Relationship between individual features of the major European banks and their ratings

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RELATIONSHIP BETWEEN INDIVIDUAL FEATURES OF THE MAJOR EUROPEAN BANKS AND THEIR RATINGS

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Preface

In the recent years, credit rating agencies and more generally, every actor of the financial markets underwent heavy criticism for the excessive risks they have been taking and their lack of transparency. Indeed, the 2007 subprime crisis highlighted a big problem of today's economy: the opacity of the financial markets. Banks and other financial institutions have been disclosing only few, if any, information regarding their way of working. This complicated significantly the evaluation of their health for individuals and regulators. In order to provide some insights on the economic strength of a firm, credit rating agencies evaluate its creditworthiness by analyzing its macro-economic, financial and non-financial characteristics. Credit ratings are emitted in the form of letter grades which can be easily interpreted for every investor. Although the problem seems to be solved, it is not entirely. Indeed, very few is known about the methodologies used by credit rating agencies to assess the creditworthiness of firms. After the 2007 crisis, credit rating agencies have been accused of being unable to assess a firm's creditworthiness properly. For these reasons, it is interesting to conduct research that aim at identifying the components taken into account by credit rating agencies and their individual importance in the rating assignation process. In this paper, an empirical research is conducted in order to find the different impacts that financial characteristics of the major European banks have on the ratings they are assigned by the two biggest credit rating agencies (Moody's and S&P).

Key Words: Credit rating agencies - credit ratings - creditworthiness - Moody's - S&P - Financial characteristics - European banks

List of abbreviations

BCA = Baseline Credit Assessment

CRAs = Credit Rating Agencies

EAD = Exposure At Default

EL = Expected Loss

E.U. = European Union

GDP = Gross Domestic Product

IG = Investment Grade

IOSCO = International Organization of Securities Commissions

JCIF = Japan Center for International Finance

JCR = Japan Credit Rating (agency)

LGD = Loss Given Default

NIG = Non-Investment Grade

NPLs = Non-Performing Loans

NRSROs = Nationally Recognized Statistical Rating Organizations

M = Maturity

POD = Probability Of Default

ROA = Return On Assets

ROE = Return On Equity

R&I = Rating and Investment (information)

SEC = Securities and Exchange Commission

S&P = Standard and Poor's

U.K. = United Kingdom

U.S. = United States

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Introduction

After the 2007 subprime crisis, and over the following 10 years, the interest rates for both short-term and long-term deposits have been decreasing continuously. Currently, the interest rates are stabilized between 0% and 1%, making savings accounts and riskless investments look very unattractive. Therefore, an individual or an institution willing to grow their assets should start investing in risky assets, which often present a better return.

There are many areas in which one can invest, all of them have different features, risks and return prospects. All these factors must be considered when making an investment decision. Let's take the example of a real estate investment.

The real estate market can be quite attractive and investing in real estate is often thought to be a safe bet. This was especially true from 2002 to 2007, when central banks, banks and the whole economy were confident and promoted this kind of investment (Nayak, 2013; Ravier & Lewin, 2012). However, real estate is linked to high risks, like the liquidity risk[1] that cannot be neglected. The real estate market is composed of many different types of properties, such as houses, industrial areas, shopping centers, apartments, offices, etc. Properties can be bought in order to be rented or to be sold with a margin. These elements must be taken into account when making an investment. Someone wishing to invest in real estate may have a limited knowledge of this domain. A good option would be to seek the help of an expert. There are two main ways of doing this: investing in a real estate fund or seeking the advice of a specialized analyst, e.g. an estate agent.

The same is true for other investments. When someone wishes to buy a painting, he can ask for advice from an art gallery. If an investor wants to buy some shares, he can ask a broker or a banker, what the best suited investment is. If an investor or a financial institution wants to buy a bond or lend money to a firm, a bank or a sovereign, they can rely on the credit ratings emitted by the credit rating agencies (called CRAs) to evaluate its ability to pay back its debt.

Credit ratings agencies have been heavily criticized in the recent years for their inability to forecast high profile bankruptcies such as Enron and WorldCom (Gütller & Wahrenburg, 2007). More recently, in 2008, they were also unable to predict the fall of a very

[1] The *liquidity risk* is the risk of not being able to sell an asset at its fair price in a reasonable delay.

important bank, Lehman Brothers. The crisis of 2007 increased concern about the lack of transparency of banks, credit rating agencies and other financial institutions. Indeed, the methodologies used by CRAs are confidential and not much is known about them.

The aim of this paper is thus to describe and understand how credit ratings work. In particular, this thesis will seek to answer the following question: what are the financial and accounting factors that influence the ratings assigned by Moody's and Standard and Poor's (S&P) to the major European banks?

This thesis will be divided into two main sections. The first one will be a literature review, sampling information about credit ratings and CRAs from different scientific sources. The aim of this first part is to bring together insightful pieces of information about the CRA market, the different types of credit ratings, and the use of credit ratings in general. The second part will be an empirical analysis, which will try to give some statistically based answers to the paper's question. The computations will try to determine how the banks' accounting and financial features affect the ratings they obtain. In order to do so a sample of major European banks will be analyzed. The goal of the empirical analysis is to find a relationship between several financial characteristics of the banks and the ratings assigned by the two major rating agencies, Moody's and S&P.

1 Literature Review

1.1 What is a credit rating?

1.1.1 Why are credit ratings needed?

In 1984, Ramakrishnan and Thakor explained that no financial player has the same information as the others, leading to a horizontal asymmetry of information. This is still the case nowadays. An institutional or individual investor willing to lend money to a company will use public information to assess the borrower's creditworthiness. However, this public information is often incomplete and is not sufficient to evaluate the exact creditworthiness of a firm within a large scope. Information asymmetry discourages investors from putting their money on the financial market and lead to an inefficient allocation of financial resources (Stiglitz & Weiss, 1981). To support this theory, Ayman, Sougné and Lakhal (2015) shed light on the benefits of information disclosure. They found that information disclosure significantly reduces the information asymmetry, which increases the firms' visibility and the market's liquidity. The lack of disclosure increases the importance of a firm's reputation when trying to borrow funds on the financial market (Mattarocci, 2015). This means that a firm with a bad reputation or a low level of disclosure will have to borrow money at a higher cost and will have more difficulty finding investors.

In order to reduce information asymmetry, firms can use the judgments emitted by information providers (e.g. Credit Rating Agencies), which summarize all the public and reserved information regarding an issuer or an issue (Cowan, 1991). Rating agencies help to reduce information asymmetry between borrowers and lenders by evaluating financial issues and issuers using a standardized methodology (Kuhner 2001). This evaluation, called "credit rating" is then provided to the market in a clearly readable manner to allow unskilled investors to interpret them correctly (Krahnen & Weber, 2001).

Whenever an investor lends money to a borrower, he bears a credit risk. The credit risk is "*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). Therefore, it is important for investors to be able to evaluate the creditworthiness of a firm or an asset before investing in it. The creditworthiness can be defined as the possibility that the borrower will default on his debt obligation. The higher the likelihood that a borrower will default, the worse his creditworthiness. The computation of creditworthiness takes into account factors such as repayment history and credit score.

1.1.2 How are credit ratings computed and displayed?

Krahnen and Weber (2001) define the credit rating as the mapping of the probability of default (POD) of a company. According to them, the probability of default is the frequency of the non-payment of the principal or the interests of a loan. Two other concepts are introduced, the loss given default (LGD) and the expected loss (EL). The LGD is the amount of money lost by a lender if a borrower defaults on his loan. The EL is the amount of money that is expected to be lost regarding a loan. It is computed as follows.

$$EL = POD * LGD$$

Once the investor is aware of the expected loss related to a loan, he will be able to assess whether he thinks the return offered by an asset is worth its risk or not.

Credit ratings are published in the form of letters, going from AAA (representing the best grade) to D (which represents the state of default). Each letter represents a category of creditworthiness which is linked to a certain probability of default (Krahnen & Weber, 2001). Moody's and Standard and Poor's, the two leading credit rating agencies, use the following symbols (Kliger & Sarig, 2000):

Moody's: Aaa, Aa, A, Baa, Ba, B, Caa, Ca, C and D

S&P: AAA, AA, A, BBB, BB, B, CCC, CC, C and D

Those symbols are completed with 3 different subratings. The subratings are indicated with modifiers. S&P uses the + sign for the most creditworthy issuers of the rating category, while the - sign indicates which are the least creditworthy issuers within the rating. No modifier means that the issue is of an average creditworthiness within the rating category (Kliger & Sarig, 2000). Moody's uses subratings as well, but presents them in a numerical form, using the numbers 1, 2 and 3, respectively for the worse creditworthy firms, the neutral firms, and the best firms within a rating category. A complete rating could be, for instance, one of these ratings AA+, B-, CCC+ for S&P and Aa1, Baa3 for Moody's. The different ratings possible for Moody's and S&P can be found in Appendix I.

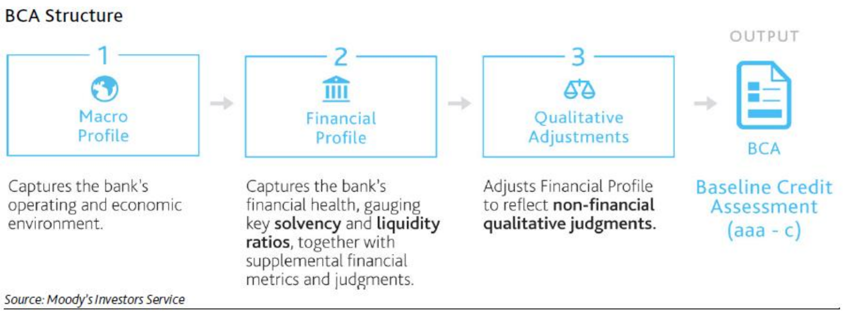
The default state (D) has no modifier, since it is a state from which the issuer can't come back. Once an issuer has defaulted, he cannot be rated anymore. It is interesting to mention that the rating scale can be divided into two broad categories: investment grades (IG) and non-investment grades (NIG), also called speculative grades. The investment grades are composed of safer assets compared to the non-investment grades assets. The IG assets have a limited risk while the NIG are more likely to default (de Servigny & Renault, 2004). Therefore, NIG assets often have higher return prospects and are used for speculative purposes. The IG starts at the Baa3 rating for Moody's and BBB- rating for S&P, as represented in Appendix I.

The methodology used to compute a credit rating includes two types of information, quantitative and qualitative elements. It is still very unclear which qualitative and quantitative factors are used and what their weights are in the computation methods used by each CRA (Ederington, 1986). Jorion, Liu & Shiu (2005) found that the ratings' relevance has increased since the incorporation of qualitative aspects in the computation. This means that the qualitative part, which includes interviews with the management, analysis of confidential information, etc. should not be neglected when considering a credit rating.

S&P's rating services provided a guide in which the credit rating process is briefly explained. In Appendix II, one can see the numerous steps a rating analyst must go through in order to compute a rating.

In a report emitted in January 2016, Moody's gave some insights about the methodology it uses to compute the Baseline Credit Assessment (BCA) of banks. A bank's BCA is the intrinsic financial strength of the bank. The BCA is combined with the counterparty risk assessment and the computation of the expected loss to obtain the final rating of the bank (Moody's Investors Service, 2016).

Figure 1: The Baseline Credit Assessment Structure



Source: Moody's Investors Service (2016)

The first step is to analyze the macro-economic features of the bank. The country in which the bank is operating will influence the rating obtained by the bank itself. A wealthy and rich country, providing high quality services in order to promote growth will positively impact the rating of all its firms (Altman, 2005). It is even more important for firms located in developing countries, since the rating obtained by a firm within a developing country cannot be higher than the rating assigned to the country itself. This maximum is called the country ceiling (Altman, 2005). In addition, Kerwer (2001) argue that the sector features impact the riskiness of a firm as well. Moody's Investors Service (2016) state in its report that, in order to compute the Baseline Credit Assessment, it analyzes economic variables of the country in which the bank is operating. Economic variables are, for instance, the Gross Domestic Product (GDP) and the real interest rates. Moody's also analyzes the country's link to external sectors (e.g. the capital flows, the reserves and the exchange rate), credit variables (e.g. the private-sector credit compared to the GDP and its growth) and the asset prices (mainly real-estate values).

The second dimension which is evaluated according to Moody's Investors Service (2016), is the financial profile. According to Moody's, the financial strength of a bank and its viability are linked to its solvency and its liquidity. The solvency is a combination of asset risk, leverage and earnings, as explained by Moody's Investors Service (2016) in its report. Studies from Kaplan & Urwitz (1979) and from Sengupta (1998) also identified several determinants of the credit ratings (Cheng & Neamtiu, 2009). Cheng & Neamtiu (2009) used the total assets, the leverage, the interest coverage and the profit margin as accounting variables for their computations.

The third step in the computation of the BCA is the quality adjustments. Moody's Investors Service (2016) identified 3 important non-financial qualitative factors that influence the health of a company. These factors are namely the "business diversification", the "opacity and complexity" and the "corporate behavior". The business diversification is defined as:

> "*the breadth of a bank's business activities, whether it is dependent on a single business, or spread across multiple activities, exposing it to or protecting it from problems in a single activity*" (Moody's Investors Service, 2016, p. 11).

The opacity and complexity reflect the extent to which the complexity of the firm may increase the risk of errors made by the management. The corporate behavior of a bank is defined by Moody's Investors Service (2016) as being the influence of the bank's management, strategy and corporate policies on its risk profile.

Moody's Investors Service (2016) further state that macro-economic, financial and qualitative factors are sufficiently comprehensive to capture the many features that can influence a bank's standalone creditworthiness. It adds that the BCA corresponds roughly to their view of the standalone creditworthiness of a bank across the world. The BCA is a sound starting point for Moody's analysis. It is important for the company to keep a certain flexibility to assign scores reflecting a broader evaluation of the credit factors, because a scorecard cannot predict every circumstance that influences or will influence the BCA (Moody's Investors Service, 2016)

An example of a BCA scorecard can be found in Appendix III, it displays the computation process used by Moody's to determine the preliminary rating. The 3 different steps explained previously can be identified in the scorecard. In addition, we can see that the asset risk, capital, profitability, funding structure and liquidity have important roles in a bank's BCA. Therefore, these factors will be analyzed in the empirical part of this report.

1.1.3 Main perks and disadvantages of credit ratings

As stated previously, credit ratings help to reduce informational asymmetries on the financial market (White, 2002). The main advantage is that ratings take into account reserved information without making it public (Goh & Ederington, 1993). This is interesting for issuers, because this way they are able to prove they are healthy and well monitored, without having to disclose confidential information to the market. Issuers are then able to get a better credit ratings and to have an easier access to capital. From the investor's point of view, using ratings is interesting because they reflect the opinion of an expert who has access to information that could not be obtained from publicly available economic and financial documents (Fight, 2001). The ratings allow the investor to choose their investments not only by looking at the revenues of an asset, but also by analyzing its underlying risk (Pagano & Volpin, 2003).

Although credit rating agencies have a big influence on the financial markets, they also have been heavily criticized for several reasons. First of all, the different CRAs claim that their ratings are their personal 'opinions' regarding the creditworthiness of an issuer or an issue based on quantitative and qualitative information (Mattarocci, 2014).

> *"The analyses, including ratings, of S&P (...) are statements of opinion (...) and not statements of fact or recommendations to purchase, hold, or sell any securities or make any investment decisions. S&P Global Ratings assumes no obligation to update any information following publication. Users of ratings or other analyses should not rely on them in making any investment decision. S&P Global Ratings' opinions and analyses do not address the suitability of any security. While S&P Global Ratings has obtained information from sources it believes to be reliable, it does not perform an audit and undertakes no duty of due diligence or independent verification of any information it receives. Ratings and other opinions may be changed, suspended, or withdrawn at any time."* (Standard and Poors, 2016, p.3).

Consequently, CRAs cannot be held responsible when a loss is incurred by an investor that used an agency's rating to select its investment. This means that if a rating turns out to be wrong, and the issuer defaults, the credit rating agency is not legally responsible for the investor's loss.

The second reason why CRAs have been criticized is for their inability to prevent the high-profile bankruptcies of firms such as Enron and WorldCom (Gütller & Wahrenburg, 2007) in a timely manner (Cheng & Neamtiu, 2009). In addition, the lack of transparency regarding rating computation also raises some concerns. Löffler (2005) argues that market participants should, for the purpose of assessing the ratings' quality, require the CRAs to reveal, at least partly, their rating policies. Frost (2007) adds that very few information is available regarding analyst meetings and credit rating monitoring, which leaves many users frustrated and highlights the need for more research in the area.

For all these reasons, lenders and regulators pay more attention to the quality of the ratings produced by CRAs. Consequently, the conflict of interest resulting from the CRAs pricing methodology became more and more heavily debated as well. All these matters will be addressed later in this paper.

