from 0 at all levels anymore. First, the factor total assets is attributed a positive coefficient equal to 0.000000555 (compared to 0.000000569 with the fixed effects). In short, if assets increase, so does the rating difference. Then, the variable total liabilities seems to have a negative impact (-0.00000206) on the gap between letter grades assigned by both CRAs. The same conclusion about the convergence of ratings can be drawn as in the case of the fixed effects transformation. Finally, a negative coefficient equal to -0.00000255 is assigned to the factor total enterprise value (TEV), meaning that an increase in TEV can thus reduce the amplitude of the rating difference.

As a conclusion, the results showed here that both fixed and random effects transformations gave the same results more or less. There is only the question of the impact of the banking sector on the dependent variable $Ratingdiff$ that may require further investigation. Thus, all the financial characteristics pointed out here tend to modify in one way or another the amplitude of the split rating (increase or decrease). By taking the absolute value of the coefficients, it can be shown that some have a greater impact than others and this could be the result of differences in methodology applied by both CRAs. It is important to note again that the scale used to measure the rating difference is rather limited and that it could explain the presence of such low coefficients. This would not be the case if the dependent variable was continuous with a greater variation allowed.

2.3.3. Logit model for $Dummyrtgdifgen$

In order to answer the research question of this paper, several regressions have been performed so far: on the ratings themselves and on the numerical rating differences. However, it could be interesting to discover which financial characteristics influence the probability of occurrence of a split rating in general. Therefore, a binary response model, logit in particular, is used with the variable $Dummyrtgdifgen$. The results can be found in the two last columns of the table in appendix 19.

As explained earlier, the dependent factor $Dummyrtgdifgen$ is a dummy variable for which the event is defined as the occurrence of a split rating. In other words, the 1-state represents the case where ratings assigned by both CRAs are not equal and the 0-state, the opposite. Nonetheless, it cannot be determined through this mechanism whether Standard & Poor's ratings are higher than Moody's or inversely. With the help of the software Stata, the logit model was applied to the variable in question. This one was preferred over the probit regression so as to be able to make fixed as well as random effects transformation and compare them afterwards. Nowadays, it is rather common for researchers to do that even if using the logit model or the other usually generates similar results (Wooldridge, 2013).

In order to generate results, Stata was run following the same process as with the previous regressions. It was thus composed of two steps: first, a logit model with a random effects transformation and then the one with fixed effects. Nevertheless, the software did not generate the expected results. Indeed, the first regression provided the same output as with the linear models described here above, namely a table with coefficients, standard errors, t-statistics as well as p-values that can be found in the last two columns of appendix 19. But the software could not find a solution for the second one related to the fixed effects feature. This might be due to an algorithm that does not manage to converge or to a maximum likelihood function made a bit more complicated with the big amount of data. Thus, in the remaining part of this section, only the results related to the random effects transformation will be presented.

Besides, using a logit model (with the robust function) was relevant for the type of problem studied but presents a major drawback: the format of the results. In other words, when a logistic regression is applied, a table is produced in Stata with coefficients, standard errors, t-statistics as well as p-value just as previously. This can be found in the third column of appendix 19. Those results can be interpreted in a general way by describing their signs and their significance. Yet, they cannot be translated as straightforwardly as with classic linear regressions. They have to be transformed and manipulated to be able to express them as real marginal effects. Therefore, the command "margins" was used in Stata to get the same type of coefficients as there were in the previous sections. The results of the command are displayed in the fourth column of appendix 19. It is worth mentioning that the significant variables in the model were the same even if "margins" was not applied. Only the real value of the coefficients changed.

With regard to the outcomes of the logistic regression on $Dummyrtgdifgen$ using a random effects transformation, it can be observed that multiple variables are significant at least at a 90% confidence level: netinc, totassets, curassets, mktcap, liquidity and dummybank. On one hand, net income is in this case only statistically different from 0 at 90% as its p-value is included between 5 and 10%. The influence of this variable on the probability of a split rating occurrence is reflected by its coefficient, which is equal to 0.00000922. Although the positive impact is low, this means that a split rating is more likely to occur if net income increases. This may require further investigation. On the other hand, the binary variable dummybank comes into play with a positive and high coefficient that is worth 0.2214837. In other words, the probability of occurrence of a split rating increases by 0.22 when the company analysed is a bank. This finding confirms what Morgan (2002, as cited in Livingston et al., 2007) affirmed in his study: split ratings tend to occur more often for banks than for other sectors.

At the 95% confidence level, the variable mktcap is statistically different from 0 with a coefficient equal to -0.00000545. The conclusion can be thus drawn that the market capitalization of a company has a negative (but rather low) impact on the probability of occurrence of split ratings. In brief, the higher the market capitalization, the less likely is a firm to have to deal with rating differentials. This goes in line with Bowe and Larik's (2014) findings stating that bigger and more lucrative enterprises experience less split ratings.

Finally, with regard to the 99% confidence level, three variables of the model emerge: totassets, curassets and liquidity. First, the total amount of assets a company owns is proven to impact positively the probability of occurrence of a split rating (0.000000570). This means that an increase in assets makes it more likely for a rating differential to occur. On the contrary, the influence of current assets on the dependent variable here is negative with a coefficient equal to -0.00000719. These results seem to be rather contradictory since the effect of assets on the probability should logically go in the same direction, no matter the type (normal or current ones). Lastly, according to the results of the study realized here, liquidity impacts positively the probability of a split rating given its coefficient that is worth 0.006056. This would mean that rating differentials are more likely to occur for companies that are in a good liquidity situation. It is a rather surprising result since it contradicts slightly the findings of Bowe and Larik (2014) previously mentioned. Also, it seems unreasonable to admit that a company with a good financial situation would experience more split ratings while the hardest and the most subjective task for CRAs is to assign ratings to NIG issuers.

In summary, the logit model used with a fixed effects transformation pointed out five variables that could have an influence on the likelihood of split ratings: total assets, current assets, liquidity, market capitalization, net income and the binary dummybank. The most striking one concerns the impact of the sector on the dependent variable, namely increasing it by 0.22 in presence of banks. Besides, it is rather surprising that none of the dummy variables in link with the financial crises revealed to be significant. Indeed, it could have been assumed beforehand that in period of crisis, split ratings occur more often as more risk is present on the market which makes it thus harder to assess properly. This might require further investigation. It is worth mentioning again that, apart from the binary variable linked to banks, all the factor present small coefficients and that this phenomenon can be explained by fact that the dependent variable ranges only from 0 to 1 as it represents a probability.

2.3.4. Linear regression for $Dummyrtgdif3$

By way of conclusion, a last variable called $Dummyrtgdif3$ was created and studied more in depth with the help of a linear regression. As mentioned previously, this limited dependent factor works approximately as a dummy variable, except for the existence of an additional third value -1. In brief, this functions as follows: the value 1 is attributed in the event of Standard & Poor's assigning higher ratings than Moody's to an issuer and -1 in the opposite case. Obviously, the 0-state refers to equal ratings from both CRAs. In comparison with $Dummyrtgdifgen$, the aim was to reveal the real nature of split ratings that occurred by mentioning which institution was more conservative in every case. As for the previous regressions, coefficients with both random and fixed effects features will be computed and then compared. The results can be found in appendix 20.

After having considered the potential use of a logit model, a linear regression was employed to approximate the effect of the exogenous variables on the pseudo-dummy variable in question. This choice was made keeping in mind that a binary response model would not fit properly given the fact that the dependent variable is not a dummy one strictly speaking. Indeed, logit models apply when the endogenous factor can take only the values 0 or 1. However, the approximation provided by the application of a linear regression is not flawless: the estimation is accurate within the range [-1;1] but not really for extreme values.

Also, as $Dummyrtgdif3$ can take here a limited set of values only (three in total), the function "robust" had to be used in Stata in order to correct for the heteroskedasticity implied by the model. As mentioned by Wooldridge (2013), when the variance of the unobserved error term cannot be assumed as being constant, traditional linear regressions tend to provide biased and inconsistent results. This happens especially with data including a temporal dimension, which is the case in the study realized for the purposes of this paper. Thus, by including the robust command in Stata, the resulting coefficients should be rather accurate.

Concerning the outcomes of the linear regression performed on the dependent variable $Dummyrtgdif3$, it can be firstly stated with the use of a random effects transformation that six factors are statistically different from 0 at least at a 90% confidence interval. The six variables are the following: totequity, totassets, TEV, leverage, CFLTdebt and dummybank. Among those, none of them were solely significant at 90% but well also at higher confidence levels. If the one of 95% is considered, three factors are especially relevant. First, the total equity displays a coefficient equal to -0.00000495, meaning that its impact is rather negative although low. So, when the amount of total equity is raised, the dependent variable tends to move toward the 0- or -1-state. Also, another variable that comes into play but with a positive influence this time is leverage (0.000210). In other words, the higher the leverage is, the more

$Dumm\square rtgdif3$ departs from the -1-event to get closer to 0 or 1, resulting in more equal letter grades or split ratings where S&P assigns a higher creditworthiness assessment. Finally, the ratio cash flows on long-term debt is attributed a negative coefficient equal to -0.0274. Just as with the variable total equity, this means that CFLTdebt impacts negatively the endogenous factor of this regression and makes it go in the 0- or -1-direction in function of its initial state. It could be assumed that factors displaying a negative coefficient tend to be taken more into account by Moody's and inversely.

At the 99% confidence level, three factors of the model emerge anew: totassets, TEV, dummybank. The first one seems to influence $Dummyrtgdif3$ in a positive but weak way given its coefficient that is worth 0.000000602. This goes in the same direction as with the factor leverage mentioned here above: the higher the total amount of assets is, the closer to the 0 or 1-state. Then, the total enterprise value is proven to impact negatively the dependent variable of this model with a coefficient equal to -0.00000225. Indeed, this means that when the value of a company is raised, $Dummyrtgdif3$ is more likely to get closer to 0 or -1. It would thus not be surprising that the occurrence of a potential split rating would be caused originally by superior Moody's ratings due to a higher consideration of this factor in the rating process of the institution. At last, the effect of the binary variable dummybank created for the purposes of the study is highly negative (-0.881). Put differently, if the company studied operates in the banking sector, then $Dummyrtgdif3$ draws very closer to the -1-event while other sectors tend not to experience this phenomenon.

With regard to the dependent variable $Dummyrtgdif3$, it can be observed with the fixed effects transformation feature that the results differ very slightly. As a matter of fact, the following variables are significant at least at the 90% confidence level: totassets, TEV, totequity, leverage, CFLTdebt, totliab. The main difference between the results generated by both the random and fixed effects transformations is that the binary variable dummybank is not significant anymore. This can sound a bit surprising, as there is no apparent reason for the effect of the banking sector to be eliminated through the second transformation. This might require further investigation. However, in this case, only the total amount of liabilities is statistically different from 0 at 90% as its p-value is included between 5% and 10%. The influence of this factor on the pseudo-dummy variable is reflected by its coefficient, which is equal to -0.000000627. This finding is new compared to the ones made with the random effects feature since the model did not recognize it as being significant before, whereas it is now at 90%. In brief, an increase in total liabilities impacts negatively $Dummyrtgdif3$ by making it move toward the 0- or -1-state.