1.1.4 How do credit ratings influence financial markets?

Credit ratings have an important influence on the financial market. They are often used to price the credit risk and to build investment strategies (Altman & Rijken, 2004). Several studies have tried to identify the real impact of ratings on the market by analyzing the occurrence of rating changes. Indeed, because the market conditions and the features of a company may change over time, ratings should be adjusted regularly. Nowadays, no specific rule regarding the frequency of rating adjustments exists. However, since the CRAs' reputation is very important, they have a strong incentive to provide correct ratings and subsequently, to monitor them frequently. The analysis of the rating changes provided some insight into the real impact of the credit rating agencies on the financial market (especially the stock-market and the bond-market).

Relevant authors express diverging opinions regarding the usefulness of credit rating agencies. Some authors say that the ratings lack timeliness and that the market has already reacted to the change in a firm's creditworthiness by the time the credit rating change of the company is announced (Altman & Saunders, 2001). Others, such as Cowan (1991), claim that rating change announcements convey new information on the firm itself and not only on its debt.

The first group of authors, that doubt the usefulness of the credit ratings, affirm that rating announcements do not provide new information to the market. For instance, Altman & Saunders (2001) claim that ratings lack flexibility and are not able to predict a firm's default. They add that credit ratings only reflect information that is already included into the prices and do not provide new information to the market. An abnormal reaction of the market prices before a rating change is called a pre-announcement drift. Several studies have been conducted regarding pre-announcement drifts in order to try and understand why and how the market reacts before a new rating is announced. One of the features often cited is the service provided by the main CRAs, called the credit watch. Through this service, CRAs provide additional information about a possible change of ratings (Bannier & Hirsch, 2010). Some CRAs put firms on a watchlist if they feel that new information or a corporate event may affect the rating in the short term (Bannier & Hirsch, 2010). A rating may be put on watch for an upgrade, a downgrade, or if it is uncertain whether it will be upgraded or downgraded.

The second group of authors analyzes the reaction of the markets to rating downgrades and upgrades. Hand et al. (1992) claim that bond prices are affected negatively by downgrades and respond positively to upgrades. Billet et al. (1998) also found that bond prices were impacted negatively by bond downgrades. This conclusion seems logical, since the demand for low quality bonds is lower than the demand for high quality bonds, the return required for low quality bonds will be significantly higher in order to attract investors. One could expect the results to be similar for stock prices. However, interestingly, Goh & Ederington (1993) found that a distinction should be made between two different types of downgrades. A downgrade linked to the deterioration of a company's creditworthiness would have a negative impact on stock prices, while a downgrade due to an expected increase in leverage would positively affect stock prices. Additional studies from Holthausen & Leftwich (1986), Ederington & Goh (1998) and Gropp & Richards (2001) also analyzed the reaction of stock prices to upgrades and downgrades. The three papers have diverging results. The authors of the first two articles found that stock prices are negatively impacted by downgrades but are less influenced by rating upgrades. This is because rating upgrades are more anticipated than downgrades. Therefore, the market has already reacted to the new information by the time the rating has changed (Ederington & Goh, 1998). Gropp & Richards (2001), on the other hand, argue that both upgrades and downgrades impact stock prices (positively for the upgrades and negatively for the downgrades).

Since the first publication of the "international standards on the capital adequacy for banks" by the Basel Commission in 1998, credit ratings have played an important role in the regulation of the banking sector as well (Krahnen & Weber, 2001). This further increased their influence on the financial markets (Altman & Rijken, 2004). In short, the required capital held by banks must match the default risk of its assets. The credit ratings can be used in order to group the different assets in various risk categories with a certain probability of default (Krahnen & Weber, 2001). The credit rating influences the required amount of capital to be held as shown in Appendix IV. In addition, credit ratings are also used to regulate the investing activities of financial institutions and individual investors (Ferri et al., 2013). This use of credit ratings as part of the regulation of the banking sector has been criticized by Altman & Saunders (2001). According to them, credit ratings move slowly, suggesting that a capital adequacy based on credit ratings follows the business cycle instead of leading it. This means that banks would have to increase their capital during recessions. Banks would then have to reduce the amount of money they lend when the borrowers need it the most (Gropp & Richards, 2001). For these reasons, credit ratings are believed to "*provide little if any new* *information to the market, but rather reflect information already incorporated in market prices"*. (Altman & Saunders, 2011, as cited in Gropp & Richards, 2001, p. 375).

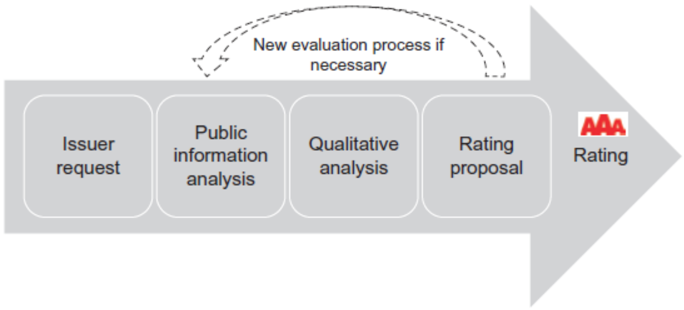
1.1.5 Important distinctions

Many types of credit ratings exist within the financial market. Therefore, the need for precision is important in order to ensure one does not mix up the various concepts. Two important distinctions should be made. Firstly, the distinction between an issuer rating and an issue rating, and secondly, the differences between a solicited and an unsolicited rating.

Let's start by looking at the differences between an issuer rating and an issue rating. An issuer rating takes into account all the characteristics of a firm and analyzes the planned investments to predict its future growth (Mattarocci, 2014). For instance, the computation method of the BCA, detailed previously, takes into account various factors that influence the issuer rating for banks. Issuer ratings have to be requested and paid by the issuers themselves (Kliger & Sarig, 2000). One could wonder why someone would pay to be rated. Could it be that the purpose is to get better ratings? Kliger & Sarig (2000) argue that this is not the case because a CRA that provides inflated ratings could alter its own reputation. Yet, the reputation of a CRA is a very valuable asset which allows it to obtain a competitive advantage. Reputational gains and losses are observed ex post, when it is possible to verify the accuracy of the rating (Kuhner, 2001). An issuer may want to pay for a rating in order to obtain access to cheaper borrowing, by winning the investors' trust without disclosing confidential information. An issue rating analyses the creditworthiness of a particular asset. In order to compute the issue rating, the CRA uses the issuer risk exposure as a starting point (Blume, Lim & Mackinlay, 1998), and adjusts it to features that are specific to the issue itself (Pinches & Mingo, 1973). The issue's features that are always evaluated are the expiration date, the main contractual clauses, the degree of subordination and the real or personal guarantees (Crouhy et al., 2001). Sometimes, differences between the issuer rating and the issue rating can arise, especially when the issue's features significantly change the risk exposure of the investment (Ritter & Miranda, 2000).

The second important distinction to make is the one between solicited and unsolicited ratings. A solicited rating is a rating ordered by the issuer being rated, while an unsolicited rating is performed by the CRA without the request of the issuer (Behr & Guttler, 2008). Hereunder, you will find the process used to produce solicited ratings.

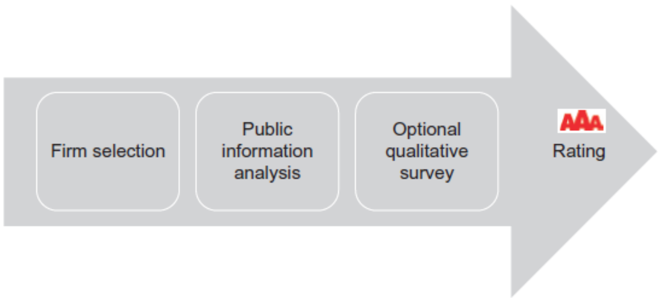
Figure 2: The Solicited Credit Rating model



Source: Mattarocci, 2014

For the issuer, the main advantage of the solicited rating is that it is allowed interact and exchange views with the evaluating entity (Mattarocci, 2014). Furthermore, the whole rating process allows the issuer to be informed of a preliminary rating before choosing whether the rating should be disclosed or not. Kliger & Sarig (2001) stated that S&P followed this process, by allowing the issuer to ask for a better rating if they provide additional information, while Moody's disclosed the ratings simultaneously to both the issuer and the market. The process for unsolicited ratings is different. It is much shorter and simpler, because no interaction with the issuer is required (Mattarocci, 2014).

Figure 3: The Unsolicited Credit Ratings model



Source: Mattarocci, 2014

Unsolicited ratings are mainly produced by small CRAs in order to acquire experience and develop their reputation (Bannier & Tyrell, 2005; Frost, 2007). Unsolicited ratings are merely summaries of the public information available and are supposed to be useful to potential users (Mattarocci, 2014). Mattarocci (2014), explains that these ratings are often less favorable for the issuer than solicited ratings (Poon, 2003), which creates an incentive for the issuer to solicit a rating (Van Roy, 2006; Mukhopadhyay, 2006; as cited in Mattarocci, 2014). Although the information used to compute unsolicited ratings is less complete, the objectivity of the rating is assured (Shimoda & Kawai, 2007).

1.2 The credit rating market

Nowadays, the credit rating market is dominated by few participants. The oligopolistic structure of the market has led to some criticism regarding the lack of accountability of the main participants and their excessive power (Kuhner, 2001). In order to understand how the market evolved this way, we need to go back in time.

1.2.1 The origin and evolution of the credit rating market

Credit risk has existed since the first lending activities took place. Its origin is estimated to be around 1800 B.C, and is reportedly the oldest type of financial risk (Caouette et al. 1998). Credit risk has been managed in many ways throughout the centuries, but rating activities as such is a much more recent concept.

In 1841, a company called "The Mercantile Agency" decided to start selling financial information, following the bankruptcy of a big textile company (Olegario, 1998, 2006; Sandage, 2005, as cited in Degos et al., 2012). Companies analyzing credit risk entered the market to fulfill the growing need for information (Degos et al. 2012)

It was only in 1909 that the first bond ratings appeared under their current form. The first publicly available bond rating was emitted by Moody's and was linked to railroad bonds (White, 2010). The first competitors to enter the market were Poor's Publishing Company in 1916, the Standard Statistics Company in 1922 and the Fitch Publishing Company in 1924. The credit rating market is characterized by numerous mergers and acquisitions. A great example is the merger that happened in 1941, between the Poor's Publishing Company and the Standard Statistics Company that gave birth to the Standard and Poor's Company (White, 2010). Following the crisis of 1929, the expansion of the credit rating businesses stopped. Investors stopped purchasing credit ratings due to the CRAs' failure to predict big drops in bond prices (Cheick, 2011). The main goal of the CRAs during this period, and during the first half of the 20th century in general, was to acquire market shares (Mattarocci, 2014). It was only during the 1980's and the 1990's that the market started growing rapidly, as a result of the globalization of financial markets, the increasing complexity of financial products and the inclusion of credit ratings in the financial regulation (Frost, 2007 as cited in Bannier & Hirsch, 2010). Numerous small CRAs entered the market during that period.

1.2.2 The credit rating market today

Nowadays, the credit rating market is composed of more than 160 local and international CRAs (Langohr, H. & Langohr, P., 2008). Every year, the EU market shares are disclosed by the European Securities and Markets Authority (ESMA). The market shares of 2016, displayed hereunder, are based on the 2015 turnover of rating activities.

Figure 4: The Credit Rating market shares in Europe in 2015

Registered Credit Rating Agency	Market share
AM Best Europe-Rating Services Ltd. (AMBERS)	0.93%
ARC Ratings, S.A.	0.03%
ASSEKURATA Assekuranz Rating-Agentur GmbH	0.21%
Axesor S.A.	0.05%
BCRA-Credit Rating Agency AD	0.02%
Capital Intelligence (Cyprus) Ltd	0.14%
CERVED Group S.p.A.	0.88%
Creditreform Rating AG	0.50%
CRIF S.p.A.	0.05%
Dagong Europe Credit Rating Srl	0.04%
DBRS Ratings Limited	1.89%
The Economist Intelligence Unit Ltd	0.80%
Euler Hermes Rating GmbH	0.21%
European Rating Agency, a.s.	0.00%
EuroRating Sp. Zo.o.	0.01%
Feri EuroRating Services AG	0.40%
Fitch Group[7]	16.56%
GBB-Rating Gesellschaft für Bonitätsbeurteilung mbH	0.34%
ICAP Group SA	0.12%
INC Rating Sp. Zo.o.[8]	0.00%
ModeFinance S.A.[9]	0.05%
Moody's Group[10]	31.29%
Rating-Agentur Expert RA GmbH[11]	0.00%
Scope Ratings AG	0.39%
Spread Research SAS	0.09%
Standard & Poor's Group[12]	45.00%
TOTAL	**100.00%**

Source: ESMA

Source: ESMA (2016)

The market is clearly dominated by three main CRAs, namely Moody's, S&P and Fitch. If we combine their respective market shares, we see that 92,85% of the market shares are held by the 3 leaders. This domination of the market can be explained by the existence of several barriers for newcomers.

The main barrier according to Williamson (1969, as cited in Mattarocci 2014) is the presence of scale economies. Evaluating an existing customer is cheaper than evaluating a new one. Therefore, the well established CRAs, which have already a wide range of customers, are able to offer lower prices than newcomers.

The second one is the fact that the three companies have had the time to acquire a strong experience and a great reputation throughout the years, creating a big gap between the new rating agencies and the well-established ones. The reputation of a CRA is very important. It is a strong asset (good-will) to the agency in order to acquire market shares (Ferri et al., 2013). Since the quality of a ratings produced by a CRA can positively or negatively affect an agency's reputation, we can argue that a good reputation implies quality ratings. Therefore, the investors' trust in these "good" ratings increases, and so does the demand.

The third historical reason of the predominance of the 3 leaders on the market is the acceptance of their ratings as part of regulation. In 1975, the Securities and Exchange Commission (SEC) required some issuers in specific markets to obtain ratings from Nationally Recognized Statistical Rating Organizations (NRSROs) (Ferri et al., 2013). The SEC simultaneously published a list of NRSROs. The NRSROs issued ratings that were recognized to be a good basis for making an investment decision (Bolton et al. 2012). The first version of this list only contained three CRAs: Moody's, S&P and Fitch. This gave an incredible advantage to the three companies over their competitors. The list included new companies in 1982 (Duff and Phelps), 1983 (McCarthy, Crisanti & Maffei), 1991 and 1992, but all of these new companies were rapidly acquired by the 3 main CRAs, which allowed them to maintain their leading position (Ferri, 2013). Since 2003, the NRSRO list has included an increasing number of rating agencies, but the reputation acquired between 1975 and 2003 by the main CRAs remains a huge competitive advantage. The list of the currently recognized NRSROs is displayed in Appendix V.

1.3 The pricing model

Not only the credit rating evolved over the past decades, the whole pricing model has changed as well. At the very start, the CRAs were selling their ratings to investors interested in acquiring some information about a particular institution's creditworthiness.

This pricing model was not sustainable anymore because of the free-riding risk (Shapiro & Varian, 1998 as cited in Mattarocci, 2014). Free-riding is the process of benefiting from the use of a common good without paying for it. This problem increased rapidly with the development of the high-speed photocopy. It became way easier to obtain a free copy of a rating book (White, 2010). The free-riding risk is most relevant when the costs of producing the information are high, which is the case with credit ratings (Mattarocci, 2014).

White (2010) identified additional reasons that could explain the change in the business model. The bankruptcy of the Penn-Central Railroad in 1970 altered the investors' trust in bonds. Consequently, obtaining a good rating would prove the low risk of default of a bond and increase investments. This made companies willing to acquire credit ratings. White (2010) added that the CRA industry is a two-sided market, where both the issuer and the investor may be willing to pay for the rating.

For these different reasons, the pricing model switched to an issuer fee model. With this pricing method, the issuers request the ratings themselves and are the ones paying for it (White, 2010).

This new model has been heavily criticized for bringing a conflict of interest to the market. Indeed, an issuer who does not get the rating he wishes may appoint another rating agency, which will provide him with a better rating. This gives the CRAs an incentive to inflate their ratings in order to gain market shares. However, different articles found some indications that is not the case.

1.4 Ethical issues and biases regarding Credit Rating Agencies

This chapter will address the different ethical issues that may appear within the credit ratings industry. There are several types of biases that could affect the accuracy of the ratings provided by CRAs. The first issue analyzed in this chapter is the conflict of interest created by the issuer-fee pricing model used by CRAs. The second problem introduced here is the home preference bias, which appears when CRAs assign better ratings to firms in the same country than to foreign firms. The third behavior described in this chapter is rating shopping. In this case, the unethical behavior is on the issuer's side.

The three aforementioned behaviors result in a situation in which inflated ratings are assigned. Inflated ratings are ratings that over-estimate the creditworthiness of an issuer and do not reflect the real financial situation of the firm. They result in the intentional misleading of the investors using credit ratings.

As explained by Luetge & Jauernig (2014) the financial markets have increasingly fed the debate of business ethics. According to them, the lack of control, management and transparency of the financial markets has lead to a high demand for ethics in the area. Indeed, regulators failed to monitor the financial market in a proper way, further urging the implementation of a systematic ethical behavior when doing business. However, Luetge & Jauernig (2014) wonder if ethics provide a concrete solution. They wonder what "we should not be greedy" really implies. The two authors affirm that if it means that one should not seek profit, it makes no sense to apply it to the financial markets, since its aim is to increase profit. However, if it means that the search for profit should not alter other important features such as morality and fairness, ethics could be useful.