Then, if the confidence level is raised to reach 95%, the three variables totequity, leverage and CFLTdebt remain. First, the total amount of equity in the companies analysed by this study seems in general to impact negatively the dependent variable of the present linear regression (-0.00000501). In other words, the higher the total equity, the more $Dummyrtgdif3$ moves to the 0- and -1-events. Then, leverage displays a coefficient equal to 0.000211, which is positive just as with the random effects transformation. The same conclusion can thus be drawn. Finally, the last variable CFLTdebt that is significant at this confidence level influences negatively the endogenous factor with a coefficient that is worth -0.0273. Put differently, if the ratio increases by 1, it makes the dependent variable go closer to the 0- or -1-state.

At last, for a 99% confidence level, only totassets and TEV are statistically different from 0 and are thus significant at all levels. On one hand, the variable total assets seems to have a positive influence (although weak) on $Dummyrtgdif3$ (0.000000590). This means that if a company experiences an increase in its total assets, it is more likely to deal with either equal ratings or a split rating due to higher S&P letter grades (+1). On the other hand, the variable total enterprise value comes into play by impacting negatively the endogenous factor of this regression. Indeed, its coefficient is equal to -0.00000226. This finding can be interpreted as follows: an increase in the value of a company makes it experience either more equal ratings (0) or differentials caused by higher Moody's creditworthiness assessments (-1).

In conclusion, the results generated both by random and fixed effects transformations were rather similar apart from a few exceptions. Only the question of the impact of the sector of banks on the pseudo-dummy dependent variable remains and may require to be analysed more in depth. Thus, all the financial and accounting characteristics highlighted here tend to influence in one way or another the nature of split ratings (towards to +1- or -1-state). Again, it is important to note that the presence of rather small coefficients can be justified by the fact that the dependent variable can only range in a really limited interval (between -1 and 1).

2.4. Concluding remarks and recommendations

This section of the third chapter will attempt to conclude by giving a final answer to the research question of this paper. To this end, all the results of the four steps of the process described here above were gathered in a summary table that can be found in appendix 21. A discussion will be thus run on the impacts of the findings related to this empirical study. Also, potential drawbacks or critics will be pointed out. At the same time, indications for further studies will be proposed.

Firstly, from a general point of view and on the basis of the table in appendix 21, the financial characteristics (with the three dummy variables included) that were chosen for inclusion in X can be divided into three categories: not relevant, slightly explanatory or very significant. In the first category, current liabilities, gross profit and long-term debt can be put since they were never statistically different from 0 in any step of the process. Indeed, they were never attributed a coefficient during the whole study. This seems a bit surprising since they should still be representative characteristics of the financial situation of a company. Then, the second category includes the exogenous factors that have a light explanatory power but that still emerged during the manifold regressions. There are fifteen characteristics of this type out of twenty-two: net income, total debt, total equity, total liabilities, current assets, total revenue, return on equity, market capitalization, total enterprise value, levered cash flows, unlevered cash flows, return on assets, liquidity, cash flow to long-term debt and the dummy variable crisis2008. On the nine different computations performed (four regressions with both random and fixed effects and a logit model), they emerged in the results between one and five times. They should thus have a relatively reasonable role to play in rating process as well as on the occurrence of split ratings. Lastly, four financial characteristics seem to be very significant since they were pointed out in more than five regressions although at different levels. Those factors are the following ones: total assets, leverage, and the two dummy variables dummy variables dummybank and crisis2011. In short, this categorization gives already an idea of the relevant characteristics that could be used to answer the research question.

More particularly, conclusions can be drawn for every regression performed on the different dependent variables. With regard to $RatingM$ and $RatingSP$ it can be observed that, in general, ratings assigned by both CRAs are influenced mainly by the same financial characteristics. Those exogenous variables are the following: total assets, market capitalization, levered and unlevered cash flows, return on assets, dummybank and crisis2011.

Yet, there are subtle differences between the two rating processes. Indeed, Moody's seems to take the total revenue additionally into account as well as the dummy variable for the crisis of 2008 while Standard & Poor's does not. Instead, the institution considers more the impact of leverage.

Moreover, the results of the regression related to the variable $Ratingdiff$ showed which financial and accounting characteristics could have an impact on the amplitude (expressed as a number of notches) of occurring split ratings. The following variables of the model were statistically significant: total debt, total equity, total assets, total liabilities, return on equity, total enterprise value, leverage, cash flows to long-term debt, dummybank and crisis2011. In brief, those factors tend to modify (increase or decrease) the difference in number of notches between ratings assigned by Moody's and S&P. Taking the absolute value of the coefficients could be interesting so as to show which ones have a greater impact on the amplitude of $Ratingdiff$, which might be due to divergences in methodology used by both CRAs. However, some results were a bit contradictory and surprising, especially the influence of the binary factor dummybank on the dependent variable. Indeed, its resulting coefficient with the random effects transformation is negative, which means that banks experience lower rating differentials than companies operating in other sectors. Is this because CRAs pay more attention to the accuracy of the methodology applied when they assign ratings to financial institutions? On the contrary, evaluating risk for banks is extremely complicated and it could be logical that more split ratings occur. This may require further investigation since the reason is not especially clear.

Furthermore, the binary variable $Dummyrtgdifgen$ was analysed with the help of a logit model. From the results, it could be concluded that the probability of occurrence of split ratings was influenced mainly by six variables: net income, total assets, current assets, market capitalization, liquidity and the binary factor dummy bank. As mentioned earlier, those outcomes could only be obtained through a random effects transformation. In general, the findings confirmed rather what some researchers discovered previously, i.e. Morgan (2002, as cited in Livingston et al., 2007) and Bowe and Larik (2014). There is only one exception for the variable of liquidity that was assigned a negative coefficient. This meant consequently that companies with a higher liquidity ratio are more likely to face rating differentials whereas Bowe and Larik (2014) affirmed that big and lucrative firms usually experience less split ratings. This may require to be studied more in depth. Also, the contradictory effect of the variables total and current assets was surprising. Indeed, those two should not a priori impact differently the probability of occurrence of split ratings. In addition, the insignificance of the two dummy variables linked to the periods of financial crisis was unexpected. However, the big influence of the binary factor dummybank was rather striking.

Finally, the analysis of the dependent variable $Dummyrtgdif3$ was performed through a classic linear regression for the reasons explained previously. The results provided by the software Stata showed that the following variables were likely to influence the endogenous factor studied: total equity, total assets, total liabilities, total enterprise value, leverage, ratio of cash flows to long-term debt, dummybank. They were all statistically different from 0 but the effect of two of them was not precise. Indeed, with regard to total liabilities and dummybank, their significance varied according to the transformation feature applied. The former was statistically different from 0 only when the fixed effects transformation was applied but not with random effects, and inversely for the latter. Lastly, the nature of split ratings was supposed to be influenced in one way or another (toward 1 or -1) by the financial and accounting characteristics that emerged from the model. Thus, the hypothesis was made that variables with negative coefficients could be the ones that are more taken into account in the rating process by Moody's and the contrary for Standard & Poor's. This has still to be confirmed by further studies.

In addition to the paths of worthwhile investigation mentioned here above, it could be interesting to analyse a bigger sample on a longer timespan than the ones used in this study. In order to do so, it goes without saying that better means would be needed: more complete data, more powerful software, deeper knowledge in the area etc. As a result, this may solve the anomalies observed in the results of this empirical study.

Conclusion

The aim of this paper was initially to shed light on the CRAs' methodologies in order to better understand the whole rating process and its potential flaws. The focus was set on the two dominant institutions on the financial market, namely Moody's and Standard & Poor's mainly because of an easier access to data. More particularly, the statistical analysis realized for the purposes of this dissertation sought to discover the potential impact of financial and accounting characteristics of companies on the occurrence of split ratings. In order to fulfil this task, the structure of the paper was composed of two main parts: a literature review and an empirical analysis.

First, the literature review was realized in order to define all the concepts and terms in link with the whole world of CRAs such as the notion of credit risk, rating migration and so on. This aimed to provide a theoretical context that would favour a better understanding of all the next computations and manipulations. Also, it has permitted to propose paths of reflection before settling the definitive steps followed to carry out the statistical analysis. Then, the empirical study took place. Since the research question of this paper was to discover whether financial characteristics had an influence on the occurrence of split ratings, the process of monthly data collection and sample selection for the timespan chosen (2000-2016) was done in two phases. In the first place, the sample to consider for the study had to be determined on the basis of several criteria. The initial 600 companies belonging to the STOXX® Europe 600 index were sorted according to the data available. Indeed, it was necessary so as to conduct the study to collect information in link with long-term issuer ratings for both Moody's and Standard & Poor's. Due to data scarcity, the final sample was reduced to a number of 134 firms for which the required ratings of both CRAs were at disposal. Afterwards, the software Capital IQ was asked to report financial and accounting information about the 134 companies in question. At last, econometrics models were used and a comparison was made in order to discover which factors impact the occurrence of split ratings.

With regard to the results of the study conducted in this paper, it can be observed at first that, out of the 19 characteristics chosen initially for inclusion in X, three were not relevant: current liabilities, gross profit and long-term debt (table in appendix 21). It can be thus assumed that those variables do not have any impact on the probability of split ratings. Also, concerning the pure ratings assigned by Moody's and Standard & Poor's, it seems that they are all influenced by the same financial characteristics with some exemptions. Indeed, the only difference was the following: while Standard & Poor's takes the leverage ratio into account, Moody's does not but rather considers the total revenue and the impact of the financial crisis of 2008-2009 instead. An investor could keep that information in mind when analysing the ratings assigned by both agencies. They would be informed about the differences in methodology and potential biases, which shows that they cannot consider ratings coming from various CRAs as equivalent. This could make them thus stop relying blindly on the creditworthiness assessments.

Besides, the regression performed on the numerical rating difference (expressed as a number of notches) proved that a lot of financial characteristics impact the amplitude of the split ratings that occur. Ten exogenous variables emerged from the model: total debt, total equity, total assets, total liabilities, return on equity, total enterprise value, leverage, cash flows to long-term debt, dummybank and crisis2011. This means that investors have to pay attention to these factors when choosing for companies to invest in, since some of them can decrease the amplitude of the split ratings and others can increase it. In the second case, investors should think twice before investing in firms presenting characteristics related to highly negative coefficients because having big rating differentials is a bit suspicious.