In 2004, the International Organization of Securities Commissions (IOSCO) introduced a code of conduct for the CRAs in which it describes the fundamental principles that they should follow. The three main points described are the "quality of the ratings", "the independency and monitoring the conflict of interest", and "the responsibilities regarding the investors" (IOSCO, 2004). Even though the code of conduct is not constraining, it is seen as the end of the CRAs' auto-regulation (Collard, 2011).

Mattarocci (2014) adds that the CRAs developed a code of ethics that lays down the minimum rules of conduct for employees. Its aim is to reduce the conflict of interest as well as the risk of corruption present on the market.

1.4.1 Conflict of interest

The failure of the main CRAs to predict the important bankruptcies of Enron and WorldCom (Gütller & Wahrenburg, 2007), and their inability to forecast the 2007 subprime crisis lead to the growing concern of regulators and investors regarding the CRAs' business model, in which issuers pay a fee to get a rating. In addition Bolton et al. (2012) argue that the numerous downgrades of securities after the crisis made investors suspicious that the CRAs used relaxed standards in their model during the previous years.

However, Sinclair (2010) claims that the existence of the conflict of interest was not a one of the major causes of the subprime crisis. He argues that if a conflict of interest is well managed, it should not lead to any problem. The absence of empirical studies proving that a conflict of interest is a material problem in the industry, combined with the results of several studies (Smith & Walter, 2002; Crockett et al., 2003; Coffee, 2006; Véron, 2009 as cited in Sinclair, 2010) are proof that conflicts of interest have been monitored in the right way according to Sinclair (2010). In addition, Luetge & Jauernig (2014) defend the CRAs and argue that people *"tend to moralize (...) when the feared consequences are catastrophic and the perspective of the decision-maker is intransparent." (Luetge & Jauernig, 2014, p. 21).* For instance, investors often criticize the CRAs for their greed and their conflict of interest. This behavior totally neglects all the other factors involved, which may turn out to be the most relevant ones.

Numerous studies addressed the conflict of interest, and most of them, such as Kliger & Sarig (2000), Sinclair (2010) and Stopler (2009) agree that conflicts of interest do not influence the outcome of credit ratings. In opposition, Jiang et al. (2012) found that the implementation of the issuer-fee model immediately led to an increase of ratings. This result can be used to argue that the conflict of interest truly influences the ratings and that the issue should be tackled in the future. This study has been conducted on ratings issued between 1974 and 1978, just after S&P changed its pricing model and started charging issuers. The outcome of this study showed that the issuer-fee model increases the ratings. A limitation of this study is that, although the results were true in 1974, it is simplistic to consider that it is still the case today, since many things may have changed over the past 40 years.

Kliger & Sarig (2000), as stated previously, affirm that the importance of a CRAs' reputation prevents them from inflating ratings. If a high number of ratings provided by a particular CRA happen to be wrong, the loss of reputation the agency will face will be dramatic and could lead to its bankruptcy. This importance of the reputation prevents rating agencies from assigning inflated ratings.

Mathis et al. (2009) argue that the reputation argument only works when most of the CRAs' revenues come from rating non-complex products. This was not the case during the 2008 crisis, when the increase of mortgage-backed securities, and the use of securitization, brought the complexity of the financial market to a new level. The authors also found that CRAs can have two different goals driving their activity. They can be committed to telling the truth or following an opportunistic model, in which the only goal is to maximize profit.

The first proposition may seem more ethical than the second one. However, literature on the topic of business ethics shows that both can be considered ethical, depending on the theory used. The first goal can be linked to the utilitarianism theory, in which an action is morally right if it results in the greatest amount of good for every person (Crane & Matten, 2010). The second goal is related to Adam Smith's theory of egoism. This theory supports that an action is morally good if the decision-maker acts to achieve their own short-term or long-term goals (Crane & Matten, 2010).

Let's go back to the analysis of the CRAs' behavior developed by Mathis et al. (2009). When a CRA decides to be opportunistic, two scenarios with different outcomes may arise. If most of the CRA's revenue comes from issuing simple ratings, the CRA will always tell the truth. In this case, all the CRAs will easily find the adequate rating, and an opportunistic CRA which inflates ratings will rapidly be discovered. However, if most of the revenue comes from the rating of complex products, the CRA will always be too lax when its reputation is good enough. In this case, confidence cycles appear, in which the investor's confidence in CRAs varies over time (Mathis et al. 2009). It can therefore take a significantly long time to discover an opportunistic CRA and the reputational argument is not strong enough to prevent conflicts of interest from having an impact on the assigned ratings.

Kedia et al. (2017) identified another conflict of interest on the credit rating market. This new conflict is linked to the shareholding structure of the CRAs. The authors test if the CRA's large shareholders have an influence on their ratings. Their results show that Moody's, which is partly held by two financial companies, Berkshire Hathaway (16,4%) and Davis Selected Advisors (6,9%), assigns better (inflated) ratings to those two companies. The study also analyzed S&P. This case is quite different since S&P is a privately held by McGraw-Hill. Kedia et al. (2017) found that S&P inflated the ratings assigned to McGraw-Hill's shareholders, but to a lesser extent than Moody's. Therefore, they argue that the conflict of interest regarding the shareholding structure is bigger in the case of a direct ownership than in the case of an indirect ownership. The authors claim that these results are concerning, but that Moody's main shareholder, Berkshire Hathaway, is a well-established and trusted company that has a good monitoring system and that inflating their ratings is not a big issue. However, they add that new opportunistic shareholders may acquire Moody's shares with the sole purpose of getting an inflated rating.

1.4.2 Home bias

Nowadays, with the opening of capital markets, it is easier for companies to raise capital abroad. Nevertheless, when we analyze individuals' portfolios, we can see that investors prefer investing in local firms than investing in foreign firms (Bell et al. 2012). This attitude of overweighting the portfolio's concentration in local firms is called the home bias (French & Poterba, 1991, as cited in Bell et al. 2012).

This home bias has also been found on the CRAs market. Shin & Moore (2003) found that the U.S. rating agencies (Moody's and S&P) systematically assigned lower ratings to Japanese firms than the Japanese rating agencies. At that time, there were complaints that U.S. agencies did not take into account the special nature of the Japanese governance. Shin & Moore (2003) argue that this is not the case, and that the differences between the US based ratings and the Japanese based ratings are due to a home preference bias from the Japanese rating agencies. The authors highlight that the biggest Japanese CRAs, JCR and R&I, are respectively held by financial institutions and by an economic newspaper. This ownership is similar to the shareholding conflict of interest described previously, but in this case, the shareholder's influence is even more likely since the whole CRA is held by financial institutions.

In contrast, Güttler & Wahrenburg (2007) argue that U.S. issuers do not benefit from a home bias from Moody's and S&P. On the contrary, they found that they often had lower ratings than those of non-U.S. issuers This is probably because the U.S. based CRAs have a deep understanding of the U.S. market, and are better to forecast its evolution (Güttler & Wahrenburg, 2007).

Ammer & Packer (2000) also tested whether U.S. agencies assign worse grades to foreign firms than to domestic firms. Their study followed the assessment made in 1999 by the Japan Center for International Finance (JCIF), stating that U.S. agencies were too harsh when rating Japanese firms (Ammer & Packer, 2000). The JCIF supports its opinion by arguing that the default rate of Japanese firms is lower than the one predicted by Moody's ratings. Nevertheless, this is also the case for the firms located in the U.S., which shows there is no substantial difference between ratings assigned to issuers from various countries (Ammer & Packer, 2000).

1.4.3 Rating shopping

Another major issue leading to rating inflation is known as rating shopping. This process exists solely because issuers pay for their assigned rating only if they want to make the rating public (Bolton et al., 2012). This means that if an issuer appointed a CRA, and that it does not deliver a good rating, the issuer can decide not to pay for the rating, and try to get a better one with another rating agency.

Rating shopping eases the access to capital for investments that would not be attractive according to the traditional net present value standards (Sangiorgi & Spatt, 2016). Consequently, this leads to the increase of the probability of default of investment grades and reduces the reliability of the credit ratings (Sangiorgi & Spatt, 2016).

Skreta & Veldkamp (2009) found two factors that ease the credit shopping process. The factors are the assets' complexity and the number of CRAs on the market. The authors claim that with simple assets, different CRAs will almost always assign the same ratings, reducing the opportunities to obtain a higher rating with another agency. On the contrary, when complex assets are evaluated, because the various CRAs use different methodologies, the rating assigned to the complex issue may diverge. It is precisely in this case that an issuer may demand several ratings, only to disclose the best of them to the market. The number of agencies offering rating services also influences rating shopping. The higher the number of CRAs, the higher the chances to find split ratings[2]. Consequently, it is easier to engage in credit shopping when many credit rating firms are available. This is one of the reasons why the oligopolistic structure of the credit ratings market is tolerated nowadays. Introducing more

[2] Split ratings occur when two CRAs assign different ratings to the same issuer or issue. Many studies have analyzed them.

competition would reduce the efficiency of the credit rating market (Skreta & Veldkamp, 2009; Bolton et al., 2012).

1.4.4 Proposed solution

In order to fight the conflict of interest on the CRA market and increase the trust of the rating users, Mathis et al. (2009) introduced a new model, called the platform-pays model. They claim that the CRA market needs an exchange, a clearing house or a central depository that would operate as a central platform. This platform would be the intermediary between the issuer and the credit rating agency, to eliminate any direct contact between the two of them. An issuer who needs to be rated by a NRSRO would contact the platform. The platform would then choose one of the rating agencies to be in charge of the computation of the rating.

The payment system would be as follows. The issuer would have to pay a pre-issue fee to the central platform, before receiving the ratings. The platform would further pay the CRA that produced the rating, independently of the outcome of the rating.

Mathis et al. (2009) argue that this system removes several problems that were present on the market. Firstly, the conflict of interest between the issuer and the credit agency will be removed there will no longer be any direct commercial link between the two parties. Secondly, the fact that the fees are independent from the rating outcome leaves no incentive for the CRA in charge to allocate inflated ratings. Thirdly, the authors imagined that the CRA working for the platform would have to get a license, which would be withdrawn in the event of an overly elevated default rate. This prevents the CRAs from becoming too lax when assigning ratings.

The platform-pays model would have to be created and governed by the users on the buy-side and the sell-side (investors and issuers). Indeed, the authors state that if this model happened to be implemented by credit ratings agencies themselves, it would have a high risk of collusion.

Although complicated to implement, this idea looks very interesting and promising. Nevertheless, it has been neither implemented nor discussed publicly since its publication, back in 2009.

1.5 Regulation

Because these conflicts of interest and biases may affect the market if the main players decide to behave in unethical ways, regulations are needed. Regulations can be defined as "*rules that are issued by actors and other delegated authorities to constrain, enable or encourage particular business behaviors. Regulation includes rule definitions, laws, mechanisms, processes, sanctions and incentives*." (Crane & Matten, 2010, p. 494). Hemraj (2015) adds that regulations are needed to incentivize ethical behaviors. The regulations should ensure transparency, the elimination of conflicts of interests and the reliability of the ratings CRAs provide.

1.5.1 The 2008 financial crisis

As discussed several times throughout this document, the credit rating agencies have been deeply linked to the 2008 crisis. In order to understand the role they played, we first have to understand why and how the crisis happened.

Everything started in the U.S., in the summer of 2007, with the subprime crisis, and was worsened by high profile bankruptcies such as Lehman Brothers, AIG, Washington Mutual, and CitiGroup (Chihi-Bouaziz, 2014). The high use of securitization and mortgage-backed securities increased the complexity and the opacity of the financial market, which resulted in a financial crisis.

Securitization is the process of incurring corporate debt through securities and not through loans (Nayak, 2013). The process is based on the pooling of loans, debts, mortgages, receivables and their repackaging into asset-backed marketable securities (Nayak, 2013). The author explains it means that the credit risk lies on the investors' side and not on the banks' side anymore. It allowed institutions to get cash, meet their capital adequacy targets, eliminate the maturity mismatches and diversify their risk. At the beginning, it looked very attractive for both the investors and the financial institutions. However, the banks rapidly took advantage of the situation and started behaving in an opportunistic way. They took excessive risks believing that they were "too big to fail" (Rossi & Malavasi, 2016). As a result, the quality of the derivatives diminished and the default rate increased from 6% in 2005 to 17% in 2009 (Palmer, 2015).

The use of these innovative financial products, combined with the Federal Reserve's low interest rates policy, led to an over-indebtedness of households. The big failures of companies such as Lehman Brothers and AIG led to a loss of trust in the financial markets. The banks which incurred losses refused to lend money to each other, resulting in an substantial liquidity crisis. The increase of the default risk triggered the tightening of credit conditions. All of these reactions lowered the global demand and helped to spread the financial crisis to the entire global economy (Chihi-Bouaziz et al., 2014).

That being said, one can ask oneself: What exactly was the role of the CRAs in the financial crisis? The answer is that they assigned inflated ratings and didn't manage to correctly identify the different risks that were linked to the complex financial products (Nayak, 2013). Some argue that the inflated ratings came from the conflict of interest and the opportunistic behavior of CRAs. However, Skreta & Veldkamp (2009) argue that the ratings were right, but that the use of securitization dramatically increased the complexity of the products evaluated and introduced the possibility for issuers to engage in rating shopping and obtain higher ratings.

In addition, Credit Rating Agencies have been criticized for not evaluating the systematic risk adequately. This opinion was already expressed by Kuhner in an article published in 2001. In this article, Kuhner (2001) describes his incredibly farsighted suspicion that CRAs would not communicate information adequately when the economy is threatened by a significant systematic risk. He defines systematic risk as

> "*the danger that a certain 'shock' event will trigger a series of successive losses along a chain of institutions or markets comprising a system. The shock event may be a sudden monetary contraction that causes a substantial shift of the yield curve, or a cumulative correction of expectations in response to disastrous incidents, like the breakdown of an important market player or the bursting of a speculative bubble."* (Kuhner, 2001, p. 5)

To support this underestimation of the systematic risk, Rossi & Malavasi (2016) argue that big institutions, believed to be "too big to fail", are assigned better ratings (or inflated ratings). Consequently, these firms are allowed to access investments more easily, increasing their leverage and the risk they are able to take. Since taking higher risks potentially offers higher returns, and knowing that the shareholders' main goal is to maximize profits, big companies started to take excessive risks.

Nayak (2013) further argues that the systemic fall of the whole economy was due to the inadequate model used by safeguards. Indeed, the author highlights that the model on which safeguards were built assumed that the level of probability of failure of a particular instrument was known. The problem was that the change in these probabilities following the crisis prevented the safeguards from working properly. For instance, a bank using inflated ratings to compute its capital adequacy ratio did not take into account the real risk it was exposed to, and ended up having insufficient capitalization in comparison to its risk

During the crisis, several banks and big firms defaulted, which had huge consequences. Therefore, adequate regulations had to be put into place to make sure such a crisis would never happen again.

1.5.2 The Basel accords

The first Basel accord was introduced in 1999 by the Basel Committee on Banking Regulation (called the Basel Committee for short), in order to monitor the banking system. New versions of the document were published in 2004, and in 2010.

The Basel II requirements introduced a three-pillar supervisory framework that is still used in the Basel III Framework, as shown in Appendix VI. The first pillar is the "minimal capital requirement". The aim of this pillar is to verify the capital adequacy of the bank regarding its credit, market and operational risk. Several capital ratios were introduced, and banks are now required to attain a certain threshold in order to comply with the law. In Appendix VII, you will find the current and future requirements regarding banks' capital and liquidity ratios. The second pillar is the "Supervisory review process". This pillar lays down new key principles of supervisory review, risk management guidance and supervisory transparency and accountability. The Basel Committee wanted an increased transparency in order to verify the capital adequacy of the banks in an easy way, and to incentivize banks to adopt an adequate risk management framework. The third and last pillar is the "Market Discipline". In accordance with the second pillar, the third pillar empowers the regulators and increases the banks' disclosure requirements. This improved disclosure encourages market discipline by allowing other market players to access and analyze key information about the bank. (The Basel Committee on Banking Regulation, 2006).

When the Basel II requirements were created, back in 2004, the Committee decided to give the banks the choice between 2 methodologies for computing their capital requirements. Since then, each bank has been given the choice between a Standardized Approach and an Internal Ratings-based Approach.

The Standardized Approach was developed by the Committee in the Basel I requirements (in 1998) to provide the banks with a standardized way of computing their capital requirements. The method uses a risk weighting process, which allocates a different weight to each asset held by the bank according to the issuer's creditworthiness. Simultaneously, several risk-based capital ratios were developed. Every bank is required to comply with those ratios. The whole method is based on external credit assessments, meaning that the weights are based on ratings emitted by NRSRO recognized credit rating agencies. A table displaying the weights assigned to the assets according to their credit risk, which are used to compute the capital requirements of the banks can be found in Appendix IV.

1.5.3 The internal rating-based approach

In order to reduce the over-reliability on external credit rating agencies, the Basel Committee decided to allow banks to develop and use their own internal rating-based approach. The banks can assess their clients' credit risk using their own method. However, the rating system must be presented to and approved by the bank’s supervisor.

It is still unclear what a good internal rating model should take into account since no specific regulations and no computation method has been given by the Basel Committee or regulators.

Nevertheless, the Basel Committee explained in their Basel II requirements (2006) that the internal estimates of risk must at least take into account the probability of default (POD), the loss given default (LGD), the exposure at default (EAD) and the effective maturity (M). The EAD is the total value a bank is exposed to at the time a borrower defaults. If there is a possibility to recover the amount owed by the defaulted borrower partly or entirely, the LGD will be lower than the EAD. The maturity is the end date of a financial instrument or financial transaction. At this date, the asset must be renewed or will cease to exist.

In addition, several papers tried to lay down the key features an internal model should include. Krahnen & Weber (2001) gave the following desirable features of a good rating system. A rating system should be comprehensive, complete, complex, monotonic, fine, reliable and provide its own definition for the probability of default. The model must be back-tested, informationally efficient and continuously developed. The data used must be easily available, whether it is current or past data. An appropriate reward system must be implemented, avoiding the creation of any conflict of interest. The internal rating model must be internally and externally compliant. This means that the model must be controlled by the bank's management itself, and also by a neutral outside controller (Krahnen & Weber, 2001).

1.5.4 CRA 3

Not only have the banks been more regulated since the 2008 crisis, but CRAs have also received more attention from regulators. In 2013, the European Parliament and the Council of the European Union emitted the Regulation (EU) n°462/2013, amending the Regulation (EC) n°1060/2009 on credit rating agencies.

Harry Edwards (2013) highlighted three ideas that came out of this new law. The decrease of the reliance on CRAs, the civil liability of CRAs and the mandatory rotation of credit ratings.

In order to reduce the reliance on CRAs the regulators incite the financial institutions to develop their own credit assessment models. This is in line with the Basel Committee which introduced the internal rating models.

The second important point is the civil liability of the CRAs. As explained earlier, rating agencies have been criticized a lot for not taking any responsibility for their mistakes when emitting ratings, since they are only expressed as opinions. The new article 35a is a first step towards giving CRAs some liabilities. An issuer can now pursue a rating agency if he incurs a damage that results from an intentional error or a gross negligence from the CRA. However, the issuer must prove the mistake and link it to it to one of the infringements listed in the regulation, which may be very complicated.

The last point is the mandatory rotation of credit agencies. The aim of this new rule is to reduce the oligopolistic structure of the rating market, in which Moody's, S&P and Fitch dominate the market (Edwards, 2013). This rule enhances agency rotation, by requiring the companies to change the CRA that rates its assets regularly. However, it is only required for “resecuritisations”. This process is a “*securitisation where the risk associated with an* *underlying pool of exposures is tranched and at least one of the underlying exposures is a securitisation position*." (Edwards, 2013, p. 188).

This new Regulation is not strict enough to ensure the strict supervision of the credit rating industry. Nevertheless, it is a first step towards reducing the power of the CRAs and fighting the oligopolistic structure of this particular market. The new law may also open the door to new regulations which could go one step further in increasing the supervision of CRAs.

It may now be interesting to ask a new question. Does an increased supervision help to improve the efficiency of the credit rating market?

1.5.5 The effect of increased regulation

The high number of new regulations that followed the financial crisis could have been expected. The increased criticism regarding the CRAs and banks combined with the demand from the market for higher regulatory standards brought about the implementation of new regulations for the financial market. One could wonder if these new rules really have a significant impact on the financial market and the quality of financial information.

Cheng & Neamtiu (2009) argue that more regulations triggered a greater timeliness and a higher quality of the ratings produced by the CRAs. They found that following a tightening of the regulations, several desirable features of ratings were improved. They found that the different credit rating agencies enhanced both the timeliness and the accuracy of their ratings without increasing the volatility, meaning that the ratings' quality improved.

However, the main CRAs are highly opposed to more regulation of their market. They claim that it reduces their independence, which is a crucial feature of their credibility and reputation (Cheng & Neamtiu, 2009).

2 Empirical analysis

As explained previously, the aim of this paper is to explain which accounting and financial variables influence the ratings assigned to European banks. Once identified, the paper will try to find to what extent the identified variables influence the ratings outcome. The ratings analyzed are the ones assigned by the two main CRAs, Standard & Poor's (S&P) and Moody's. These two rating agencies have been chosen because of their vast experience and their significant market shares in Europe. Indeed, as a reminder, S&P owns 45% of European market shares, while Moody's controls 31,29% of the market (ESMA, 2016).

This section of the paper is further divided into three subsections. The first subsection will explain how the ratings and financial variables were selected and extracted. The second part presents the methodology of the empirical research. This section will describe the different existing methodologies available to perform the empirical analysis. It will also explain the methodology that was chosen to be used in this paper. Finally, the third part will present and interpret the main results obtained with the computation. It will be followed by a conclusion and several recommendations for future studies.

2.1 Data selection and extraction

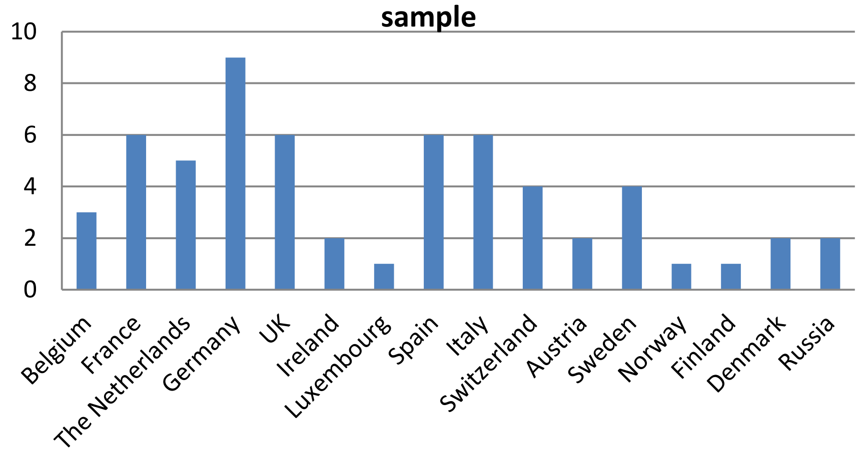
In order to answer the main question of this thesis, we first have to obtain data that can be analyzed in a significant manner. The sample of banks used and the accounting and financial variables studied must be chosen with care. In this subsection, we will explain the choices made regarding data collection and management

2.1.1 Banks sample selection and collection

As explained earlier, this thesis focuses on the effect of financial and accounting variables on the credit ratings of major European banks. Consequently, the banks selected are all located on the European continent, but are not necessarily included in the E.U. The second criterion of selection was the banks' size in terms of total balance sheet. Because of their big balance sheets, these banks are believed to have the biggest influence on the European market. A list of the 61 biggest European banks can be found in Appendix VIII.

The initial sample contained 61 banks coming from several countries in Europe. The distribution among the countries was as follows:

Figure 5 : Number of banks per country in the sample



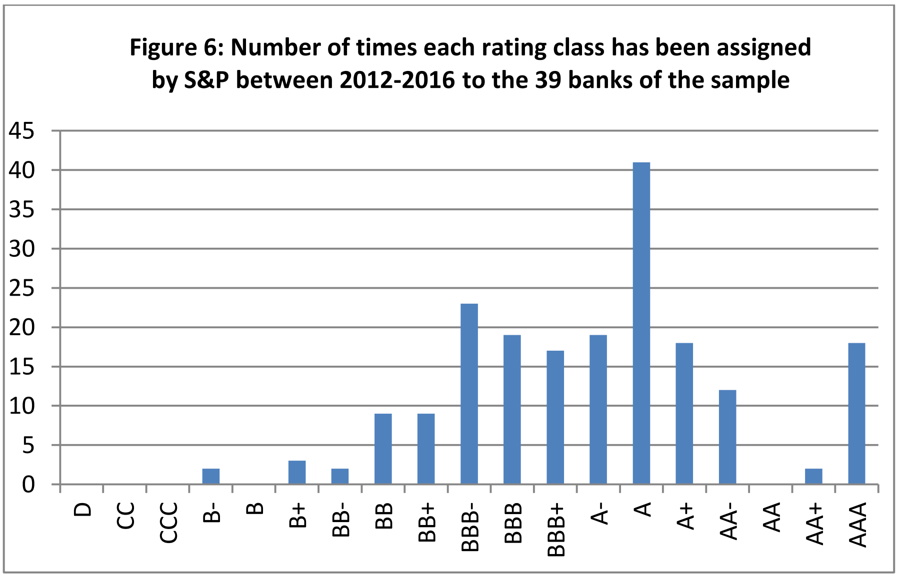
The next step was to obtain the ratings of these banks. As mentioned before, the credit ratings used are the ratings emitted by Moody's and S&P for reliability and access reasons. This paper works with Moody's senior unsecured debt ratings and with S&P's long-term local issuer credit ratings. The reason why this thesis uses only long-term issuer ratings is to avoid any external influence on the data. This way, short-term changes and issue related features are less likely to create a change in the banks' credit ratings. The ratings were extracted from the

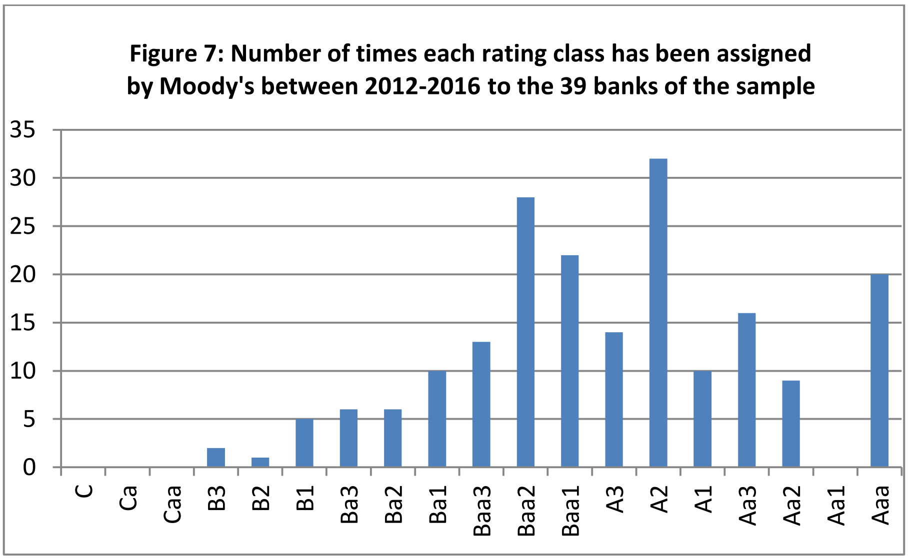
Bloomberg platform, which provides access to the credit rating changes over time for banks and big corporations. The ratings used in this paper are the ratings assigned to the banks at the end of each year. If several rating changes occurred during one year, only the latest change is taken into account. Several of the banks' ratings are preceded by a (P), which means that the rating is provisional. Nevertheless, these ratings have been integrated to the sample as they are expected to be correct. When an temporary rating is withdrawn, it is noted WR in Bloomberg. In this case, the rating change has been ignored and the rating of the previous year has been used.

Only the banks rated both by Moody's and S&P have been retained. Indeed, it is more insightful to compare the results from several CRAs than presenting the outcome of one of them. A quantitative analysis only makes sense when it can be compared or scaled. This reduced the sample to 39 banks. The remaining 39 banks are displayed in Appendix IX.

The credit ratings of the 39 banks have been extracted for the 2012-2016 period. This gave a total of 195 rating observations for both Moody's and S&P, although the actual number of observations was 194 since the Sberbank of Russia was not rated before 2013.

We can now take a first look at the ratings that will be used in the computations that will follow. It may be useful to mention several characteristics of the sample. Firstly, the number of observations for each rating class is as follows:





We can clearly see that the ratings assigned by Moody's and S&P are quite similar. However, differences appear due to the presence of split ratings. Split ratings occur 50% of the time according to Livingston et al. (2010). The authors further affirm that in 65% of the split ratings, Moody's assign a lower rating to the issuer. In order to allow for comparisons, the alpha-numeric ratings were transformed into numerical ratings (assigning the number 20 to the AAA/Aaa rating class and the number 1 to the C rating class), as it will be detailed further in this paper. This way, the mean rating assigned by both CRAs to the banks of the sample can be computed. The mean for S&P and Moody's are respectively 13,87 and 13,86. This shows that ratings assigned by Moody's and S&P to the banks of the sample are very similar. A mean of 13,87 corresponds to an average rating situated between BBB+/Baa1 and A-/A3. It is closer to A-/A3, meaning that the average ratings are considered as investment grades with low credit risk. It is however important to mention that this only represents the mean of the sample and that several ratings are below this average, in the non-investment grade category.

2.1.2 Accounting characteristics selection and collection

Before starting a new study, it is always important to analyze the findings of the existing literature regarding the assessed topic. This subsection aims at consolidating the outcomes of previous research about the influence of accounting and financial variables on the ratings assigned by Moody's and S&P. This will help us with the identification of ratios and variables that are worth analyzing in this paper. As explained previously, the methodologies used by CRAs to compute their credit ratings are not disclosed in their entirety. This is the reason why it is interesting to do some empirical research and get a clearer view of the subject.

A good starting point is to analyze the information that has been published by the CRAs themselves. For instance, S&P disclosed several factors that are taken into account when computing a credit rating for industrial bonds. S&P explained that the industry's characteristics, the company's competitive position (e.g. the company's marketing strategies, technology, etc) and the management are analyzed in order to determine the business risk (Caouette et al. 1998). The financial risk is determined through the evaluation of the company's financial characteristics, financial policy, profitability, capital structure, cash flow protection and financial flexibility (Caouette et al. 1998).

Moody's Investors Service went even further in the details of their report published in 2016. In this report, Moody's explains which factors influence the ratings emitted in the banking sector. Moody's states that macro-economic variables are analyzed. These variables are the economic features of the country in which the bank is operating, as well as its business sector (Moody's Investors Service, 2016). In addition CRAs make a qualitative judgment of the health of the assessed bank. This is based on non-public information that is only disclosed to the CRA. Meetings with the banks' management also allow the CRA to have a broader view of the company's future. These two elements (the country economic variables and the qualitative non-disclosed data) are not analyzed in this paper due to a lack of access. The third element is the financial profile of the bank. The different aspects analyzed are the asset risk, the capital structure, the profitability, the funding structure and the liquidity of the bank (Moody's Investors Service, 2016). This study will consequently focus on these different features.

In 1986, Ederington analyzed the occurrence of split ratings, using industrial bonds that were issued between 1975 and 1980. The author proposed the hypothesis that a split rating can occur due to three different reasons. The first possibility is that split ratings are the consequence of diverging views among the CRAs regarding the meaning of each rating class. The second hypothesis is that split ratings are due to systematic differences in the procedures used by the CRAs to compute credit ratings. The last possibility is that split ratings are caused by non-systematic differences that emerge due to the complexity of the rating process which may be influenced by minor subjective aspects (Ederington, 1986). Ederington's results showed that both S&P and Moody's assign the same probabilities of default to their respective rating categories (for instance a bond rated AA+ by S&P has the same probability of default as a bond rated Aa1 by Moody's). In addition, the 2 CRAs assign the same weights to the main financial accounting variables (Ederington, 1986). This means that the split ratings are caused by random differences that result from the complexity of computing creditworthiness. In order to conduct his analysis, the author used the following variables: the subordination status, the issuer's total assets, the leverage, the coverage forecast, the profitability and the cash flow forecasts (Ederington, 1986). It is easy to identify the overlapping variables, used both in Moody's report (2016) and in Ederington's article (1986). These are the leverage, the profitability and the liquidity (cash flow forecasts).

The total assets are also an interesting to analyze. It makes sense to analyze them as CRAs are often suspected of assigning inflated ratings to big firms, especially banks (Rossi & Malavasi, 2016).

Shen et al. (2011) decided to study the information asymmetry, which is high in the banking sector. The authors managed to find that information asymmetry systematically influences the relationship between a bank's financial ratios and its credit rating. In order to increase the reliability of their results, the authors used data from banks in 86 different countries during the timeframe of 2002-2008. The authors tried to explain why banks with similar accounting and financial ratios sometimes come up with different ratings. The results showed that high-income countries have a positive influence on the ratings of the banks operating on their territory. Indeed, those banks are believed to have a lower information asymmetry and, consequently, provide better quality financial ratios. Therefore, more weight is given to the financial ratios of banks in high-income countries compared to banks operating in middle-income and low-income countries (Shen et al, 2011). This is in line with the report published by Moody's (2016) which explained that the features of a given country play a role in the rating assignation to the companies located on its territory.