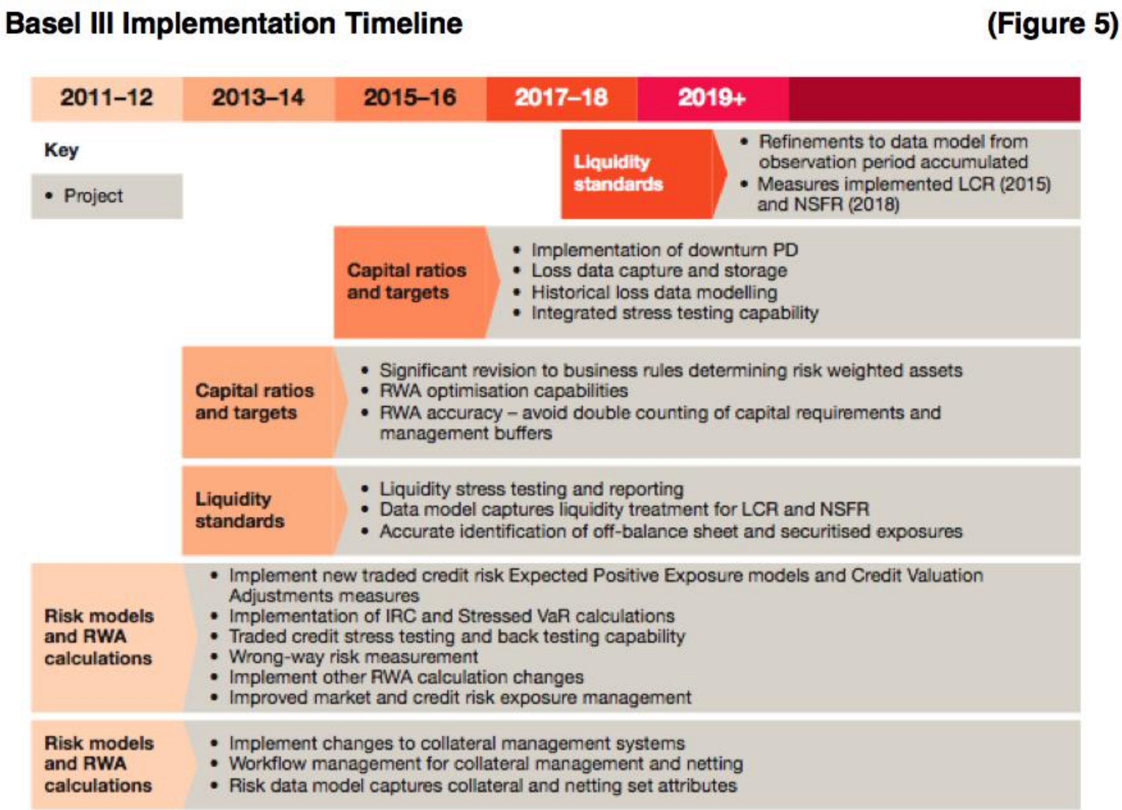
Most importantly, the analysis made on the probability of occurrence of split ratings revealed important findings in order to answer the research question of this paper. It was observed that the likelihood of a split rating was influenced by six variables: net income, total assets, current assets, market capitalization, liquidity and the binary factor dummy bank. In general, the results confirmed previous studies but some inconsistencies were still pointed out concerning the effect of liquidity, total and current assets. The variable with the biggest impact was the binary one in link with the banking sector, which means that investing in banks increases the probability of occurrence of rating differentials for the investors. They should thus not consider this option if they want to face as few split ratings as possible. Also, the factors with a negative coefficient (market capitalization and current assets) should be privileged when choosing companies to invest in so as to reduce the likelihood of rating differentials.

Finally, a classic linear regression attempted to study the real nature of split ratings, namely due to higher Standard & Poor's ratings than Moody's or inversely. The results showed with limited relevance (due to the model chosen) that a certain number of factors tend to influence the dependent variable in question: total equity, total assets, total liabilities, total enterprise value, leverage, ratio of cash flows to long-term debt, dummybank. Yet, the impact of two of them (total liabilities and dummybank) was not precisely defined and this might require further investigation. In brief, the practical implication linked to this finding is that the factors with a negative coefficient such as total equity, total enterprise value or the ratio cash flows on long-term debt would rather provoke a split rating moving toward -1 in this case, namely higher Moody's ratings than Standard & Poor's. Thus, it could mean that those variables are more carefully assessed in the rating process of the first CRA.

As a final conclusion, some limitations have to be highlighted and suggestions for deeper research to be made. Indeed, as mentioned earlier, the results show some inconsistencies at several levels that might require further investigation. For example, the contradictory effect of current assets and total assets on the probability of occurrence of split ratings is a problem to solve among others. Then, with regard to the amplitude of the analysis itself, studying kind of the same sample but with a larger number of companies could be interesting to draw more general conclusions. Also, the timespan could be extended to many years before 2000 for a similar study, for example 1982 when Moody's started using notches. Moreover, it could be considered to analyse a bigger number of financial characteristics or to focus solely on a certain type. Obviously, this would require better means to conduct the study, such as more powerful software products e.g.

Appendices

Appendix 1: Evolution of the Basel Agreements from 2011 to 2019



Source: Boehm, K. (2013). *Credit Rating Agencies (CRAs): The EU Regulatory Framework Assessment*, 1-42. Retrieved from https://www.theseus.fi/handle/10024/63164

Appendix 2: Comparison of the main credit risk models

Figure 5

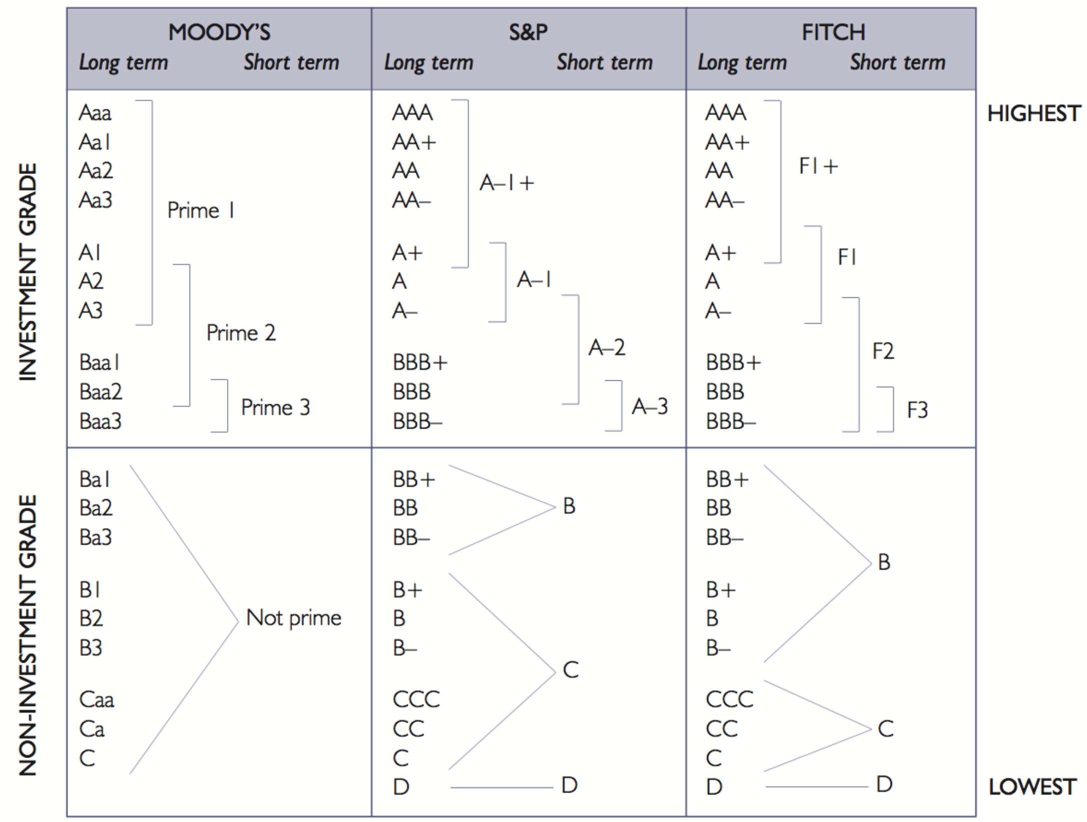
Overview of Four Credit Portfolio Models

	KMV Portfolio Manager	RMG CreditMetrics (CreditManager)	CSFB CreditRisk+	McKinsey CreditPortfolioView
Approach	Asset Volatility	Asset Volatility	Actuarial Model	Factor Model
Considers effects of default and downgrades?	Both	Both	Default Only	Both
Probability of default	Endogenous (from Credit Monitor) or Exogenous	Exogenous	Exogenous	Endogenous
Loss given default	Exogenous	Exogenous	Exogenous	Exogenous
Correlation	Asset Correlation via a factor model	Equity (index) correlation via a factor model	Default correlation via segments and default volatility	Default/migration correlated via macro factor model

Source: Smithson, C. W., & Hayt, G. (2001). The State of the Art in Credit Portfolio Modelling. *The RMA Journal,* March 2001, 34-38. Retrieved from https://cms.rmau.org/uploadedFiles/Credit_Risk/Library/RMA_Journal/Credit_Portfolio_Management/The%20State%20of%20the%20Art%20in%20Credit%20Portfolio%20Modeling.pdf