In order to obtain their results, Shen et al. (2011) evaluated 5 financial and accounting features. These features are namely the profitability, the liquidity, the capital adequacy, the efficiency (ratio cost/income) and the asset quality (loan loss provision). While the profitability and the liquidity have already been identified in the other studies, the capital adequacy and the asset quality are two new features that are interesting to take into account.

The effect of improved reporting standards on ratings has been studied partly by Cheng & Neamtiu (2009). The authors tried to prove that increased regulatory pressure and high investor criticism improve certain rating desirable properties such as the timeliness, accuracy and reduced volatility of ratings. Their research was based on two samples of ratings. The first one, called the PRE period, comprises ratings emitted between the 1st of January 1996 and the 25th of July 2002. The second sample, called the POST period, is composed of ratings assigned between the 25th of July 2002 and the 31st of December 2005. The terms PRE and POST are used by the authors to characterize the period before (PRE) and the period after (POST) the increase of regulatory pressure and criticism regarding the CRAs. The results of their empirical analysis showed that the timeliness and the accuracy of ratings were higher in the POST period, while the volatility of the ratings was lower. These findings support Cheng & Neamtiu's initial hypothesis. In order to prove that their empirical results were not due to the simultaneous increase in financial reporting and higher accountability standards, Cheng & Neamtiu (2009) analyzed the effect of 4 accounting variables (the log total assets, the leverage, the interest coverage and the profit margin) on the credit ratings in the PRE and the POST periods. The results are interesting, since they found that the influence of accountability variables diminished during the increased regulatory period.

Finally, Horrigan (1966), who studied the utility of accounting data in long-term credit administration, explained that accounting data has a limited utility when expressed in absolute value since it only conveys information about the size of the firm. In addition, many elements of the financial statements appear to be highly correlated when analyzed in absolute value (Horrigan, 1966). For these reasons, the accounting data used in this paper will mainly be financial ratios.

It is now time to present the different accounting variables that will be included in this empirical study. First, we will use the different aspects presented in the report published by Moody's Investors Service (2016). These features are the asset risk, the capital structure, the profitability, the funding structure and the liquidity of banks. In addition, we will account for the total assets of the banks, as it has often been used as a variable in the relevant literature as well. The following table presents the ratios and accounting variables that have been used in order to represent each of these features.

Table 1: Chosen financial and accounting variables

Accounting or financial features	Ratio/accounting variable chosen
Asset risk/Quality of the assets	Non-performing loans ratio
Capital adequacy	Tier 1 capital ratio
Profitability	Return on equity
Liquidity	Current ratio
Funding structure	Leverage ratio
Bank's ability to absorb potential losses	Coverage ratio
Total assets	Total assets in Euros
Variables analyzed	**7**

In order to account for the quality of a bank's assets, it is interesting to analyze its non-performing loan ratio. Indeed, non-performing loans have a big impact on banks since they lower a bank's profitability, increase its capital requirements and raise its funding costs (European parliament, 2016).

Regarding the capital adequacy of the banks, the ratio chosen is the tier 1 capital ratio. The Basel Committee on Banking Supervision defined the tier 1 capital as being the core equity. It is mainly composed of common shares and retained earnings, and the remainder are subordinate instruments that have *"fully discretionary noncumulative dividends or coupons and have neither a maturity date nor an incentive to redeem"* (The Basel Committee on Banking Supervision, 2011, p. 2). The tier 1 capital has a huge impact on profit margins and on a bank's ability to compete (The Basel Committee on Banking Supervision, 2006). The tier 1 capital ratio is obtained by dividing the tier 1 capital by the bank's total risk-weighted assets. It gives an idea of a bank's strength by giving a first insight into whether the bank holds enough capital regarding the risks it takes.

The third element we will be analyzing is the bank's profitability. Two ratios are often used in order to account for a firm's profitability. These are the return on equity (ROE), which is the company's return divided by its equity and the return on assets (ROA), which divides the company's return by the company's total assets. Since both the ROE and the ROA are profitability indicators, only one will be used in this paper. The ROE was chosen because the ROA would probably be highly correlated to the total assets, which are used as variable as well.

The best measure of liquidity would have been the liquidity coverage ratio, introduced by the Basel Committee. However, this ratio was not available on Capital IQ, which was the platform used to obtain the ratios and accounting variables. Therefore, the current ratio has been chosen as a substitute. The current ratio is obtained by dividing the short-term assets by the short-term liabilities. It gives the extent to which the current assets are able to cover the current liabilities. Current assets include accounts receivable, cash, and securities, while current liabilities include accounts payables, short-term notes, current portion of long term debt, and accrued expenses (Rist & Pizzica, 2015). The current ratio is not provided by capital IQ, therefore it has been computed as follows:

$$\frac{Current\ assets}{Current\ liabilities}$$

Current assets = Cash & equivalent + investment securities + trading securities + mortgage-backed securities + receivables + other receivables + restricted cash + other current assets

Current liabilities = Short term borrowings + current portion of the long term debt + current income taxes payables + other current liabilities + accrued expenses + account payables + other current liabilities

The use of the current ratio as an indicator for the liquidity has several limitations though. It does not take into account the short-term loans and deposits of the banks, as Capital IQ does not distinguish short-term and long-term loans and deposits. As these two factors can highly influence the liquidity of a bank, the outcome may not be as precise as it would have been with the liquidity coverage ratio.

In order to analyze the funding structure of a firm, one can compute the leverage ratio. The leverage ratio explains how a company finances its assets. The leverage ratio was not provided by Capital IQ either. It has been computed using this formula:

$$\frac{Total\ liabilities}{Total\ assets} = 1 - \frac{Total\ equity}{Total\ assets}$$

The coverage ratio is a good measure of a bank's ability to absorb potential losses. It is especially interesting to take this ratio into account when the number of non-performing loans is significantly high. The ratio is obtained by dividing the loan loss reserves by the impaired loans. It is interesting to mention that a bank which has a low coverage ratio does not always present a risk of under-provisioning. A low coverage ratio may appear due to rigorous lending practices (high collateralization of exposures) or due to a strong insolvency framework (where collateral repossession is easy for creditors) (The European parliament, 2016).

The last financial variable analyzed in this study is the banks' total assets. It has often been argued that big companies may get inflated ratings due to conflicts of interests. Horrigan (1966) also argued that a firm's size is positively related to the bond rating assigned. This hypothesis is worth testing. If there is a positive linear relationship between the total assets and the ratings, this hypothesis may turn out to be true.

After all the required variables have been identified, the ratios had to be extracted. As explained previously, the variables have been extracted from the software called "S&P Capital IQ". The purpose of this paper is to provide a more up-to-date view of the influence of accounting and financial ratios on the credit rating outcomes. Therefore, the period analyzed is the period between 2012-2016. For each year and for each bank, the ratios used were the 12-month ratios computed at the end of December or at the beginning of January of the following year. The total assets were extracted in millions. The currency used in Capital IQ is the local currency of the country in which the bank is operating. Therefore, the total assets of the banks had to be converted in Euros by using the exchange rate that was effective at the 31st of December of each year.

After the bank ratings were sampled, we ended up with 194 observations for both Moody's and S&P. However, the sample had to be further reduced because the "Bankia SA" had a negative equity in 2012, creating an abnormal situation that would bias our results. In addition, the "Banque du crédit mutuel" did not disclose any financial information in 2016. The final sample was consequently reduced to 192 observations.

Although full datasets (192 observations) could be obtained for several variables (the ROE, the leverage, the total assets and the current ratio), this was not the case for the remaining variables used. Only 185 observations were available for the non-performing loan ratio, 150 observations were available for the coverage ratio and 165 observations were available for the Capital Tier 1 ratio. This means that out of the 192 initial observations, only 132 were complete.

Now that the data has been obtained, we can gain some insight about the homogeneity of the sample by considering several descriptive statistics measures.

Table 2: descriptive statistics measures for the selected financial variables

	N	Moyenne	Ecart- Ecart
	Statistiques	Statistiques	Statistiques
ROE	192	,02785	,115314
Leverage	192	,93592	,066321
Non_perf_loan_ratio	185	,06331	,064055
Coverage_ratio	150	,67471	,350633
Capital_Tier1	165	,14942	,039427
Current_ratio	192	3,04335	2,950302
Total_assets	192	640909,46	554466,447
N valide (liste)	132		

The first measure N represents the number of observations for each variable. Because the mean (moyenne) may be influenced by extreme variables, it is insightful to compare it to the median of the sample. This way, we can spot whether the sample contains numerous outliers or not (Sarstedt & Mooi, 2014). We used the ratio $\frac{median-mean}{mean}$ in order to get an idea of how great the difference between the median and the mean is, relatively to the average value of each factor. We found that there is a low influence of outliers for the leverage, the coverage ratio, the capital Tier 1 (the ratio was < 15%), a medium influence of outliers was identified for the non-performing loans, the current ratio, and the total assets (the ratio < 40%) and outliers were found to have a strong influence on the ROE (86,71%).

In addition we computed the standard deviation (Ecart - Ecart). This gives us the extent to which the observations for each of the variables differ from the sample's mean. A high standard deviation implies a high dispersion and a low standard deviation implies a low dispersion. It is however complicated to evaluate whether a standard deviation should be considered high or low. Therefore, the coefficient of variation (or relative standard error) $\frac{standard\ deviation}{mean}$ is computed. This ratio measures the relative dispersion of the variables with respect to their respective mean. The main advantage of this ratio is that it is dimensionless, which means we can compare the variability of the different ratios even if they are expressed in different units or have highly different means (Aerts et al. 2015). For instance, if the ratio is

2, this implies that the dispersion of the variables is 2 times the mean, which may look significant. This ratio is quite low for the leverage, the coverage ratio and the capital tier, (<60%), it is above average for the non-performing loans ratio, the current ratio and the total assets (around 100%) and significantly high for the ROE (414%). We can see that the results obtained here are similar to those achieved when comparing the median to the mean.

We can conclude that the selected banks have very homogeneous leverage ratios, coverage ratios and capital tier 1 ratios. The sampled banks are mixed in terms of their non-performing loans ratio, current ratios and total assets, while they are very heterogeneous regarding their respective ROEs.

The last element interesting to analyze before making any computation is the multi-colinearity between the selected financial characteristics. As a matter of fact, the correlation between the chosen features may play an important role in the results obtained. If several variables are highly correlated, their individual influence on the ratings could be lesser than expected. Hereunder is the correlation matrix of the 7 variables chosen.

Table 3: Correlation matrix of the selected financial variables

	ROE	*Leverage*	*Non_perf_loans*	*Log_assets*	*Coverage_ratio*	*Tier_1_Cap*	*Current_ratio*
ROE	1						
Leverage	-0,10371	1					
Non_perf_	-0,55059	-0,093207335	1				
Log_asset	0,103079	0,108290192	-0,321526164	1			
Coverage_	0,233731	0,001870483	-0,144366555	0,027084816	1		
Tier_1_Ca	0,258259	0,049732934	-0,334582282	-0,228435107	-0,11341017	1	
Current_r	0,042145	-0,219833363	0,151265906	-0,302621094	0,075879926	-0,062308697	1

A pretty high negative correlation can be observed between the return on equity (ROE) and the non-performing loans ratio (-55%). Indeed, as the presence of non-performing loans reduces the profitability of a bank, this strong negative relationship seems coherent. Surprisingly, the ROE is positively correlated with the tier 1 capital. As the total equity is the denominator in the formula used to compute the ROE, this means that the returns increase more than the equity when the tier 1 capital is increased. The total assets are slightly negatively correlated with the non-performing loans ratio (-32%) and with the current ratio (-30%). This implies that small banks tend to have a higher amount of non-performing loans and a higher current ratio than big banks.

Now that the data has been extracted and that its characteristics have been examined, it is time to present the methodology that was used to make the computations of this paper.

2.2 Methodology

This subsection will describe in detail the methodology used to answer the research question of this paper. The first step is to study the existing methodologies and to get some insights about the research that has already be conducted previously in this area. The methodology chosen for this paper will then be detailed so that the results can be presented in a meaningful manner.

2.2.1 Existing literature

As a reminder, the aim of this study is to find out the role the financial and accounting variables play in the attribution of credit ratings. Both Moody's and S&P will be analyzed so that a comparison can be made between the weights allocated to the different variables by both CRAs. The results are therefore expected to give an insight about the homogeneity of the weights used throughout the CRA industry. Indeed, if the outcomes differ significantly, we may deduce that the different CRAs use diverging methods to account for financial variables. On the contrary, if the findings presented are alike for the two CRAs, we can pose the hypothesis that the methodologies used to evaluate the financial variables are, at least to some extent, similar.

Nowadays, a wide range of statistical methodologies have been developed. Indeed, Dey & Astin (1993) explained that the rapid advances in statistical theory and practice, together with the improvement of strong computing resources allowed the development of new techniques for the analysis of qualitative, categorical and quantitative data.

As explained by Shen et al. (2011), numerous methodologies have been used in the past to try to shed light on the external rating process. Shen et al. (2011) cited several authors who tried to explain the rating process by using various techniques such as linear regressions, linear discriminant analysis, logit and probit, ordered logit and ordered probit and artificial intelligence techniques.

Before choosing a methodology, it is important to understand the perks and flaws of the existing methods. Linear models, such as discriminant analysis or linear regressions, are useful for analyzing the effect of a certain number of independent variables on a given dependent variable. Discriminant analysis assumes that there is a linear relationship between the independent variables (also called explanatory variable) and the dependent variable (also called the explained variable). The output of linear regressions is quite straightforward to interpret as well. It explains to what degree the dependent variable would change following an increase or a decrease of the independent variables (Dey & Astin, 1993). One of the main limitations is that linear regressions cannot account for the individual contribution of each independent variable to the outcome. This means that the contribution of all the variables together can be determined, but the individual influence of each variable cannot.

A famous multivariate approach, called the Z-score model, was introduced by Altman. This approach combines and weights different ratios and categorical univariate measures in order to discriminate between firms that fail and firms that survive (Caouette et al., 1998). The discrimination is possible because failing firms have significantly different ratios than surviving firms (Caouette et al., 1998). We may therefore imagine that the surviving firms can be classified according to their ratio-levels to identify the firms that are close to bankruptcy and those that are healthy. This classification is precisely the role of credit ratings. We now have an additional reason to believe that financial ratios influence credit ratings. The methodology used by Altman tried to maximize the variance between the groups while minimizing the variance within the groups. Out of the 22 variables analyzed, 5 were selected based on statistical criteria (Caouette et al., 1998). The Z-score used the following function:

$$Z = 0.012\,X_1 + 0.014\,X_2 + 0.033\,X_3 + 0.006\,X_4 + 0.999\,X_5$$

Where Z is the survival nature of the company, X1 represents the working capital/total assets, X2 the retained earnings/total assets, X3 stands for the earnings before interest and taxes/total assets, X4 is the market value of equity/book value of total liabilities and X5 is the sales/total assets.

The logit and the probit models are very popular approaches in empirical default-prediction literature (Trueck & Rachev, 2009). These models are useful because they can be applied to situations in which the dependant variable is either ordinal or nominal and where the independent variables can be a mix of quantitative and qualitative data (Trueck & Rachev, 2009). Because only quantitative data will be used as independent variables in this study, these models will not be used as they are more complicated to interpret than simple linear regressions.

In his work, Wooldridge (2003) explains in detail how simple linear regressions, multiple linear regressions and panel econometric data work. He explains that in a simple linear model in which a dependent variable y is influenced by an independent variable x, the extent to which the independent variable x influences the dependent variable y can be found by computing the R-squared. The R-squared is a ratio that measures to what degree the explanatory variable explains the variations of the explained variable (Wooldridge, 2003). The higher the R-squared, the better the independent variable explains the variations in the dependent variable. Based on the R-squared, the adjusted R-squared can be computed. The adjusted R-squared adds a penalty for any additional explanatory variable added in the model. This means that if the added independent variable does not explain the dependent variable, the adjusted R-squared will be lower, leading to a less precise model.

Due to the nature of the collected data, simple and multiple linear regressions could not be used in this paper. Indeed, as the inputs were ratings and financial variables collected from the same banks at different points in time, panel data econometrics had to be used. Panel data, which is also called longitudinal data, brings together two different aspects: the cross-sectional aspect and the time series aspect (Wooldridge, 2003). A cross-sectional dataset contains numerous characteristics that have been collected from several individuals at a given point in time. The group of individuals analyzed can be persons, countries, governments, while the characteristics may be salaries, number of employees, wages, etc. In this study, the financial characteristics and the ratings of the main European banks will be studied. When the dataset contains observations collected at different points in time, it is referred to as a time series dataset. This type of dataset is widely used when trying to understand how features evolve throughout time. This aspect had to be considered in this paper, as the data analyzed in this study was collected over a span of 5 years.

The hypothesis that all the observations are independently distributed over time is not true for panel data. Indeed, Wooldridge (2003) explains that it is because there is an unobserved heterogeneity effect that is impossible to measure. The unobserved characteristics, noted a_i, are considered to be constant over time, but differ among the various individuals. When the unobserved effects are correlated with the exogenous factors, pooled OLS will be biased and inconsistent. In order to avoid biases and endogeneity problems, the unobserved effects must be accounted for. Two models were developed for this purpose: the fixed effects model and the random effects model (Wooldridge, 2003).