Appendix 3: Overview of the CRAs' rating structures

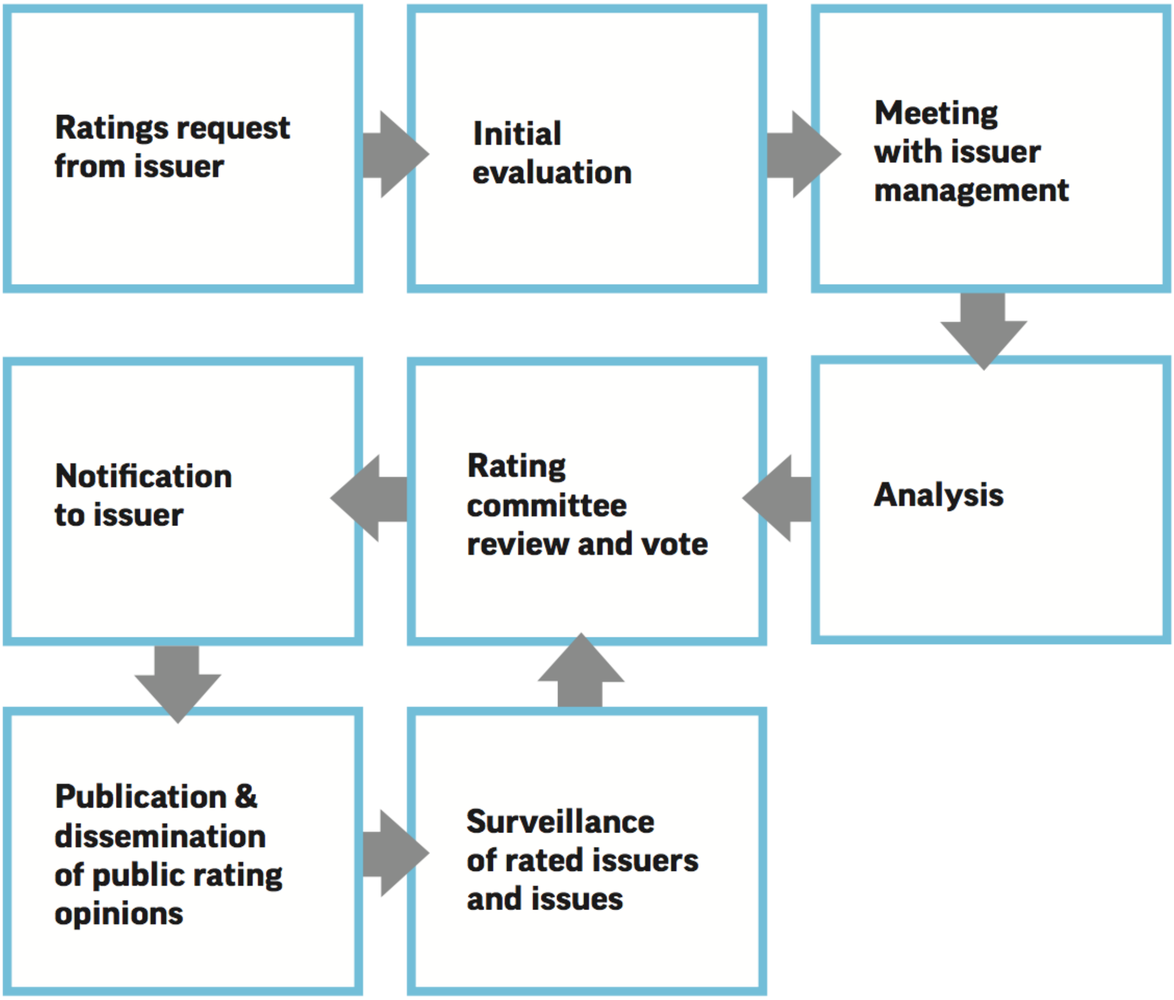
Figure 1: The ratings structure



Source: The Association of Corporate Treasurers

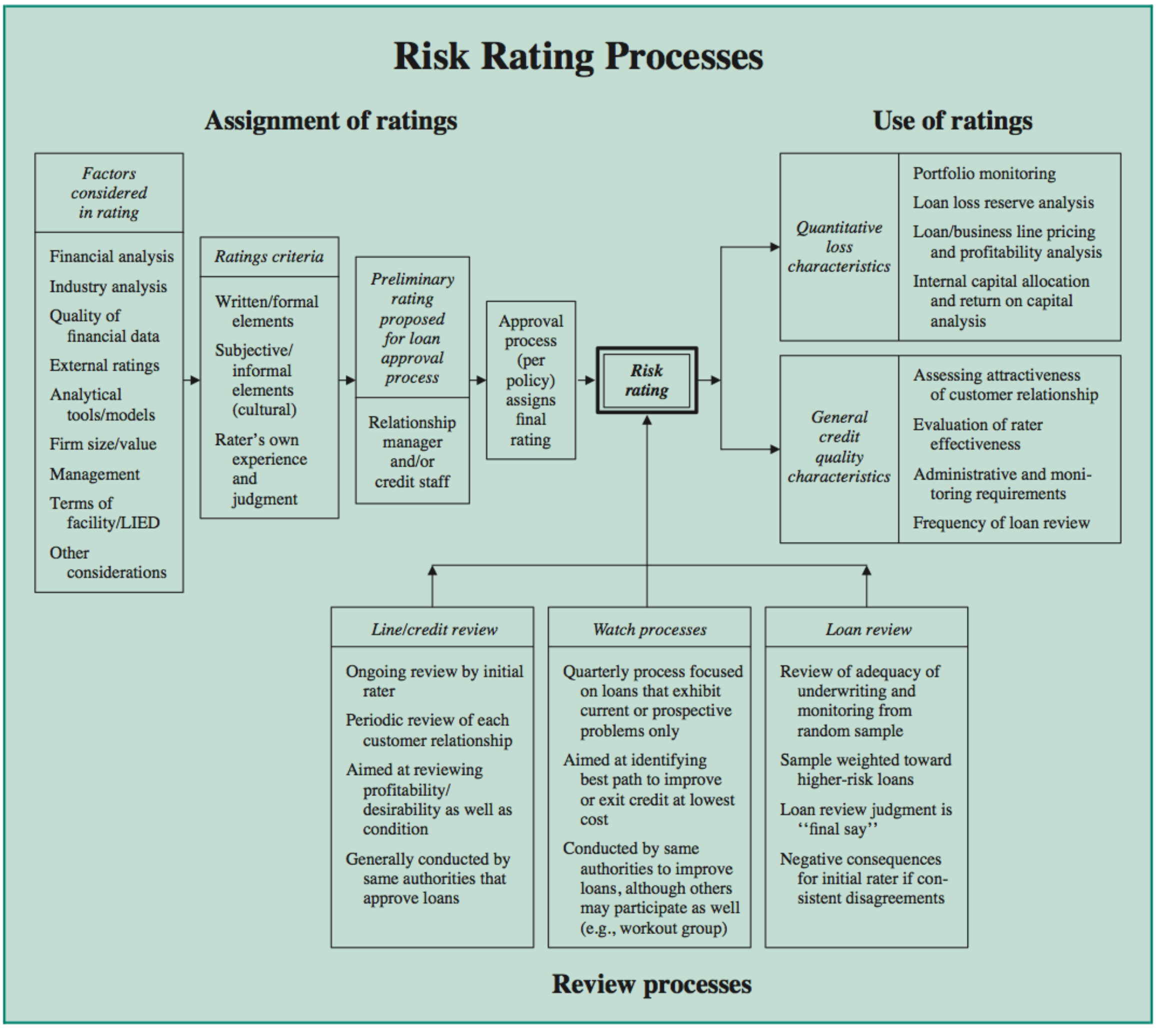
<u>Source</u>: Santos, K. (n.d.). *Corporate Credit Ratings: A Quick Guide,* 45-49. Retrieved from https://www.treasurers.org/ACTmedia/ITCCMFcorpcreditguide.pdf

Appendix 4: Description of the internal rating process



<u>Source</u>: Standard & Poor's Ratings Services (2004). *Guide to Credit Rating Essentials: What Are Credit Ratings and How Do They Work?* Retrieved from http://www.spratings.com/en_US/understanding-ratings?rd=understandingratings.com#firstPage

Appendix 5: Larger overview of the complete rating process



Source: Treacy, W., & Carey, M. (1998). Credit Risk Rating Systems at Large US Banks. *Journal Of Banking & Finance*, *24*(1-2), 167-201. doi: 10.1016/s0378-4266(99)00056-4

Appendix 6: Types of ratings issued by all CRAs in 2014

Credit Rating Agency	(Corporate) Non-Financial	(Corporate) Financial Institutions	(Corporate) Insurance	Sovereign	Structured Finance Products	Covered Bonds
AM Best Europe-Rating Services Ltd. (AMBERS)	Yes	No	Yes	No	No	No
ARC Ratings, S.A.	Yes	No	No	No	No	No
ASSEKURATA Assekuranz Rating-Agentur GmbH	No	No	Yes	No	No	No
Axesor S.A.	Yes	No	No	No	No	No
BCRA-Credit Rating Agency AD	No	Yes	Yes	Yes	No	No
Capital Intelligence (Cyprus) Ltd	Yes	Yes	No	Yes	No	No
CERVED Group S.p.A.	Yes	No	No	No	No	No
Creditreform Rating AG	Yes	No	No	No	Yes	Yes
CRIF S.p.A.	Yes	No	No	No	No	No
Dagong Europe Credit Rating Srl (Dagong Europe)	No	Yes	Yes	No	No	No
DBRS Ratings Limited	Yes	Yes	Yes	Yes	Yes	Yes
Euler Hermes Rating GmbH	Yes	Yes	No	No	No	No
European Rating Agency, a.s.	No	No	No	Yes	No	No
EuroRating Sp. Zo.o. [8]	Yes	No	No	No	No	No
Feri EuroRating Services AG	Yes	Yes	No	Yes	No	No
Fitch Group	Yes	Yes	Yes	Yes	Yes	Yes
GBB - Rating Gesellschaft für Bonitätsbeurteilung mbH	No	Yes	No	No	No	No
ICAP Group SA	Yes	No	No	No	No	No
Moody's Group	Yes	Yes	Yes	Yes	Yes	Yes
Scope Credit Rating GmbH	Yes	Yes	No	No	Yes	No
Spread Research SAS	Yes	No	No	No	No	No
Standard & Poor's Group	Yes	Yes	Yes	Yes	Yes	Yes
The Economist Intelli-gence Unit Ltd	No	No	No	Yes	No	No

Source: European Securities and Market Authority (2014). *Report ESMA/2014/1583: Credit Rating Agencies' 2014 Market Share Calculations for the Purposes of Article 8d of the CRA Regulation.* Retrieved from https://www.esma.europa.eu/sites/default/files/library/2015/11/2014-1583_credit_rating_agencies_market_share_calculation_2014.pdf

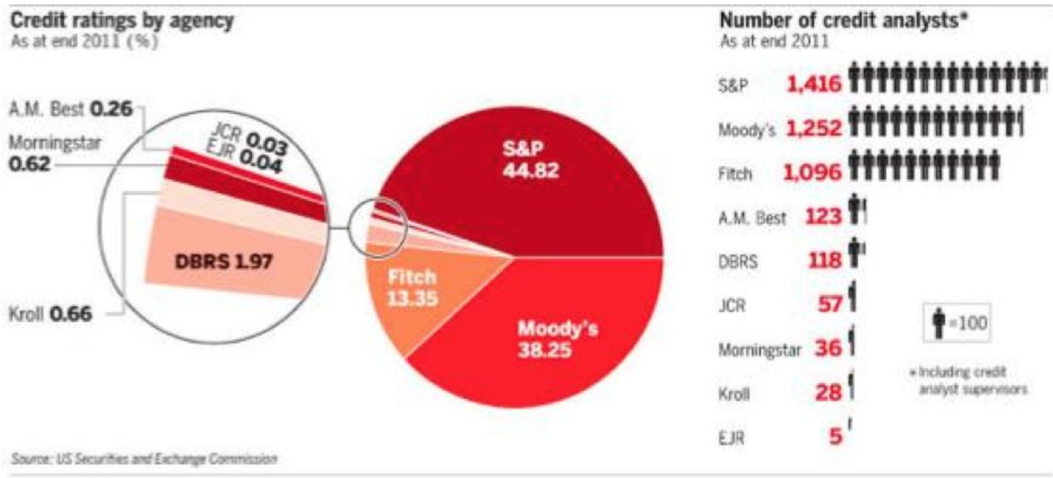
Appendix 7: CRA's market share calculation (Europe)

Registered Credit Rating Agency	Market share %
AM Best Europe-Rating Services Ltd. (AMBERS)	0.72
ARC Ratings, S.A.	0.03
ASSEKURATA Assekuranz Rating-Agentur GmbH	0.26
Axesor S.A.	0.58
BCRA-Credit Rating Agency AD	0.03
Capital Intelligence (Cyprus) Ltd	0.13
CERVED Group S.p.A.	2.19
Creditreform Rating AG	0.53
CRIF S.p.A.	0.76
Dagong Europe Credit Rating Srl (Dagong Europe)	<0.01
DBRS Ratings Limited	1.27
Euler Hermes Rating GmbH	0.24
European Rating Agency, a.s.	<0.01
EuroRating Sp. Zo.o. [4]	<0.01
Feri EuroRating Services AG	0.67
Fitch Group[5]	16.22
GBB-Rating Gesellschaft für Bonitätsbeurteilung mbH	0.33
ICAP Group SA	0.75
Moody's Group[6]	34.53
Scope Credit Rating GmbH	0.14
Spread Research SAS	0.09
Standard & Poor's Group[7]	39.69
The Economist Intelligence Unit Ltd	0.83
TOTAL	**100**

Source: European Securities and Market Authority (2014). *Report ESMA/2014/1583: Credit Rating Agencies' 2014 Market Share Calculations for the Purposes of Article 8d of the CRA Regulation.* Retrieved from https://www.esma.europa.eu/sites/default/files/library/2015/11/2014-1583_credit_rating_agencies_market_share_calculation_2014.pdf

Appendix 8: Overview of the rating industry with market shares

Market Share by Credit Rating Agency **(Figure 1)**



The largest market shares are allocated amongst S&P (44,82%), Moody's (38,25) and Fitch (13,35%).

Source: Boehm, K. (2013). *Credit Rating Agencies (CRAs): The EU Regulatory Framework Assessment*, 1-42. Retrieved from https://www.theseus.fi/handle/10024/63164

Appendix 9: Notion of credit rating defined by the Big Three

Fitch Ratings Definition	Moody's Ratings Definition	Standard & Poor Ratings Definition
"Fitch Ratings' credit ratings provide an *opinion* on the *relative* ability of an entity to meet financial commitments… Credit ratings, as opinions on *relative* ranking of vulnerability to *default*, do not imply or convey a specific statistical *probability of default*, notwithstanding the agency's published *default* histories that may be measured against ratings at the time of *default*. Credit ratings are opinions on *relative* credit quality and not a predictive measure of specific *default probability*." (Fitch, 2013).	Moody's rates and publishes *independent credit opinions* on fixed-income securities, issuers of securities and other credit obligations… Investors use Moody's ratings to help price the credit *risk* of fixed-income securities or debts they may buy, sell or lend." (Moody's 2013).	"A credit rating is Standard & Poor's *opinion* on the general *creditworthiness* of an obligor, or the *creditworthiness* of an obligor with respect to a particular debt security or other financial obligation." (Standard & Poor's 2013a).

<u>Source</u>: Boehm, K. (2013). *Credit Rating Agencies (CRAs): The EU Regulatory Framework Assessment*, 1-42. Retrieved from https://www.theseus.fi/handle/10024/63164

Appendix 10: Rating categories and their meanings for The Big Three

S&P		Moody's		Fitch		Meaning
Long term grade	Short term	Long term grade	Short term	Long term grade	Short term	
Investment grade						
AAA	A1+	Aaa		AAA	F1+	Highest rating
AA+ AA AA-	A1	Aa1 Aa2 Aa3	P1	AA+ AA AA-	F1	High rating
A+ A A-	A2	A1 A2 A3	P2	A+ A A-	F2	High capabilities of debt repayment
BBB+ BBB BBB-	A3	Baa1 Baa2 Baa3	P3	BBB+ BBB BBB-	F3	Sufficient capabilities of debt repayment
Speculative grade						
BB+ BB BB-	B	Ba1 Ba2 Ba3		BB+ BB BB-	B	Speculative, credit risk rises
B+ B B-		B1 B2 B3	Second-class	B+ B B-		Highly speculative, low possibilities of protection
CCC+, CCC, CCC-, CC, C	C	Caa, Ca,		CCC, CC, C	C	High risk of default
D	D	C		RD/D	RD/D	Default

<u>Source</u>: Host, A., Cvečić, I., & Zaninović, V. (2012). Credit Rating Agencies and Their Impact on Spreading the Financial Crisis on the Eurozone. *Ekon. Misao Praksa Dbk*, *God XXI. (2012.)* (Br. 2.), 639-662. Retrieved from https://www.researchgate.net/publication/260002009_Credit_Rating_Agencies_and_their_Impact_on_Spreading_the_Financial_Crisis_on_the_Eurozone

Appendix 11: Moody's long-term rating scale

Global Long-Term Rating Scale	
Aaa	Obligations rated Aaa are judged to be of the highest quality, subject to the lowest level of credit risk.
Aa	Obligations rated Aa are judged to be of high quality and are subject to very low credit risk.
A	Obligations rated A are judged to be upper-medium grade and are subject to low credit risk.
Baa	Obligations rated Baa are judged to be medium-grade and subject to moderate credit risk and as such may possess certain speculative characteristics.
Ba	Obligations rated Ba are judged to be speculative and are subject to substantial credit risk.
B	Obligations rated B are considered speculative and are subject to high credit risk.
Caa	Obligations rated Caa are judged to be speculative of poor standing and are subject to very high credit risk.
Ca	Obligations rated Ca are highly speculative and are likely in, or very near, default, with some prospect of recovery of principal and interest.
C	Obligations rated C are the lowest rated and are typically in default, with little prospect for recovery of principal or interest.

Note: Moody's appends numerical modifiers 1, 2, and 3 to each generic rating classification from Aa through Caa. The modifier 1 indicates that the obligation ranks in the higher end of its generic rating category; the modifier 2 indicates a mid-range ranking; and the modifier 3 indicates a ranking in the lower end of that generic rating category. Additionally, a "(hyb)" indicator is appended to all ratings of hybrid securities issued by banks, insurers, finance companies, and securities firms.*

Note: For more information on long-term ratings assigned to obligations in default, please see the definition "Long-Term Credit Ratings for Defaulted or Impaired Securities" in the Other Definitions section of this publication.

* *By their terms, hybrid securities allow for the omission of scheduled dividends, interest, or principal payments, which can potentially result in impairment if such an omission occurs. Hybrid securities may also be subject to contractually allowable write-downs of principal that could result in impairment. Together with the hybrid indicator, the long-term obligation rating assigned to a hybrid security is an expression of the relative credit risk associated with that security.*

Source: Moody's Investors Service (2016). *Rating Symbols and Definitions*. Retrieved from https://www.moodys.com/sites/products/AboutMoodysRatingsAttachments/MoodysRatingSymbolsandDefinitions.pdf

Appendix 12: Standard & Poor's long-term rating scale

Long-Term Issuer Credit Ratings*

Category	Definition
AAA	An obligor rated 'AAA' has extremely strong capacity to meet its financial commitments. 'AAA' is the highest issuer credit rating assigned by Standard & Poor's.
AA	An obligor rated 'AA' has very strong capacity to meet its financial commitments. It differs from the highest-rated obligors only to a small degree.
A	An obligor rated 'A' has strong capacity to meet its financial commitments but is somewhat more susceptible to the adverse effects of changes in circumstances and economic conditions than obligors in higher-rated categories.
BBB	An obligor rated 'BBB' has adequate capacity to meet its financial commitments. However, adverse economic conditions or changing circumstances are more likely to lead to a weakened capacity of the obligor to meet its financial commitments.
BB; B; CCC; and CC	Obligors rated 'BB', 'B', 'CCC', and 'CC' are regarded as having significant speculative characteristics. 'BB' indicates the least degree of speculation and 'CC' the highest. While such obligors will likely have some quality and protective characteristics, these may be outweighed by large uncertainties or major exposures to adverse conditions.
BB	An obligor rated 'BB' is less vulnerable in the near term than other lower-rated obligors. However, it faces major ongoing uncertainties and exposure to adverse business, financial, or economic conditions which could lead to the obligor's inadequate capacity to meet its financial commitments.
B	An obligor rated 'B' is more vulnerable than the obligors rated 'BB', but the obligor currently has the capacity to meet its financial commitments. Adverse business, financial, or economic conditions will likely impair the obligor's capacity or willingness to meet its financial commitments.
CCC	An obligor rated 'CCC' is currently vulnerable, and is dependent upon favorable business, financial, and economic conditions to meet its financial commitments.
CC	An obligor rated 'CC' is currently highly vulnerable. The 'CC' rating is used when a default has not yet occurred, but Standard & Poor's expects default to be a virtual certainty, regardless of the anticipated time to default.
R	An obligor rated 'R' is under regulatory supervision owing to its financial condition. During the pendency of the regulatory supervision the regulators may have the power to favor one class of obligations over others or pay some obligations and not others.
SD and D	An obligor rated 'SD' (selective default) or 'D' is in default on one or more of its financial obligations including rated and unrated financial obligations but excluding hybrid instruments classified as regulatory capital or in non-payment according to terms. An obligor is considered in default unless Standard & Poor's believes that such payments will be made within five business days of the due date in the absence of a stated grace period,or within the earlier of the stated grace period or 30 calendar days. A 'D' rating is assigned when Standard & Poor's believes that the default will be a general default and that the obligor will fail to pay all or substantially all of its obligations as they come due. An 'SD' rating is assigned when Standard & Poor's believes that the obligor has selectively defaulted on a specific issue or class of obligations but it will continue to meet its payment obligations on other issues or classes of obligations in a timely manner. An obligor's rating is lowered to 'D' or 'SD' if it is conducting a distressed exchange offer.
NR	An issuer designated 'NR' is not rated.

*The ratings from 'AA' to 'CCC' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories.

Source: Standard & Poor's Ratings Services (2014). *Standard & Poor's Ratings Definitions*. Retrieved from http://www.spratings.com/en_US/understanding-ratings?rd=understandingratings.com#secondPage

Appendix 13: Example of a S&P transition matrix

Global Corporate Average Transition Rates (1981-2014) (%)									
From/to	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC/C**	**D**	**NR**
One-year									
AAA	87.03	9.03	0.54	0.05	0.08	0.03	0.05	0.00	3.19
	(7.11)	(7.16)	(0.83)	(0.25)	(0.25)	(0.17)	(0.35)	(0.00)	(2.44)
AA	0.54	86.53	8.14	0.54	0.06	0.07	0.02	0.02	4.07
	(0.52)	(5.30)	(4.32)	(0.70)	(0.20)	(0.21)	(0.07)	(0.08)	(1.93)
A	0.03	1.83	87.55	5.38	0.35	0.14	0.02	0.07	4.64
	(0.10)	(1.04)	(3.61)	(2.19)	(0.39)	(0.28)	(0.07)	(0.11)	(1.84)
BBB	0.01	0.11	3.58	85.44	3.75	0.56	0.13	0.20	6.23
	(0.04)	(0.16)	(1.71)	(3.91)	(1.59)	(0.73)	(0.23)	(0.27)	(1.68)
BB	0.01	0.03	0.14	5.16	76.62	6.96	0.66	0.76	9.64
	(0.06)	(0.10)	(0.27)	(1.90)	(4.56)	(3.31)	(0.79)	(0.89)	(2.55)
B	0.00	0.03	0.10	0.21	5.40	74.12	4.37	3.88	11.89
	(0.00)	(0.09)	(0.22)	(0.23)	(2.09)	(4.53)	(2.35)	(3.49)	(2.31)
CCC/C	0.00	0.00	0.14	0.22	0.65	13.26	43.85	26.38	15.49
	(0.00)	(0.00)	(0.47)	(0.73)	(1.01)	(8.31)	(9.50)	(12.11)	(5.61)
Three-year									
AAA	65.46	21.92	2.38	0.33	0.19	0.08	0.11	0.14	9.40
	(11.58)	(12.23)	(1.71)	(0.77)	(0.45)	(0.30)	(0.42)	(0.37)	(5.33)
AA	1.27	64.84	19.20	2.22	0.38	0.24	0.03	0.13	11.68
	(0.80)	(8.57)	(5.98)	(1.33)	(0.51)	(0.46)	(0.08)	(0.19)	(4.10)
A	0.07	4.30	67.70	11.99	1.43	0.51	0.11	0.28	13.60
	(0.10)	(2.08)	(5.92)	(2.80)	(0.97)	(0.64)	(0.14)	(0.28)	(3.58)
BBB	0.02	0.32	8.54	63.59	7.04	1.83	0.33	1.01	17.31
	(0.07)	(0.42)	(3.24)	(6.99)	(2.14)	(1.34)	(0.39)	(0.97)	(3.25)
BB	0.01	0.06	0.58	11.48	45.40	11.81	1.31	4.40	24.94