In the fixed effects model, called "fixed effects transformation" or "within transformation", the unobserved heterogeneity is considered to be correlated with at least one of the independent variables (Wooldridge, 2003). The aim of this method is to remove the unobserved term by subtracting all terms their own mean. This way, time-demeaned data is obtained. The random effects transformation, on the other hand, assumes there is no correlation between the unobserved heterogeneity and the explanatory variables. Therefore, the term will not undergo any modification, but generally least squares will be used to solve the serial auto-correlation problem.

Both models have their perks and flaws. The fixed effect transformation is sometimes considered to lead to inefficient estimators, while the random effect transformation has been criticized for posing a too strong hypothesis about the uncorrelated terms. Because the fixed effects model allows arbitrary correlation between the unobserved effects and the explanatory variables, it is often preferred to the random effects model for estimating ceteris paribus effects (Wooldridge, 2003). However, the random effect has an advantage on the fixed effect model. The advantage is that explanatory variables that remain constant over time will be eliminated by the fixed effects transformation while it is not the case with the random effects transformation. The choice of using the fixed or the random effects is often based on whether the unobservable effects are considered as parameters to be estimated or as outcomes of a random variable. If a_i is believed to be correlated to the explanatory variables, the fixed effects model should be used. Otherwise, the random effects model would be a better fit. It is common use to compute both the fixed and the random effects models, in order to determine whether the unobserved effects are correlated to an explanatory variable or not.

In his book, Wooldridge (2003) presents the following equation for the fixed effect:

$$y_{it} = \beta_1 x_{it1} + \beta_2 x_{it2} + \cdots + \beta_k x_{itk} + a_i + u_{it}\ , t = 1,2, \ldots , T$$

This equation displays the relationship between the dependent variable y and the independent variables x over the period of time T. β_1 is the parameter associated to the explanatory variable x_{it1}, β_2 is associated to x_{it2} and so on. When multiplied together, the β parameter and the associated x determine the real impact of a particular explanatory variable on the dependent variable. The two remaining terms are $a_i\ and\ u_{it}$, which compose the composite error (v_{it}). As explained previously, a_i represents the unobserved effect of the i_{th} individual. There is no t associated to the a_i because the unobserved effect is constant over time (Wooldridge, 2003).

When several independent variables are combined in order to predict the effect on a dependent variable, it may be difficult to assign the exact individual contribution to each of the independent variables. Indeed, because the explanatory variables influence the dependent variable in different ways, and that they may be correlated with each other, identifying the respective impact of each variable can turn out to be very difficult. One way to allocate the impact of each variable could be to divide the combined influence obtained through multiple linear regressions (e.g. the adjusted R-squared) by the number of explanatory variables. Nevertheless, this solution is too simplistic. Therefore, a formula called the "Shapley value" is used to identify the real contribution of each factor in a given model.

The Shapley value was introduced in 1953 to assign a unique distribution among the players of a surplus generated by a coalition of players. The Shapley value uses strong axioms that allow it to compute the contribution of a given player by adding up all the marginal contributions of the player in all the permutations possible for the coalition (Liao et al., 2015).

Before describing the axioms used by the Shapley value, we should introduce the notations that will be used. N represents the number of players while v stands for the coalition function, which assigns all the subsets K of N a certain value v(K). This value reflects the economic abilities of K. All the coalitions that could be joined by a player i are Φ (i). Φi (N, v) represents the payoff/contribution of the variable i in the coalition v (Hiller, 2016).

It is now time to present the four axioms on which the Shapley value is based, which have been explained by Hiller (2016). The first axiom is the additivity. The marginal contribution of a player in different coalitions should be summed to obtain the total payoff of the player.

$$\phi\mathrm{i}\ (\mathrm{N},\mathrm{v}) + \phi\mathrm{i}\ (\mathrm{N},\mathrm{w}) = \phi\mathrm{i}\ (\mathrm{N},\mathrm{v}+\mathrm{w})\ ,\mathrm{i} \in \mathrm{N}$$

The second axiom is the symmetry. If two players i and j have the same marginal contribution, both should obtain the same payoff:

$$\mathrm{If}\ \mathrm{v}(\mathrm{K} \cup \{\mathrm{i}\}) - \mathrm{v}(\mathrm{K}) = \mathrm{v}(\mathrm{K} \cup \{\mathrm{j}\}) - \mathrm{v}(\mathrm{K}), \mathrm{then}\ \phi\mathrm{i}\ (\mathrm{N},\mathrm{v}) = \phi\mathrm{j}\ (\mathrm{N},\mathrm{v})$$

The third axiom is the null player. A player that does not contribute to the coalition (null player) does not get any payoff.

$$If\ i \in \mathrm{N\ is\ a\ null\ player,\ then}\ \phi\mathrm{i}\ (\mathrm{N},\mathrm{v}) = 0$$

The last axiom is the efficiency. It assumes that the worth v(N) is distributed to the players and that all players cooperate.

$$For\ i \in \mathrm{N}, \phi\mathrm{i}\ (\mathrm{N}, \mathrm{v}) = \mathrm{v}(\mathrm{N})$$

The Shapley value is the only value that satisfies the four axioms. Given a coalitional game (N, v), the Shapley value distributed the payoff among the players as follows (Bilbao & Edelman, 2000):

$$\phi\mathrm{i}\ (\mathrm{N}, \mathrm{v}) = \sum_{\{S \in 2^{\mathrm{N}} : \mathrm{i} \in \mathrm{S}\}} \frac{(s-1)!\,(n-s)!}{n!} [v(S) - v(S \backslash i)]$$

Liao et al. (2015) identified 3 desirable properties of the Shapley value. It is easy to compute, has a real economic significance as it allocates benefits based on individual contributions to the coalition, and provides a unique solution. The Shapley value will therefore be used in this paper. The different players will be represented by the financial variables, while the benefits will be the combined influence of the ratios on the rating outcome.

2.2.2 Methodology used in this paper

Now that we have selected a sample of banks, chosen the variables that will be analyzed, extracted the data and taken a look at the existing methodologies used to process this type of data, it is time to explain the methodology developed in this thesis.

As the credit ratings are expressed in letters, it is quite difficult to conduct a quantitative analysis using them in this form. Therefore, the first step is to convert the alpha-numeric ratings into numeric values. To do so, two different approaches will be used throughout this paper, and their results will be compared later.

The first procedure used to convert the alpha-numeric ratings into numeric ratings is the assignation of a number to each rating grade as presented in table 4. This method has been widely used in studies on this topic. Indeed, in order to make their computations, Cantor & Packer (1995) assigned the value 16 to the AAA/Aaa ratings and 1 to the B3/B- rating (which was the lowest rating at the time). This method has also been used by Shen et al. (2011), by Livingston et al. (2007) and many others. The main advantage of this method is its intuitiveness and the ease with which its results can be interpreted.

Table 4: Assigned numeric values for each rating class

S&P's ratings	Moody's ratings	Numeric value for the ratings
AAA	Aaa	20
AA+	Aa1	19
AA	Aa2	18
AA-	Aa3	17
A+	A1	16
A	A2	15
A-	A3	14
BBB+	Baa1	13
BBB	Baa2	12
BBB-	Baa3	11
BB+	Ba1	10
BB	Ba2	9
BB-	Ba3	8
B+	B1	7
B	B2	6
B-	B3	5
CCC+	Caa1	4
CCC	Caa2	3
CCC-	Caa3	2
CC+ - D	Ca-C	1

This data processing method does, however, have limitations such as the fact that it assumes that the differences between two subsequent ratings are equivalent. This is not the case as the difference between the probabilities of default of an AAA/Aaa rated bank and a AA+/Aa1 rated bank is much smaller than the difference between the probabilities of default of a C+/C1 rated bank and a C/C2 rated bank.

Therefore, a different methodology will be used to transform the alpha-numeric ratings into numeric ratings. In this alternative method, the alpha-numeric ratings will be converted into probabilities of default. The probabilities of default assigned to each letter in this paper are the 10-year cumulative probabilities of default of global issuers, for the 1983-2015 period published by Moody's, as displayed in the 10th column of the table 5. Ederington (1986) found that Moody's and S&P assigned the same creditworthiness or risk of default to the various ratings. Therefore, the same probabilities of default will be used for both Moody's and S&P.

Table 5: Average cumulative issuer-weighted global default rates by alphanumeric rating. 1983-2015

Rating	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Aaa	0.000	0.013	0.013	0.039	0.068	0.102	0.139	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143	0.143
Aa1	0.000	0.000	0.000	0.057	0.103	0.153	0.157	0.157	0.157	0.157	0.157	0.157	0.238	0.336	0.446	0.486	0.486	0.486	0.486	0.486
Aa2	0.000	0.013	0.114	0.243	0.362	0.450	0.546	0.652	0.774	0.943	1.091	1.256	1.400	1.466	1.539	1.687	1.953	2.249	2.535	2.709
Aa3	0.047	0.126	0.181	0.257	0.392	0.517	0.657	0.767	0.837	0.899	1.020	1.204	1.367	1.477	1.564	1.637	1.695	1.869	2.219	2.577
A1	0.075	0.224	0.450	0.670	0.889	1.131	1.354	1.554	1.717	1.911	2.123	2.339	2.579	2.880	3.186	3.490	3.804	4.095	4.251	4.415
A2	0.051	0.156	0.329	0.553	0.814	1.172	1.538	1.932	2.338	2.753	3.155	3.512	3.866	4.290	4.776	5.326	5.989	6.640	7.145	7.620
A3	0.060	0.187	0.414	0.615	0.918	1.171	1.466	1.808	2.186	2.500	2.789	3.099	3.489	3.926	4.511	5.041	5.419	5.982	6.596	7.246
Baa1	0.143	0.379	0.655	0.954	1.225	1.497	1.760	1.952	2.150	2.430	2.802	3.310	3.863	4.345	4.963	5.730	6.482	7.056	7.339	7.539
Baa2	0.189	0.481	0.811	1.242	1.617	2.029	2.446	2.852	3.294	3.786	4.414	5.070	5.759	6.372	6.921	7.371	7.867	8.500	9.293	9.908
Baa3	0.276	0.684	1.131	1.651	2.282	2.913	3.456	4.103	4.769	5.432	6.031	6.592	7.282	8.061	8.712	9.686	10.858	11.981	13.142	13.888
Ba1	0.483	1.543	2.826	4.141	5.512	6.821	7.886	8.740	9.549	10.474	11.464	12.451	13.312	14.046	15.111	16.188	16.978	18.069	19.898	21.457
Ba2	0.764	1.947	3.405	4.915	6.263	7.346	8.346	9.508	10.792	12.107	13.294	14.527	15.305	16.183	17.455	18.272	19.165	19.904	20.917	21.069
Ba3	1.500	4.149	7.366	10.832	13.694	16.444	19.005	21.371	23.489	25.485	27.161	28.737	30.650	32.864	34.732	36.601	38.107	39.356	40.261	40.985
B1	2.217	5.940	9.947	13.708	17.504	20.923	24.422	27.518	30.162	32.188	33.783	35.218	36.954	38.946	40.328	41.396	42.627	44.088	45.579	47.157
B2	3.288	8.286	13.322	17.965	21.785	25.239	28.228	30.648	32.939	34.964	36.508	37.902	39.006	39.944	41.203	42.321	43.015	43.649	43.926	44.822
B3	5.435	11.688	17.922	23.220	28.153	32.612	36.385	39.428	41.688	43.175	44.385	45.430	46.133	46.845	46.986	47.335	48.556	48.935	48.935	48.935
Caa1	5.140	11.935	18.228	23.422	27.934	31.596	34.192	35.805	37.642	39.966	41.388	42.252	43.308	43.727	43.727	43.727	43.727			
Caa2	11.461	20.604	28.049	34.270	39.418	43.589	47.183	50.951	53.920	56.536	58.273	58.792	58.792	58.792	59.625	61.267	61.748	61.748	61.748	61.748
Caa3	20.501	32.464	40.874	46.503	51.223	53.446	55.946	58.933	59.582	59.582	59.582	59.582	59.582	59.582	59.582	59.582	59.582			
Ca-C	27.691	36.530	42.928	47.960	50.839	51.625	52.021	52.913	53.395	53.395	54.087	55.182	55.872	55.872	55.872	55.872	55.872	55.872	55.872	55.872
Inv Grade	0.100	0.265	0.477	0.718	0.982	1.255	1.523	1.791	2.063	2.346	2.647	2.963	3.304	3.647	4.009	4.396	4.800	5.225	5.622	5.963
Spec Grade	4.209	8.601	12.791	16.480	19.682	22.441	24.856	26.932	28.757	30.339	31.643	32.833	33.951	35.097	36.235	37.252	38.155	39.066	40.118	41.019
All rated	1.615	3.250	4.758	6.048	7.141	8.067	8.861	9.546	10.155	10.704	11.199	11.674	12.147	12.617	13.096	13.569	14.030	14.502	14.962	15.349

* Data in percent.

Source: Moody's Investors Service (2016)

Obviously, using the probabilities of default specific to the banking sector (especially the European banking sector) would be even more relevant to this study, but such information has not been publicly disclosed by Moody's and S&P yet. Nevertheless, the PODs assigned to each rating category of global companies are probably close to the PODs assigned to the ratings of the banking sector as it seems unlikely that Moody's and S&P assign substantially different PODs to the same rating class across various sectors.

For the purpose of this study, the extracted probabilities of default have been transformed into probabilities of survival (1-POD). This way, the highest values are attributed to the best ratings and the lowest values to the worst ratings. This makes the comparison of the results obtained using the two different methodologies easier.

Before starting the different computations, the dataset must be prepared properly. The data collected has been displayed in an excel file that comprises various columns. Each column contains the data linked to one of the seven variables selected previously. Because the relationship between the total assets and the ratings is not expected to be linear, the logarithm of the total assets has been used instead. This smoothens the differences between the big and small companies. Two columns were used to represent the numerical ratings assigned by S&P and Moody's. In addition, two other columns were used for the probabilities of survival linked to the ratings assigned by the two rating agencies.

Once the excel file was completed, the real computation of this paper could begin. The calculations were made using the E-views analytics software. The first step to getting an insight on a possible relationship between each variable chosen and the ratings emitted by S&P and Moody's is to perform ordinary least squares (OLS) regressions, using the ratings as independent variable and the financial ratios as independent variables. The OLS regressions were performed using the fixed and the random effects estimations to account for the unobserved effects. In addition, OLS regressions with fixed and random effects transformations were computed for the probabilities of survival as well. This way, the consistency of the results could be tested. If the results differed significantly, the adequacy of transposing the alpha-numeric letters into numbers could be put into question.

Although this paper focuses mainly on the influence of financial and accounting variables, it is interesting to integrate some non-financial variables in the model as well. As explained by Moody's Investors Service (2016), macro-economic features and banks' non-financial characteristics also play an important role in the rating attribution. Therefore, after the most relevant financial variables had been identified, additional computations could take place, including additional non-financial variables. The country ratings were used to represent the economic climate of the country in which the banks operate. Indeed, according to Altman (2005), the ratings of a bank is affected by the country in which it bank operates. A wealthy country, which provides high quality services and promotes growth impacts positively the rating of all its firms (Altman, 2005). S&P's country were extracted for this purpose. Furthermore, two bank-specific features, were also analyzed in the additional computations. The two characteristics were the affiliation to the EU of the countries in which the bank are located, and the systematically of those banks. As mentioned earlier in this paper, credit rating agencies have been criticized for not evaluating the systematic risk adequately. Kuhner (2001) argued that CRAs would not communicate information adequately when the economy is threatened by a significant systematic risk. Therefore, it is interesting to get some insights on whether the ratings assigned to systematic banks get any kind of adjustment or not. The fact that a bank is in the E.U. could also have an impact on the rating it is assigned, because the regulations and the economic environment may differ significantly. However, banks located in the E.U. and banks located in the U.K. are all subject to the same regulatory authority, the European Banking Authority (EBA). Therefore, this variable is not expected to have a big impact using this sample. The systematic banks of the sample have been identified with the list of European systematic banks published by the European Parliament (2017), displayed in Appendix X. Additional OLS regressions were computed, including the most relevant financial variables, the country ratings and dummy variables to represent the affiliation to the E.U. and the systematical nature of the banks. Dummy variables are binary variables that take the value 1 if a characteristic is observed and takes the value 0 if not. The random effects transformations had to be used in this case, as the fixed effects transformation do not tolerate explanatory variables that are constant over time (Wooldridge, 2003).

The Shapley value was then computed in order to dig deeper. The Shapley value was very useful to allocate the exact weight of each individual variable. This way, we could take the combined impact found with multiple linear regressions, and use it to find the individual impact that each financial variable really has on the ratings. The individual influences of each variable obtained with the Shapley value are more precise than the results obtained using linear regressions, as they now take into account the correlations between the independent variables. Because the inclusion of additional variables increases the computations required by the Shapley value exponentially, only the most relevant variables have been selected. The variable selection was based on the results obtained with the OLS regressions computed previously.

2.3 Main results

In this section, the results of the various computations of this paper will be presented and interpreted. All the computations have been performed using the E-views analytics software. As a reminder, the aim of this paper is to shed light on the relationship between the financial and accounting ratios of major European banks and the ratings assigned by Moody's and S&P. The first calculations made were OLS regressions on the simple numeric ratings assigned by Moody's and S&P, using the fixed effects and the random effects transformation features. The second part of this subchapter will display the OLS regressions on the probability of survival of each bank, also using the fixed effects and the random effects models. In the third part of this sub-section, OLS regressions with the most relevant financial variables and non-financial variables will be computed. Finally, the Shapley value will be computed, using the most relevant variables identified with the previous computations.

2.3.1 OLS regressions using simple numeric ratings

The first computation, as displayed in the table 6, was the ordinary least squares regression using the fixed effects estimations for the ratings provided by S&P.

Table 6: OLS with fixed effects transformations for S&P

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-10.40657	10.80493	-0.963132	0.3380
COVERAGE_RATIO	0.098407	0.487891	0.201698	0.8406
CURRENT_RATIO	-0.172781	0.063085	-2.738883	0.0074
LEVERAGE	0.741069	0.895670	0.827391	0.4102
LOG_ASSETS	4.351252	1.903408	2.286033	0.0246
NON_PERF_LOANS	-6.349780	3.994240	-1.589734	0.1154
ROE	2.832359	1.148077	2.467045	0.0155
TIER_1_CAP	-6.582031	2.832764	-2.323537	0.0224

As it is common use, results that do not have a 90% significance level (which have a p-value lower than 10%) are not considered reliable. When analyzing the table here above, we see that the coverage ratio, the leverage and the non-performing loans ratio are not significant at a 90% confidence level. Therefore, no conclusions can be taken from the analysis of their coefficients in this case.

At a 95% confidence level (when the p-value is lower than 5%), we find that four variables are significant. These are namely the current ratio, the log assets, the return on equity (ROE) and the tier 1 capital ratio. As the log assets have a positive coefficient, the total assets of a bank has a positive impact on the rating that it will obtain from S&P. This makes sense as the more assets a bank possesses, the more likely it is to fulfill its financial obligations. This is also in line with what Horrigan (1966) and Rossi & Malavasi (2016) argue. Horrigan (1996) states that a firm's size improves its bond rating, while Rossi & Malavasi (2016) add that big institutions may be considered to be "too big to fail" and may be assigned better ratings consequently. The return on equity also has a high positive coefficient. This means that a bank's profitability has a positive influence on the ratings assigned by S&P. Indeed, profitability is a very important feature for any company. A company capable of generating high earnings compared to its expenses is more likely to be healthy and to obtain a good credit rating. In contrast, the tier 1 capital has a negative impact on the ratings assigned by S&P. This is quite surprising because a company with a high tier 1 capital ratio has a high equity capital compared to its risk-weighted assets computed according to Basel III. One reason for this negative impact of the tier 1 capital may be that a company with a very high equity capital has a low leverage and does not leave a lot of room for investments, meaning that it will probably have a lower profitability.

Only one variable is significant at a 99% confidence level in this case, the current ratio. The current ratio has a coefficient of -0.173, which implies that the current ratio has a small but negative impact on the ratings assigned by S&P. This is very surprising because the liquidity is a desirable feature for a company. However, this result is similar to the findings of Shen et al. (2011) who found that the liquidity and the capital adequacy ratio of badly-rated banks is generally higher than the liquidity and the capital adequacy ratios of well-rated banks.

Let's now have a look at the outcomes of the OLS regression using the random effects transformation on the simple numeric ratings assigned by S&P.

Table 7: OLS with random effects transformations for S&P

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.73347	3.990735	3.691919	0.0003
COVERAGE_RATIO	0.304973	0.422178	0.722381	0.4714
CURRENT_RATIO	-0.208496	0.056931	-3.662235	0.0004
LEVERAGE	1.018058	0.888499	1.145817	0.2541
LOG_ASSETS	-0.135013	0.650659	-0.207502	0.8360
NON_PERF_LOANS	-17.63562	3.013199	-5.852791	0.0000
ROE	2.090794	1.112726	1.878984	0.0626
TIER_1_CAP	-4.571114	2.720090	-1.680501	0.0954

With the random effects transformation, three variables are not significant at a 90% confidence level. Here again, neither the coverage ratio nor the leverage are significant. The total assets are not significant in this case.

Once again, the ROE has a strong positive relationship with the ratings assigned by S&P, with a coefficient of 2.066 at a 90% confidence level. This positive relationship is in line with Moody's Investors Service (2016). Moody's defines a bank's profitability as being the measure of the bank's ability to generate capital and recover from shocks. It adds that a company with a low profitability is considered worse than a company with a high profitability, ceteris paribus. As it was also the case with the fixed effect transformations, the tier 1 capital ratio has a negative impact on the ratings assigned by S&P with the random effect transformations. Although the negative impacts of the liquidity and capital ratios is surprising, they are consistent with Shen et al. (2011)'s findings. The authors found that the liquidity and the capital adequacy were higher for CCC rated banks than for AAA and BBB rated banks. Shen et al. (2011) made the hypothesis that banks with a CCC rating have higher liquidity and capital adequacy ratios than banks with better ratings because they have to avoid bankruptcy. Therefore, they will inject a lot of cash in and improve the quality of their equity.

Both the current ratio and the non-performing loans ratio are significant at a 99% confidence level. The non-performing loans ratio has a very strong negative impact on the ratings assigned by S&P. It is clear that non-performing loans (NPLs) are undesirable for banks. Indeed, NPLs constitute a big barrier to the development of any economic activity. As a matter of fact, NPLs lower the profitability while increasing the need for capital and the funding costs (The European Parliament, 2016). All these features are very undesirable and may jeopardize the health of a bank. Regarding the current ratio, a negative impact on the ratings assigned to banks has been found, similarly to the what was found with the OLS regression with the fixed effects model.

We can now make some statements about the results obtained with the ratings assigned by S&P. The first thing to note is that both the coverage ratio and the leverage are not statistically significant with the fixed effects and the random effects transformations. With the random effects transformations, it was possible to see that the non-performing loans ratio had the biggest impact on the ratings assigned by S&P. This influence is negative because NPLs constitute a barrier to the proper functioning of a bank. Surprisingly, the current ratio had a small negative impact on the ratings emitted by S&P both in the fixed and the random effects models. Finally, we found that the total assets and the return on equity influenced the ratings assigned by S&P positively. These results are not surprising as both the size (Horrigan, 1966) and the profitability (Moody's Investors Service, 2016) of a bank are expected to increase the ratings it is assigned.

Simultaneously, the ratings emitted by Moody's were analyzed, using the same fixed and random effects transformations. The OLS using the fixed effects model for the numeric ratings emitted by Moody's can be found hereunder.

Table 8: OLS with fixed effects transformations for Moody's

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-37.34967	12.64144	-2.954542	0.0040
COVERAGE_RATIO	0.506332	0.570819	0.887028	0.3774
CURRENT_RATIO	-0.135361	0.073807	-1.833983	0.0699
LEVERAGE	-0.806110	1.047907	-0.769257	0.4437
LOG_ASSETS	9.194505	2.226931	4.128779	0.0001
NON_PERF_LOANS	-11.21323	4.673143	-2.399505	0.0185
ROE	4.817119	1.343216	3.586257	0.0005
TIER_1_CAP	0.933898	3.314250	0.281783	0.7788

As it was already the case for S&P, the coverage ratio, the leverage ratio and the tier 1 capital ratio are not significant at a 90% confidence level.

At a 90% confidence level, the current ratio has a low negative impact on the ratings assigned by Moody's. This is consistent with the results obtained for S&P.

When we examine the variables at a 95% confidence level, we see that non-performing loans have a strong negative influence on the ratings emitted by Moody's. Here again, the results are significantly similar to those obtained with S&P's ratings. A coefficient of -11.21 implies that if a bank sees its non-performing loans increase by 8,92%, the rating it would obtain would be reduced by one notch, everything else remaining the same.

Two variables are still significant at a 99% confidence level: the total assets and the return on equity. The log assets and the ROE have higher coefficients with the ratings emitted by Moody's (9.195 and 4.817 respectively) than with the ratings assigned by S&P (4.351 and 2.832 respectively). This means that the total assets and the ROE have a bigger influence on the ratings emitted by Moody's than on the ones emitted by S&P. Both Moody's and S&P give a lot of importance to the total assets and the profitability. These two elements influence the outcomes of the ratings positively, as expected.

The final table to analyze in this subsection is the outcome of the OLS regression using Moody's numerical ratings and applying the random effects transformations.

Table 9: OLS with random effects transformations for Moody's

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.230685	5.261892	1.184115	0.2387
COVERAGE_RATIO	0.581611	0.512907	1.133951	0.2590
CURRENT_RATIO	-0.199747	0.068327	-2.923384	0.0041
LEVERAGE	-0.768286	1.041730	-0.737509	0.4622
LOG_ASSETS	1.439543	0.871318	1.652144	0.1011
NON_PERF_LOANS	-16.21962	3.739841	-4.336980	0.0000
ROE	4.122805	1.311857	3.142723	0.0021
TIER_1_CAP	2.272583	3.218211	0.706163	0.4814

Here again, with the random effects transformations, the coverage ratio, the leverage ratio and the capital tier 1 and the total assets are not significant at a 90% confidence level.

With the random effect transformations, three variables are significant at 99% confidence level. The first variable is the current ratio, which once more has a small negative influence on the ratings. The second variable is the non-performing loans ratio which has a strong negative impact on the ratings, exactly as in the previous results. The last variable is the ROE which has a pretty strong positive influence on the ratings.

The results obtained for S&P's ratings and Moody's ratings are very similar. It is not surprising as Ederington (1986) already explained that there is no proof that Moody's and S&P give different weights to financial ratios in order to compute their ratings. They are believed to use similar standards.

The main findings were that the independent variable with the biggest impact on the ratings is the non-performing loans ratio. The return on equity, which represents the bank's profitability has a strong positive influence on the ratings. A positive relationship was also found between the total assets and the ratings emitted by both Moody's and S&P. The most surprising results were the negative influence of the current ratio and the tier 1 capital ratio on the ratings. However, Shen et al. (2011) obtained the same results and concluded that companies with a CCC rating had the highest liquidity and capital adequacy in their sample.

2.3.2 OLS regressions using the probabilities of survival

In this subchapter, OLS regressions were computed using the probabilities of survival of both S&P and Moody's. As explained previously, the probabilities of survival were used instead of the probabilities of default in order to compare the results with the ones obtained using the simple numerical ratings in an easier manner.

The first regressions computed were the OLS regressions using the fixed effects and the random effects transformations for S&P's ratings.

Table 10: OLS with fixed effects regressions using S&P's probabilities of survival

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.037402	0.231879	4.473889	0.0000
COVERAGE_RATIO	0.004918	0.010470	0.469702	0.6397
CURRENT_RATIO	-0.001685	0.001354	-1.244776	0.2164
LEVERAGE	0.007384	0.019222	0.384137	0.7018
LOG_ASSETS	-0.011618	0.040848	-0.284431	0.7767
NON_PERF_LOANS	-0.245244	0.085718	-2.861037	0.0052
ROE	-0.006424	0.024638	-0.260724	0.7949
TIER_1_CAP	-0.010221	0.060793	-0.168133	0.8669

Table 11: OLS with random effects transformations using S&P's probabilities of survival

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.982613	0.084668	11.60554	0.0000
COVERAGE_RATIO	0.002574	0.009023	0.285272	0.7759
CURRENT_RATIO	-0.001507	0.001218	-1.236542	0.2186
LEVERAGE	0.011280	0.019063	0.591702	0.5551
LOG_ASSETS	-7.13E-05	0.013782	-0.005175	0.9959
NON_PERF_LOANS	-0.512749	0.064268	-7.978255	0.0000
ROE	0.008030	0.023859	0.336573	0.7370
TIER_1_CAP	-0.021684	0.058301	-0.371924	0.7106

Unfortunately, the results obtained with the probabilities of S&P are not very insightful. Only the non-performing loans are significant at a reasonable confidence level (with a p-value < 10%) with the fixed and random effects transformations. The non-performing loans have a negative impact on the probabilities of survival of the banks. This is consistent with the results obtained previously. It has already been explained that non-performing loans reduce the profitability, the access to capital and are an obstacle to the healthy functioning of a bank.

The results of the OLS regressions obtained with Moody's probabilities of survival are displayed hereunder.

Table 12: OLS regression using the fixed effects transformations using Moody's probabilities of survival

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.464837	0.408169	1.138836	0.2578
COVERAGE_RATIO	0.007717	0.018431	0.418714	0.6764
CURRENT_RATIO	-0.003441	0.002383	-1.443932	0.1522
LEVERAGE	0.017808	0.033835	0.526324	0.5999
LOG_ASSETS	0.092987	0.071903	1.293213	0.1992
NON_PERF_LOANS	-0.643181	0.150887	-4.262664	0.0000
ROE	0.245274	0.043370	5.655379	0.0000
TIER_1_CAP	-0.107690	0.107011	-1.006343	0.3169

Table 13: OLS regression using the random effects transformations using Moody's probabilities of survival

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.943567	0.136051	6.935375	0.0000
COVERAGE_RATIO	-0.000593	0.015308	-0.038725	0.9692
CURRENT_RATIO	-0.001997	0.002091	-0.955006	0.3414
LEVERAGE	0.019766	0.033484	0.590323	0.5561
LOG_ASSETS	0.007056	0.021832	0.323183	0.7471
NON_PERF_LOANS	-0.671170	0.107396	-6.249475	0.0000
ROE	0.228605	0.041674	5.485526	0.0000
TIER_1_CAP	-0.088537	0.101459	-0.872638	0.3846

In this case, significant results are obtained for the non-performing loans and the ROE. Here again, the results are similar to the results of the previous point. The non-performing loans have a negative impact on the probability of survival and the ROE has a positive impact on the probability of survival. As the profitability reflects the capability of a company to generate profits, it makes sense to conclude that a company that has a higher income than costs is healthy and has a lower probability of defaulting on its financial obligations.

The outcomes of the computations of this subsection are unfortunately less useful than the results obtained using the simple numeric ratings. The insignificance of most variables is believed to be caused by the small size of the sample rather than by the inadequacy of the explanatory variables. Indeed, as the probabilities of default used do not strictly increase as the ratings get worse, many more observations are probably needed in order to find a conclusive correlation between the financial ratios and the probabilities of survival of the banks.

2.3.3 OLS regressions including non-financial variables

As explained previously, banks' non-financial variables play an important role in the ratings they obtain. Therefore, the aim of this section is to find whether the country ratings, the affiliation to the EU and the fact of being systematic have an impact on the ratings obtained by European banks. The OLS regressions computed in this section include the most relevant financial features found previously (the NPLs, the ROE, the total assets and the current ratio), as well as three non-financial variables (the country rating, the affiliation to the E.U., the fact of being a systematic bank or not). The random effects transformations were used to cope with the unobserved heterogeneity as the fixed effects transformation do not accept explanatory variables that do not change through time.

Table 14: OLS regressions using the random effects transformations with non-financial variables for S&P

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.078469	4.834909	-0.429888	0.6678
COUNTRY_RATING	0.556713	0.090452	6.154766	0.0000
CURRENT_RATIO	-0.050511	0.034730	-1.454386	0.1476
SYSTEMATICALITY	-0.817292	0.856765	-0.953928	0.3414
EU	0.967748	0.692071	1.398336	0.1638
LOG_ASSETS	1.164000	0.804721	1.446463	0.1498
NON_PERF_LOANS	-13.47102	2.607672	-5.165917	0.0000
ROE	1.361992	0.949744	1.434062	0.1533

For S&P, being in the E.U. or being systematic do not affect the ratings obtained by European banks. In this model, the current ratio, the log assets and the ROE are not significant at a reasonable level of confidence. NPLs have once more an important negative influence on the ratings assigned by S&P. The most interesting result of this table is that the rating of the country in which banks operate influence highly the ratings obtained by the banks themselves, with a 99% confidence level. A coefficient of 0.56 means that if the rating of a country changes by two notches (e.g from A- to A+), the rating assigned to its banks will increase by a little bit more than one notch, which is very significant. A bank located in a poorly rated country will be penalized compared to a bank which operates in a well rated country, everything else remaining equal.

Table 15: OLS regressions using the random effects transformations with non-financial variables for Moody's

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-12.35454	5.277447	-2.341007	0.0203
COUNTRY_RATING	0.648263	0.099980	6.483893	0.0000
CURRENT_RATIO	-0.057823	0.036239	-1.595608	0.1124
SYSTEMATICALITY	-1.714271	0.945866	-1.812382	0.0716
EU	0.842330	0.768199	1.096499	0.2744
LOG_ASSETS	2.704920	0.879125	3.076833	0.0024
NON_PERF_LOANS	-7.244076	2.737063	-2.646660	0.0089
ROE	3.574817	0.988442	3.616617	0.0004

Interestingly, the results for Moody's are way more insightful than the ones obtained with the ratings emitted by S&P. We can observe at a 99% confidence level, that the log assets and the ROE have positive impacts on the ratings, while the NPLS affect the ratings emitted by Moody's negatively. These results are similar to the outcomes of the computations carried out earlier.