Source: Standard & Poor's Ratings Services (2014). *Default, Transition, and Recovery: 2014 Annual Global Corporate Default Study and Rating Transitions*. Retrieved from https://www.nact.org/resources/2014_SP_Global_Corporate_Default_Study.pdf

Appendix 14: Companies belonging initially to the potential sample

3I GRP	ASTRAZENECA	BURBERRY
A.P.MOLLER-MAERSK B	ATLANTIA	CAIXABANK
ABB	ATLAS COPCO A	CAP GEMINI
ABERTIS INFRAESTRUCTURAS	ATOS	CAPITA GRP
ACCOR	AVIVA	CARLSBERG B
ACTELION	AXA	CARNIVAL
ADECCO	BAE SYSTEMS	CARREFOUR
ADIDAS	BALOISE	CENTRICA
ADMIRAL GRP	BANK OF IRELAND	CHR HANSEN HLDG
AEGON	BARCLAYS	CHRISTIAN DIOR
AENA	BARRATT DEVELOPMENTS	CIE FINANCIERE RICHEMONT
AGEAS	BASF	CNH INDUSTRIAL NV
AHOLD	BAYER	COLOPLAST B
AIR LIQUIDE	BCO BILBAO VIZCAYA ARGENTARIA	COMMERZBANK
AIRBUS GROUP SE	BCO SABADELL	COMPASS GRP
AKZO NOBEL	BCO SANTANDER	CONTINENTAL
ALLIANZ	BEIERSDORF	CREDIT AGRICOLE
ALTICE NV A	BERKELEY GRP HLDG	CREDIT SUISSE GRP
AMADEUS IT HLDG	BHP BILLITON	CRH
ANGLO AMERICAN	BMW	CRODA INTERNATIONAL
ANHEUSER-BUSCH INBEV	BNP PARIBAS	DAIMLER
ARCELORMITTAL	BOUYGUES	DANONE
ARM	BP	DANSKE BANK
ASHTEAD GRP	BRENNTAG	DASSAULT SYSTEMS
ASML HLDG	BRITISH AMERICAN TOBACCO	DCC
ASSA ABLOY	BRITISH LAND COMPANY	DELHAIZE GRP
ASSICURAZIONI GENERALI	BT GRP	DEUTSCHE BANK
ASSOCIATED BRITISH FOODS	BUNZL	DEUTSCHE BOERSE

DEUTSCHE POST	GENMAB	INTERTEK GRP
DEUTSCHE TELEKOM	GIVAUDAN	INTESA SANPAOLO
DEUTSCHE WOHNEN	GKN	INVESTMENT KINNEVIK B
DIAGEO	GLAXOSMITHKLINE	INVESTOR B
DIRECT LINE INSURANCE GROUP	GLENCORE PLC	ITV
DIXONS CARPHONE	GRIFOLS	JOHNSON MATTHEY
DNB	GRP BRUXELLES LAMBERT	JULIUS BAER GRP
DSV B	GRP SOCIETE GENERALE	KBC GRP
E.ON	HAMMERSON	KERING
EDP ENERGIAS DE PORTUGAL	HANNOVER RUECK	KERRY GRP
EIFFAGE	HEIDELBERGCEMENT	KINGFISHER
ELECTROLUX B	HEINEKEN	KLEPIERRE
ENAGAS	HEINEKEN HLDG	KONE B
ENDESA	HENKEL PREF	KONINKLIJKE DSM
ENEL	HENNES & MAURITZ B	KPN
ENGIE	HERMES INTERNATIONAL	KUEHNE + NAGEL
ENI	HEXAGON B	L'OREAL
ERICSSON LM B	HSBC	LAFARGEHOLCIM
ERSTE GROUP BANK	IAG	LAND SECURITIES
ESSILOR INTERNATIONAL	IBERDROLA	LEGAL & GENERAL GRP
EXPERIAN	ILIAD	LEGRAND
FERROVIAL	IMPERIAL BRANDS	LINDE
FIAT CHRYSLER AUTOMOBILES	INDUSTRIA DE DISENO TEXTIL SA	LINDT & SPRUENGLI REG
FORTUM	INFINEON TECHNOLOGIES	LLOYDS BANKING GRP
FRESENIUS	INFORMA	LONDON STOCK EXCHANGE
FRESENIUS MEDICAL CARE	ING GRP	LONZA
GAS NATURAL SDG	INGENICO	LUXOTTICA
GEA GRP	INMARSAT	LVMH MOET HENNESSY
GEBERIT	INTERCONTINENTAL HOTELS GRP	MARKS & SPENCER GRP

MERCK	RANDGOLD RESOURCES	SEVERN TRENT
MICHELIN	RANDSTAD	SGS
MONDI	RECKITT BENCKISER GRP	SHIRE
MORRISON (WILLIAM) SUPERMARK	RED ELECTRICA CORPORATION	SIEMENS
MUENCHENER RUECK	REED ELSEVIER PLC	SIKA
NATIONAL GRID	RELX NV	SKANDINAVISKA ENSKILDA BK A
NESTLE	RENAULT	SKANSKA B
NEXT	REPSOL	SKF B
NN GROUP	REXAM	SKY
NOKIA	RIO TINTO	SMITH & NEPHEW
NORDEA BANK	ROCHE HLDG P	SMITHS GRP
NOVARTIS	ROLLS ROYCE HLDG	SNAM RETE GAS
NOVO NORDISK B	ROYAL BANK OF SCOTLAND GRP	SODEXO
NOVOZYMES	ROYAL DUTCH SHELL A	SOLVAY
OLD MUTUAL	RSA INSURANCE GRP	SONOVA
ORANGE	RWE	ST.JAMES'S PLACE CAPITAL
ORKLA	RYANAIR	STANDARD CHARTERED
PADDY POWER BETFAIR	SABMILLER	STANDARD LIFE
PANDORA	SAFRAN	STATOIL
PARTNERS GRP HLDG	SAGE GRP	STEINHOFF N.V.
PEARSON	SAINT GOBAIN	SVENSKA CELLULOSA B
PERNOD RICARD	SAMPO	SVENSKA HANDELSBANKEN A
PERSIMMON	SANDVIK	SWATCH BEARER
PEUGEOT	SANOFI	SWEDBANK
PHILIPS	SAP	SWEDISH MATCH
PORSCHE PREF	SCHINDLER P	SWISS LIFE HLDG
PROSIEBENSAT.1 MEDIA	SCHNEIDER ELECTRIC	SWISS PRIME SITE
PROVIDENT FINANCIAL	SCOR	SWISS REINSURANCE COMPANY
PRUDENTIAL	SCOTTISH & SOUTHERN ENERGY	SWISSCOM
PUBLICIS GRP	SES	SYMRISE

SYNGENTA	TUI	VINCI
TAYLOR WIMPEY	UBS GROUP	VIVENDI
TECHNIP	UCB	VODAFONE GRP
TELECOM ITALIA	UNIBAIL-RODAMCO	VOLKSWAGEN PREF
TELEFONICA	UNICREDIT	VOLVO B
TELENOR	UNILEVER NV	VONOVIA SE
TELIASONERA	UNILEVER PLC	WARTSILA
TERNA	UNITED INTERNET	WHITBREAD
TESCO	UNITED UTILITIES GRP	WOLSELEY
THALES	UPM KYMMENE	WOLTERS KLUWER
THYSSENKRUPP	VALEO	WPP
TOTAL	VEOLIA ENVIRONNEMENT	YARA
TRAVIS PERKINS	VESTAS WIND SYSTEMS	ZURICH INSURANCE GROUP

Retrieved partly from
https://www.stoxx.com/document/Indices/Factsheets_Components/2016/April/SXXGR.pdf

Appendix 15: Final sample considered for the study

Companies	Supersector	Country	Weight (%)
3I GRP	Financial Services	GB	0,08
ABB	Industrial Goods & Services	CH	0,52
AEGON	Insurance	NL	0,13
AGEAS	Insurance	BE	0,1
AHOLD	Retail	NL	0,2
AIRBUS GROUP SE	Industrial Goods & Services	FR	0,49
ALLIANZ	Insurance	DE	0,92
AMADEUS IT HLDG	Industrial Goods & Services	ES	0,23
ANHEUSER-BUSCH INBEV	Food & Beverage	BE	1,14
ARCELORMITTAL	Basic Resources	LU	0,1
ASTRAZENECA	Health Care	GB	0,87
BAE SYSTEMS	Industrial Goods & Services	GB	0,28
BANK OF IRELAND	Banks	IE	0,1
BARCLAYS	Banks	GB	0,48
BASF	Chemicals	DE	0,85
BAYER	Chemicals	DE	1,14
BCO BILBAO VIZCAYA ARGENTARIA	Banks	ES	0,56
BCO SABADELL	Banks	ES	0,12
BCO SANTANDER	Banks	ES	0,86
BNP PARIBAS	Banks	FR	0,71
BOUYGUES	Construction & Materials	FR	0,13
BP	Oil & Gas	GB	1,16
BRITISH AMERICAN TOBACCO	Personal & Household Goods	GB	1,32
CAIXABANK	Banks	ES	0,09
CENTRICA	Utilities	GB	0,21
COMMERZBANK	Banks	DE	0,12
COMPASS GRP	Travel & Leisure	GB	0,36
CONTINENTAL	Automobiles & Parts	DE	0,29
CREDIT AGRICOLE	Banks	FR	0,16
CREDIT SUISSE GRP	Banks	CH	0,29
CRH	Construction & Materials	IE	0,29
DAIMLER	Automobiles & Parts	DE	0,93
DANONE	Food & Beverage	FR	0,53
DANSKE BANK	Banks	DK	0,24
DELHAIZE GRP	Retail	BE	0,13
DEUTSCHE BANK	Banks	DE	0,33
DEUTSCHE WOHNEN	Real Estate	DE	0,11
DIAGEO	Food & Beverage	GB	0,84
DNB	Banks	NO	0,14
EDP ENERGIAS DE PORTUGAL	Utilities	PT	0,11
ENAGAS	Utilities	ES	0,08
ENEL	Utilities	IT	0,38
ENGIE	Utilities	FR	0,31

ENI	Oil & Gas	IT	0,48
ERSTE GROUP BANK	Banks	AT	0,11
EXPERIAN	Industrial Goods & Services	GB	0,21
FIAT CHRYSLER AUTOMOBILES	Automobiles & Parts	IT	0,09
FORTUM	Utilities	FI	0,08
FRESENIUS	Health Care	DE	0,34
GAS NATURAL SDG	Utilities	ES	0,09
GKN	Automobiles & Parts	GB	0,09
GLAXOSMITHKLINE	Health Care	GB	1,2
GLENCORE PLC	Basic Resources	GB	0,35
GRP SOCIETE GENERALE	Banks	FR	0,4
HEINEKEN	Food & Beverage	NL	0,24
HSBC	Banks	GB	1,56
IBERDROLA	Utilities	ES	0,48
ING GRP	Banks	NL	0,61
INTESA SANPAOLO	Banks	IT	0,5
INVESTOR B	Financial Services	SE	0,2
ITV	Media	GB	0,16
KBC GRP	Banks	BE	0,17
KERRY GRP	Food & Beverage	IE	0,17
KONINKLIJKE DSM	Chemicals	NL	0,12
KPN	Telecommunications	NL	0,17
LafargeHolcim	Construction & Materials	CH	0,24
LEGAL & GENERAL GRP	Insurance	GB	0,26
LEGRAND	Industrial Goods & Services	FR	0,18
LINDE	Chemicals	DE	0,3
LLOYDS BANKING GRP	Banks	GB	0,8
LONDON STOCK EXCHANGE	Financial Services	GB	0,16
MARKS & SPENCER GRP	Retail	GB	0,12
MICHELIN	Automobiles & Parts	FR	0,23
MONDI	Basic Resources	GB	0,09
NATIONAL GRID	Utilities	GB	0,68
NESTLE	Food & Beverage	CH	2,88
NEXT	Retail	GB	0,18
NN GROUP	Insurance	NL	0,1
NOKIA	Technology	FI	0,41
NORDEA BANK	Banks	SE	0,4
NOVARTIS	Health Care	CH	2,25
ORANGE	Telecommunications	FR	0,44
PEARSON	Media	GB	0,13
PERNOD RICARD	Food & Beverage	FR	0,29
PHILIPS	Industrial Goods & Services	NL	0,33
PRUDENTIAL	Insurance	GB	0,63
PUBLICIS GRP	Media	FR	0,17
RENAULT	Automobiles & Parts	FR	0,25
REPSOL	Oil & Gas	ES	0,15

REXAM	Industrial Goods & Services	GB	0,08
ROYAL DUTCH SHELL A	Oil & Gas	GB	1,19
RWE	Utilities	DE	0,07
SAINT GOBAIN	Construction & Materials	FR	0,26
SAMPO	Insurance	FI	0,29
SANOFI	Health Care	FR	1,16
SAP	Technology	DE	0,95
SCHNEIDER ELECTRIC	Industrial Goods & Services	FR	0,46
SEVERN TRENT	Utilities	GB	0,09
SGS	Industrial Goods & Services	CH	0,14
SHIRE	Health Care	GB	0,39
SKANDINAVISKA ENSKILDA BK A	Banks	SE	0,21
SMITHS GRP	Industrial Goods & Services	GB	0,08
SNAM RETE GAS	Utilities	IT	0,15
SOLVAY	Chemicals	BE	0,09
STANDARD CHARTERED	Banks	GB	0,24
STANDARD LIFE	Insurance	GB	0,13
SVENSKA CELLULOSA B	Personal & Household Goods	SE	0,22
SVENSKA HANDELSBANKEN A	Banks	SE	0,24
SWEDBANK	Banks	SE	0,25
SWEDISH MATCH	Personal & Household Goods	SE	0,08
SWISS REINSURANCE COMPANY	Insurance	CH	0,39
SWISSCOM	Telecommunications	CH	0,17
SYNGENTA	Chemicals	CH	0,47
TELECOM ITALIA	Telecommunications	IT	0,15
TELEFONICA	Telecommunications	ES	0,6
TELIASONERA	Telecommunications	SE	0,17
TERNA	Utilities	IT	0,1
TESCO	Retail	GB	0,26
THALES	Industrial Goods & Services	FR	0,11
THYSSENKRUPP	Industrial Goods & Services	DE	0,11
TUI	Travel & Leisure	GB	0,09
UNICREDIT	Banks	IT	0,3
UNILEVER NV	Personal & Household Goods	NL	0,86
UNILEVER PLC	Personal & Household Goods	GB	0,72
UNITED UTILITIES GRP	Utilities	GB	0,11
VALEO	Automobiles & Parts	FR	0,15
VEOLIA ENVIRONNEMENT	Utilities	FR	0,14
VINCI	Construction & Materials	FR	0,5
VIVENDI	Media	FR	0,31
VODAFONE GRP	Telecommunications	GB	1,03
VOLKSWAGEN PREF	Automobiles & Parts	DE	0,3
VOLVO B	Industrial Goods & Services	SE	0,21
WOLTERS KLUWER	Media	NL	0,14
ZURICH INSURANCE GROUP	Insurance	CH	0,43

Appendix 16: Summary table of split ratings

	Rating SP																		
Rating M	D	CC/C	CCC	B-	B	B+	BB-	BB	BB+	BBB-	BBB	BBB+	A-	A	A+	AA-	AA	AA+	AAA	TOTAL
C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ca	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Caa	0	0	0	48	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	54
B3	0	0	0	0	8	8	12	0	0	0	0	0	0	0	0	0	0	0	0	28
B2	0	0	0	0	0	2	4	2	0	0	0	0	0	0	0	0	0	0	0	8
B1	0	0	0	0	0	9	10	34	19	1	0	0	0	0	0	0	0	0	0	73
Ba3	0	0	0	0	0	1	27	11	12	0	0	0	0	0	0	0	0	0	0	51
Ba2	0	0	0	0	0	0	4	42	91	0	0	1	0	0	0	0	0	0	0	138
Ba1	0	0	0	0	0	0	0	61	209	8	0	0	0	0	0	0	0	0	0	278
Baa3	0	0	0	0	7	0	0	9	95	680	316	14	14	0	0	0	0	0	0	1135
Baa2	0	0	0	0	0	0	0	5	4	128	1377	784	122	6	0	0	0	0	0	2426
Baa1	0	0	0	0	0	0	0	0	1	107	282	1473	618	111	0	23	0	0	0	2615
A3	0	0	0	0	17	0	0	0	1	81	2	234	1600	573	20	4	0	0	0	2532
A2	0	0	0	0	0	0	0	0	0	0	18	87	562	1162	561	265	1	0	0	2656
A1	0	0	0	0	0	0	0	0	0	0	4	55	185	414	1107	468	111	4	6	2354
Aa3	0	0	0	0	0	0	0	0	0	0	0	4	1	372	573	675	313	25	6	1969
Aa2	0	0	0	0	0	0	0	0	0	0	0	0	0	3	197	606	259	11	0	1076
Aa1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	102	287	316	116	29	850
Aaa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	31	2	0	108	142
TOTAL	0	0	0	48	38	20	57	164	432	1005	1999	2652	3102	2641	2561	2359	1002	156	149	18385

Appendix 17: Stata commands

```
import excel "/Users/Laupich/Documents/Data/ES 600/1Fichier stata used.xlsx",
sheet("Feuil1") firstrow

xtset Numbercomp Numbermonth

-----------------------------------------------------
```

- **REGRESSIONS ON RATINGM AND RATINGSP**

```
xtreg RatingM Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev
Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt
Dummybank Crisis2008 Crisis2011, re vce(cluster Numbercomp)

ssc install estout

estimates store reg_RatingM

esttab reg_RatingM using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell
title(Impact of financial characteristics on Moody's ratings (RE))


xtreg RatingM Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev
Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt
Dummybank Crisis2008 Crisis2011, fe vce(cluster Numbercomp)

estimates store reg_RatingMfe

esttab reg_RatingMfe using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell
title(Impact of financial characteristics on Moody's ratings (FE))


xtreg RatingSP Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev
Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt
Dummybank Crisis2008 Crisis2011, re vce(cluster Numbercomp)

estimates store reg_RatingSP

esttab reg_RatingSP using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell
title(Impact of financial characteristics on Standard & Poor's ratings (RE))
```

xtreg RatingSP Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011, fe vce(cluster Numbercomp)

estimates store reg_RatingSPfe

esttab reg_RatingSPfe using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell title(Impact of financial characteristics on Standard & Poor's ratings (FE))

- **REGRESSION ON RATINGDIFF**

xtreg Ratingdiff Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011, re vce(cluster Numbercomp)

estimates store reg_Ratingdiff

esttab reg_Ratingdiff using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell title(Impact of financial characteristics on numerical ratings differences (RE))

xtreg Ratingdiff Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011, fe vce(cluster Numbercomp)

estimates store reg_Ratingdifffe

esttab reg_Ratingdifffe using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell title(Impact of financial characteristics on numerical ratings differences (FE))

- **LOGIT MODEL ON DUMMYRTGDIFGEN (1/0)**

xtlogit Dummyrtgdifgen Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011, re vce(cluster Numbercomp)

estimates store log_Dummyrtgdifgen

esttab log_Dummyrtgdifgen using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell title(Impact of financial characteristics on the probability of occurrence of a split rating (RE))

margins, dydx(Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011) predict(pu0)

- **REGRESSION ON DUMMYRTGDIF3 (1/0/-1)**

xtreg Dummyrtgdif3 Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011, re vce(cluster Numbercomp)

estimates store reg_Dummyrtgdif3

esttab reg_Dummyrtgdif3 using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell title(Impact of financial characteristics on the probability of occurrence of a split rating with distinction (RE))

xtreg Dummyrtgdif3 Netinc Totdebt Totequity Totassets Totliab Curassets Curliab Totrev Grossprofit ROE Mktcap TEV LevCF UnlevCF Ltdebt ROA Leverage Liquidity CFLTdebt Dummybank Crisis2008 Crisis2011, fe vce(cluster Numbercomp)

estimates store reg_Dummyrtgdif3fe

esttab reg_Dummyrtgdif3fe using fichier.rtf, append star(* 0.1 ** 0.05 *** 0.01) se obslast onecell title(Impact of financial characteristics on the probability of occurrence of a split rating with distinction (FE))

Appendix 18: General impact of financial characteristics on Moody's and S&P ratings

	RatingM (Random Effects)	RatingM (Fixed Effects)	RatingSP (RE)	RatingSP (FE)
Netinc	-0.0000136	-0.0000136	-0.000000286	-0.000000338
	(0.0000231)	(0.0000232)	(0.0000205)	(0.0000207)
Totdebt	-0.000000447	-0.000000118	-0.000000645	-0.000000153
	(0.00000508)	(0.00000517)	(0.00000293)	(0.00000295)
Totequity	0.00000245	0.00000250	-0.00000617	-0.00000622
	(0.00000590)	(0.00000596)	(0.00000804)	(0.00000820)
Totassets	-0.000000289**	-0.000000268*	0.000000396***	0.000000392***
	(0.000000136)	(0.000000142)	(0.000000127)	(0.000000136)
Totliab	-0.00000134	-0.00000178	-0.00000254	-0.00000319
	(0.00000251)	(0.00000269)	(0.00000272)	(0.00000294)
Curassets	-0.00000211	-0.00000202	-0.00000159	-0.00000132
	(0.00000365)	(0.00000372)	(0.00000345)	(0.00000356)
Curliab	0.00000503	0.00000527	0.00000231	0.00000253
	(0.00000321)	(0.00000323)	(0.00000204)	(0.00000201)
Totrev	-0.0000177***	-0.0000186***	-0.00000833	-0.00000880
	(0.00000629)	(0.00000641)	(0.00000686)	(0.00000724)
Grossprofit	0.0000226	0.0000219	0.00000953	0.00000829
	(0.0000189)	(0.0000191)	(0.0000174)	(0.0000178)

ROE	-0.000167 (0.000198)	-0.000166 (0.000198)	-0.000483 (0.000325)	-0.000482 (0.000325)
Mktcap	0.0000106* (0.00000611)	0.0000102 (0.00000613)	0.0000172*** (0.00000440)	0.0000170*** (0.00000443)
TEV	0.00000116 (0.00000308)	0.00000103 (0.00000306)	-0.00000134 (0.00000273)	-0.00000147 (0.00000273)
LevCF	-0.000102** (0.0000404)	-0.000107** (0.0000412)	-0.000125*** (0.0000473)	-0.000131*** (0.0000489)
UnlevCF	0.000100** (0.0000397)	0.000105** (0.0000405)	0.000125*** (0.0000463)	0.000131*** (0.0000479)
Ltdebt	-0.00000469 (0.00000926)	-0.00000438 (0.00000938)	1.21e-08 (0.00000441)	0.000000372 (0.00000445)
ROA	5.302** (2.102)	5.323** (2.107)	3.948*** (1.307)	3.968*** (1.313)
Leverage	0.000379 (0.000402)	0.000375 (0.000402)	0.000778* (0.000412)	0.000775* (0.000410)
Liquidity	0.00344 (0.00225)	0.00334 (0.00225)	0.00371 (0.00236)	0.00358 (0.00234)
CFLTdebt	0.0144 (0.0111)	0.0143 (0.0109)	0.000466 (0.000319)	0.000473 (0.000322)

Dummybank	3.103***	0	2.217***	0
	(0.353)	(.)	(0.436)	(.)
Crisis2008	0.218**	0.211*	0.0349	0.0301
	(0.107)	(0.107)	(0.0994)	(0.101)
Crisis2011	-0.148*	-0.147*	-0.378***	-0.376***
	(0.0842)	(0.0841)	(0.0901)	(0.0898)
_cons	12.22***	12.65***	12.29***	12.52***
	(0.349)	(0.293)	(0.401)	(0.318)
N	12697	12697	15038	15038

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 19: Impact of financial characteristics on numerical ratings differences and on the occurrence of split ratings

	Ratingdiff (Random Effects)	Ratingdiff (Fixed Effects)	Dummyrtgdifgen (RE)	Dummyrtgdifgen (« Margins » Coefficients)
Netinc	0.00000700 (0.00000719)	0.00000684 (0.00000718)	0.0000426* (0.0000257)	0.00000922* (0.00000552)
Totdebt	0.00000387** (0.00000170)	0.00000396** (0.00000172)	0.00000653 (0.0000165)	0.00000141 (0.00000357)
Totequity	-0.00000594** (0.00000256)	-0.00000595** (0.00000256)	-0.00000536 (0.00000939)	-0.00000116 (0.00000204)
Totassets	0.000000569*** (8.67e-08)	0.000000555*** (8.85e-08)	0.00000264*** (0.000000379)	0.000000570*** (0.0000000792)
Totliab	-0.00000191*** (0.000000526)	-0.00000206*** (0.000000533)	0.00000884 (0.00000767)	0.00000191 (0.00000161)
Curassets	3.54e-08 (0.00000101)	7.70e-08 (0.00000103)	-0.0000333*** (0.0000102)	-0.00000719*** (0.00000213)
Curliab	-0.000000615 (0.00000119)	-0.000000535 (0.00000121)	0.00000862 (0.00000884)	0.00000186 (0.00000193)
Totrev	0.00000189 (0.00000145)	0.00000200 (0.00000149)	0.00000143 (0.00000876)	0.000000308 (0.00000190)
Grossprofit	0.00000112 (0.00000688)	0.00000102 (0.00000694)	-0.000000401 (0.0000247)	-0.0000000867 (0.00000534)

ROE	-0.000120** (0.0000569)	-0.000120** (0.0000567)	0.000146 (0.000250)	0.0000315 (0.0000541)
Mktcap	0.00000287 (0.00000198)	0.00000292 (0.00000200)	-0.0000252** (0.0000122)	-0.00000545** (0.00000248)
TEV	-0.00000255*** (0.000000947)	-0.00000255*** (0.000000947)	0.00000743 (0.00000553)	0.00000161 (0.00000119)
LevCF	0.00000324 (0.0000138)	0.00000275 (0.0000140)	0.0000499 (0.0000679)	0.0000108 (0.0000146)
UnlevCF	0.000000277 (0.0000139)	0.000000724 (0.0000142)	-0.0000237 (0.0000626)	-0.00000512 (0.0000135)
Ltdebt	-0.00000178 (0.00000158)	-0.00000167 (0.00000160)	-0.0000215 (0.0000144)	-0.00000464 (0.00000305)
ROA	-0.779 (0.828)	-0.761 (0.826)	-1.999 (2.265)	-0.4322917 (0.4842552)
Leverage	0.000246** (0.000121)	0.000246** (0.000121)	0.0314 (0.0210)	0.0067847 (0.0045063)
Liquidity	-0.000254 (0.000672)	-0.000263 (0.000671)	0.0280*** (0.00682)	0.006056*** (0.0014187)
CFLTdebt	-0.0469*** (0.0182)	-0.0455** (0.0184)	-0.0154 (0.0529)	-0.0033363 (0.0114685)
Dummybank	-1.153*** (0.151)	0 (.)	1.024* (0.560)	0.2214837* (0.1208763)

Crisis2008	-0.0995 (0.0757)	-0.100 (0.0757)	0.147 (0.311)	0.0318787 (0.0675494)
Crisis2011	-0.101** (0.0497)	-0.101** (0.0497)	-0.332 (0.214)	-0.071756 (0.0456375)
_cons	0.233 (0.147)	0.212** (0.0966)	0.262 (0.526)	
N	12266	12266	12266	
lnsig2u _cons			2.295*** (0.240)	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 20: Impact of financial characteristics on the probability of occurrence of a split rating with distinction (1/0/-1)

	Dummyrtgdif3 (Random Effects)	Dummyrtgdif3 (Fixed Effects)
Netinc	0.00000307 (0.00000576)	0.00000282 (0.00000578)
Totdebt	0.00000111 (0.000000933)	0.00000123 (0.000000970)
Totequity	-0.00000495** (0.00000194)	-0.00000501** (0.00000196)
Totassets	0.000000602*** (6.02e-08)	0.000000590*** (6.45e-08)
Totliab	-0.000000356 (0.000000313)	-0.000000627* (0.000000339)
Curassets	-0.000000267 (0.000000781)	-0.000000179 (0.000000804)
Curliab	-0.000000818 (0.000000885)	-0.000000678 (0.000000915)
Totrev	0.000000805 (0.00000113)	0.00000111 (0.00000120)
Grossprofit	1.56e-08 (0.00000644)	-5.84e-08 (0.00000658)

ROE	-0.0000241 (0.0000233)	-0.0000237 (0.0000238)
Mktcap	0.00000274 (0.00000169)	0.00000285 (0.00000174)
TEV	-0.00000225*** (0.000000753)	-0.00000226*** (0.000000755)
LevCF	0.00000437 (0.0000123)	0.00000395 (0.0000128)
UnlevCF	-0.00000192 (0.0000124)	-0.00000153 (0.0000128)
Ltdebt	-0.000000952 (0.00000109)	-0.000000748 (0.00000114)
ROA	-0.242 (0.593)	-0.222 (0.593)
Leverage	0.000210** (0.0000998)	0.000211** (0.000101)
Liquidity	-0.000242 (0.000647)	-0.000260 (0.000638)
CFLTdebt	-0.0274** (0.0124)	-0.0273** (0.0123)
Dummybank	-0.881*** (0.0903)	0 (.)

Crisis2008	-0.0581	-0.0584
	(0.0539)	(0.0541)
Crisis2011	-0.0458	-0.0463
	(0.0383)	(0.0384)
_cons	0.228***	0.163**
	(0.0817)	(0.0746)
N	12266	12266

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 21: Summary of the significant variables with the signs of coefficients and confidence levels (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

	RatingM (RE)	RatingM (FE)	RatingSP (RE)	RatingSP (FE)	Ratingdiff (RE)	Ratingdiff (FE)	Dummy-rtgdifgen (RE)	Dummyrtgdif3 (RE)	Dummyrtgdif3 (FE)
Net inc							Positive*		
Totdebt					Positive**	Positive**			
Totequity					Negative**	Negative**		Negative**	Negative**
Totassets	Negative**	Negative*	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***	Positive***
Totliab					Negative***	Negative***			Negative*
Curassets							Negative***		
Curliab									
Totrev	Negative***	Negative***							
Grossprofit									
ROE					Negative**	Negative**			
Mktcap	Positive*		Positive***	Positive***			Negative**		
TEV					Negative***	Negative***		Negative***	Negative***

LevCF	Negative**	Negative**	Negative***	Negative***					
UnlevCF	Positive**	Positive**	Positive***	Positive***					
Ltdebt									
ROA	Positive**	Positive**	Positive***	Positive***					
Leverage			Positive*	Positive*	Positive**	Positive**		Positive**	Positive**
Liquidity							Positive***		
CFLTdebt					Negative***	Negative**		Negative**	Negative**
Dummybank	Positive***		Positive***		Negative***		Positive*	Negative***	
Crisis2008	Positive**	Positive*							
Crisis2011	Negative*	Negative*	Negative***	Negative***	Negative**	Negative**			

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Executive summary

Since the beginning of the 21st century, most financial instruments have become increasingly complex. Consequently, investors without any particular knowledge or experience in the finance area encounter some difficulties in making the right investment decisions. To address this issue, credit rating agencies (CRAs, for short) assess the creditworthiness (or ability to meet financial obligations) of issuers or securities by determining a rating in the form of a letter grade. However, since every institution possesses its own methodology, divergences in opinion (also called "split ratings") can arise. The aim of this dissertation is therefore to evaluate the impact of the financial and accounting characteristics of the companies rated on the occurrence of such split ratings.

Firstly, this paper describes the context in which CRAs operate and defines related concepts such as credit risk, rating migration (or transition) and so on. Also, the two institutions chosen for the purposes of this study (Standard & Poor's and Moody's) are presented in more details with the potential differences in methodology and in interpretation of ratings. Then, an empirical study is realized on a sample composed of 134 companies of the STOXX® Europe 600 index for which the necessary financial characteristics and long-term issuers ratings are available. Econometrics models are employed thereafter and a comparison is made in order to answer the research question of this dissertation.

Finally, the results of the different models have shown that the occurrence of split ratings is indeed impacted by some business-related characteristics. By way of introduction, it was discovered that Standard & Poor's was more influenced by the leverage while Moody's takes rather the total revenue into account. Most importantly, the outcomes of the study proved that the net income, total assets, current assets, market capitalization and liquidity affected the probability of split ratings. The most striking finding was that the occurrence of split ratings was substantially higher for banks than for other companies. Nonetheless, the realization of this study has highlighted some limitations and inconsistencies that require further research.

Key Words: Financial instruments – Credit rating agencies – Creditworthiness – Rating – Split ratings – Financial characteristics – STOXX® Europe 600 – Econometrics