At a 90% confidence level, we can see that the fact of being systematic influences negatively the ratings obtained by banks. It makes sense as a systematic bank is probably way more monitored than other banks because of the huge negative economic impact its failure could have. Following the subprime crisis, financial markets started to be conscious that systematic banks could fail and should not be trusted blindly. The coefficient of -1.7 implied that Moody's assign a penalty of almost two notches to systematic banks.

As it was the case for S&P, the country ratings influence positively the ratings assigned by Moody's to European banks. The coefficient is even higher for Moody's than for S&P (0.65 against 0.56 for S&P). This means that, when assigning a rating to a bank, Moody's accord more importance to the rating of the country in which the bank is located than S&P. The positive coefficient implies that a economically strong country influences positively the ratings obtained by its banks.

The EU dummy had no statistically significant influence on the ratings emitted by S&P and Moody's. This is probably because the banks located in the UK and in the EU are subject to the same regulations and operate in similar economic conditions. As the sample almost exclusively contains banks located in the U.K. or in the E.U., this variable does not make sense in this case. Only the "Sberbank" and the "Crédit Suisse" were neither in the E.U not in the U.K. This variable would be more relevant if non-European countries were included in the sample.

2.3.4 The Shapley values

This last subsection displays the results of the Shapley values for both S&P's and Moody's numeric ratings. In order to compute the Shapley values, simple and multiple linear regressions between the financial characteristics and the numeric ratings had to be calculated. Because the dataset is in the form of panel data, the Shapley values were computed for a single year in order to avoid the use of cross-sectional and time-series data and the biases that come with it. As it is interesting to identify the possible changes in weights assigned to the variables throughout the years, the data from 2013 and 2016 was compared. The first step to computing the Shapley values is to extract the various adjusted R-squared values of the linear regressions between the independent variables and the ratings. The adjusted R-squared represents the extent to which one or several explanatory variables (the financial ratios) can explain the variations of the dependent variable (the ratings). The R-squared values for the years 2013 and 2016 are presented hereunder.

Table 16: Simple linear regressions for 2013

Explanatory variables	Adjusted R-squared for S&P	Adjusted R-squared for Moody's
ROE	0.1172	0.2597
Leverage	0.0885	0.0257
Non-performing loans	0.4871	0.5691
Log assets	-0.0253	-0.0067
Coverage ratio	-0.0011	-0.0102
Tier 1 capital	0.3503	0.2767
Current ratio	0.0898	0.0764

Table 17: Simple linear regressions for 2016

Explanatory variables	Adjusted R-squared for S&P	Adjusted R-squared for Moody's
ROE	0.1776	0.1684
Leverage	0.0822	0.0758
Non-performing loans	0.4844	0.4001
Log assets	-0.0164	-0.0025
Coverage ratio	-0.0312	-0.0232
Tier 1 capital	0.4273	0.4291
Current ratio	-0.0120	0.0143

The results of the linear regressions are consistent with what was obtained earlier in this paper. The non-performing loans are the variable that best explains the variations in the ratings for both S&P's and Moody's ratings. The ROE also has an important impact on the ratings. We can see that the tier 1 capital has a surprisingly high R-squared value both in 2013 and 2016. This means that the three variables can be used to explain the rating changes. The remaining variables (the leverage, the total assets, the coverage ratio and the current ratio) do not have a strong relationship with the ratings in this case, with R-squared values lower than 10% in 2013 and 2016 for both S&P's and Moody's ratings.

Consequently, the three variables chosen in order to compute the Shapley values were the non-performing loans, the ROE and the tier 1 capital ratio. Indeed, as these three variables seem to be the most relevant in the results obtained in the point 2.3.1 and with the simple linear regressions, they are believed to have the biggest impact on the ratings. It is interesting to notice that the impact of the tier 1 capital on the ratings rose between 2013 and 2016 for both S&P and Moody's. On the other hand, the non-performing loans' influence diminished between 2013 and 2016, especially for Moody's. The ROE's importance increased for S&P but decreased for Moody's between 2013 and 2016.

As explained earlier in this paper, we cannot simply add the R-squared values of the three variables as they are not totally uncorrelated. Therefore, multiple linear regressions had to be computed for each combination of variables possible. This way, we can identify the joint influence of the three variables on the ratings. This is an important step in computing the Shapley values.

Table 18: Multiple linear regressions for 2013

Explanatory variables	Adjusted R-squared for S&P	Adjusted R-squared for Moody's
ROE + NPLs	0.5366	0.5906
ROE + Tier 1 capital	0.4291	0.4282
NPLs + Tier 1 capital	0.6713	0.6826
ROE + NPLs + Tier 1 capital	0.6814	0.6765

In 2013, the three selected variables could explain 68.14% of the ratings. This percentage is significantly high and means that by analyzing the 3 ratios of a bank, a major proportion of S&P's rating decisions can be explained. Similar results are observable for Moody's, as the model allows to identify 67.65% of the rating decisions. It is interesting to mention that for Moody's, the adjusted R-squared diminishes as we add the ROE to the model composed of the non-performing loans and the tier 1 capital. This means that the inclusion of the ROE is not very explanatory in this case. The penalty applied by the adjusted R-squared for the addition of another explanatory variable is higher than the contribution of the ROE to the model.

Table 19: Multiple linear regressions for 2016

Explanatory variables	Adjusted R-squared for S&P	Adjusted R-squared for Moody's
ROE + NPLs	0.5283	0.4182
ROE + Tier 1 capital	0.4917	0.4822
NPLs + Tier 1 capital	0.6556	0.5774
ROE + NPLs + Tier 1 capital	0.6448	0.5643

The extent to which the three ratios can explain the ratings assigned to the banks in 2016 is significantly lower than in 2013 for S&P and especially for Moody's. This could be due to an increase in the importance of other financial variables not included in this model and lowly correlated with the three selected ratios. Another explanation could be that the importance of qualitative information has had an increasing impact on the ratings assigned. The second hypothesis is in line with the opinion of Jorion, Liu & Shiu (2005). They argue that the relevance of the ratings has improved as the qualitative aspects were included in the computation methods used by the CRAs. The interviews with the management, analysis of confidential information, and the assessment of other qualitative variables play an important role in the rating's credibility and can therefore be expected to have an increasing influence on the assigned ratings. Here again, the inclusion of the ROE reduces de precision of the model for the prediction of the ratings emitted by S&P and Moody's in 2016.

Now that all the preliminary steps are done, we can compute the Shapley values. With the Shapley value, the total contributions will be split among the different variables according to their real contribution to the model. To compute the Shapley value, all the possible combinations of the three variables must be analyzed.

In table 20, you will find the main results of the Shapley values for 2013 and 2016 for both S&P and Moody's, using the ROE, the non-performing loans and the tier 1 capital.

Table 20: Shapley values of the model comprising the ROE, NPLs and Tier 1 capital

Explanatory variables	S&P 2013 ratings	Moody's 2013 ratings	S&P 2016 ratings	Moody's 2016 ratings
ROE	0.0769	/	/	/
NPLs	0.3746	0.5016	0.3855	0.2913
Tier 1 capital	0.2299	0.1810	0.2701	0.2861
Total	0.6814	0.6826	0.6556	0.5774

As the ROE reduced the precision of the models for Moody's in 2013 and for both CRAs in 2016, it has been removed from the model for these years. This may be due to the significant correlations of the ROE with the NPLs (- 0.5506) and with the tier 1 capital (0.2583). This means that the ROE ratio can be partly explained by combining the NPLs ratio and the capital tier 1 ratio. Consequently, adding the ROE to the model does not always increase its explanatory power.

In 2013, the three ratings represented 68.14% of the rating decision. The ROE ratio was the ratio that had the lowest impact on the model (7.69%). It was mainly the NPLs and the tier 1 capital that were useful for the rating attribution, with an impact of 37.46% and 22.99% respectively on the ratings assigned by S&P. During the same year, Moody's assigned a significantly high weight to the non-performing loans ratio (50.16% of the rating decision). The remaining 18.10% were explained by the tier 1 capital ratio. These results are credible as the non-performing loans are a combination of several factors. The NPLs reduce a bank's profitability and at the same time increase its capital needs and funding costs (The European Parliament, 2016).

The results of the Shapley values in 2016 are quite similar to the 2013 results for S&P. As the ROE has been excluded from the 2016 model, the reliance on the NPLs ratio and the tier 1 capital ratio to predict the ratings increased. In 2016, the tier 1 capital ratio explains 27.01% of S&P's ratings against 22.99% in 2013. The model is a little less explanatory as is only explains 65.56% of S&P's rating decisions in 2016 while it explained 68.14% 3 years earlier. The three-variable model we use lost a lot of explanatory power in 2016 for Moody's. Indeed, the three variables could only explain 57.74% of Moody's rating decision in 2016 while is explained 68.26% in 2013. As explained previously, this may be due to the increase of the importance of another variable not included in this model, or by an increase on the reliance on the qualitative aspects. This decrease in the precision of the model is mainly due to a very high decrease of the importance of the NPLs ratio in Moody's rating methodology. Its importance was reduced by 21.03% within 3 years.

2.3.4 Conclusions and main remarks.

The aim of this section was to display the different results of the empirical research as well as to give a critical interpretation of the outcomes. In this last point, we will make a summary of what has been discovered in this paper.

Firstly, the outcomes the ordinary least squares (OLS) regressions of the numerical ratings assigned were quite similar results for Moody's and S&P with both the fixed and the random effects models. The independent variable with the biggest impact on the ratings is the non-performing loans ratio. This is not surprising as the NPLs reduce the bank's assets quality. Consequently, because of the Basel requirements, more capital is needed while the funding costs increase, reducing the bank's ability to use leverage. The profitability is therefore expected to drop as well. The second important variable is the return on equity. The ROE has a strong positive influence on the ratings. This makes sense as a higher profitability means a higher ability to generate capital and profits for the shareholders. The third variable which was often significant is the total assets. It has a positive influence on the ratings obtained by the banks. These results strengthen Rossi and Malavasi's opinion (2016), who believe that big banks obtain higher ratings due to their importance and to the belief that they are too big to fail. In addition, it is reasonable to believe that a firm possessing a high number of assets is more capable of generating profits and meeting its financial obligations. Surprisingly, the current ratio and the tier 1 capital ratio appeared to influence the assigned ratings in a negative way. This is counter-intuitive as the current ratio measures the ability of a company to meet its short-term debt and the tier 1 capital represents the capital adequacy of banks. These negative influences could be observed because banks with low ratings may need more liquidity and quality equity in order to try to avoid bankruptcy than healthy banks (Shen et al., 2011). No significant impact on the ratings has been found for the coverage ratio and the leverage ratio. This may be due to the small number of observations used in this paper. Indeed, as information on the banking sector is not always accessible, the initial sample of banks had to be significantly reduced. In the subchapter 2.1.2, we also found that the collected data was very homogeneous for these two ratios. This homogeneity combined with the small sample size may have caused the results to be insignificant. It is interesting to mention that Moody's assign more importance to the non-performing loans ratio, the ROE and the total assets when computing ratings for European banks.

The second set of computations analyzed the same variables, using the probabilities of survival of the banks. The results were quite disappointing as only the non-performing loans were significant for S&P in this model. For Moody's, both the NPLs and the ROE had a significant impact. Although many variables were insignificant, the results obtained for the non-performing loans and for the ROE were very similar to the results of the analysis using the simple numeric rating. Indeed, a strong negative relationship was found between the NPLs and the ratings emitted by Moody's and S&P. The results showed that the ROE has a positive impact on the ratings assigned by Moody's.

The results of the OLS regressions including non-financial variables showed that the rating of the country in which banks are located have an important role on the rating they obtain. With coefficient higher than 0.5, a change of 2 notches in a country rating changes the ratings assigned to the banks by more than 1 notch in the same direction. Here again, Moody's gives more importance on the country ratings. Moody's appeared to apply a penalty to systematic banks. A systematic bank is assigned a penalty of 1.7 notches, which is significant. S&P did not seem to take this feature into account. The affiliation to the E.U. had no influence on the ratings assigned by S&P and Moody's. This could be explained because the banks located in the U.K. and in the E.U. are subject to the same regulations and operate in similar economic conditions. As the sample almost exclusively contained banks located in the U.K. or in the E.U., this variable was not very insightful. This variable would be more relevant if non-European countries were included in the sample.

The computation of the Shapley value for the 2 CRAs was conducted using the ROE, the non-performing loans ratio and the tier 1 capital ratio. The ROE appeared to worsen the model in 2013 for Moody's and in 2016 for both Moody's and S&P. This may be due to the high correlation between the ROE and the two other variables. The explanatory power of the combination of the three variables decreased between 2013 and 2016, especially for Moody's. This could be the result of an increase of the importance of a financial variable not included in the model, or by the growing reliance on qualitative features. Once more, the findings showed that the non-performing loans had a very strong influence on the ratings assigned to European banks.

Conclusion

The purpose of this thesis was to identify the possible relationships between financial and accounting ratios from major European banks and the ratings they obtain from the two biggest CRAs, namely S&P and Moody's. The two CRAs with the biggest market shares were chosen because they have the biggest influence on the market. In addition, the access to their data and to documents regarding their methodologies was easier. The final goal of this paper was to clarify the methodologies by the CRAs used to attribute ratings to the European banks, as they are only partly disclosed. To do so, this paper was divided into two main sections. The first section was a literature review in which the existing studies regarding the CRAs was analyzed. The second part of this paper was an empirical research, in which statistical computations were used to shed light on the importance given by the CRAs to each financial and accounting feature of the banks.

The first important step in the literature review was to describe what a credit rating is and why it is needed. In this first subsection, important terms related to the credit ratings were clarified, the advantages and disadvantages of credit ratings were explained as well as the influence that credit ratings have on the financial market these days. Subsequently, the main credit rating agencies and the history of the CRAs market was analyzed in order to fully understand how it became an oligopolistic market. The various pricing methods used by the CRAs were also presented in order to identify the different drawbacks linked to each pricing model. Finally ethical issues such as conflicts of interests and rating shopping were presented, as well as the current regulatory framework. The literature review laid down the theoretical background needed to fully understand the computations and recommendations made in the empirical research. In addition, reading existing research about the CRAs was very insightful and gave potential paths to follow with the statistical computations.

The second part of this paper, as mentioned previously, was the empirical research. The goal of this section was to answer the paper's question: "What are the financial and accounting features that influence the ratings assigned by the CRAs to the major European banks?". To do so, a sample containing the 61 biggest European banks (in terms of balance sheet size) was analyzed. The ratings of Moody's and S&P were used as they are the two leaders of the CRAs market by far. Seven financial and accounting variables were selected based on the outcomes of the literature review. Indeed, the ratios that were selected are believed to have an important role in the rating attribution methodology used by Moody's and

S&P. A profitability ratio (the ROE), a capital ratio (Tier 1 capital ratio) and a liquidity ratio (the current ratio) were used to represent important features taken into account in order to determine the health of a company. In addition, the leverage ratio and the total assets were taken into account to find out if the extent to which a bank borrows and its size influence the ratings it obtains. Finally, the non-performing loans ratio and the coverage ratio were used to represent the quality of the assets held by the banks and their ability to meet their debt obligations. The ratings and financial variables selected were extracted for each bank for each year between 2012 and 2016. Unfortunately, due to data scarcity, the sample had to be reduced significantly as both ratings were not available for every firm and because the financial ratios were not fully disclosed each year. Out of the 600 possible observations, only 131 observations had the full set of information, which means the 2 ratings and the 7 financial variables were obtained for one year for a single bank. In addition, 3 non-financial variables were used. These were the country ratings, the membership the a E.U. country and the fact of being a systemic bank or not.

Four main computations methods were used throughout this paper. Firstly, OLS regressions were computed with simple numerical ratings, using the fixed and random effects transformations. Secondly, the same computations were made, using the probabilities of survival of the banks instead of the simple numeric ratings. Following these two computations methods, the most relevant financial variables were identified and combined with the three non-financial variables in a new model. Finally, the Shapley values were computed to determine the weight of each variable in the rating attribution methodologies used by Moody's and S&P.

The results of the OLS regressions conducted with the simple numerical ratings were very similar for Moody's and S&P. The financial ratio which had the biggest impact on the ratings turned out to be the non-performing loans ratio. NPLs reduce bank's assets quality, increase its funding costs and its need for capital. It was therefore not surprising to find a strong negative impact of the NPLS on the ratings obtained by banks. The ROE also appeared to have a significant impact on the ratings assigned by Moody's and S&P. A strong positive relationship was found between the ROE and the ratings. These results were also foreseeable as the profitability reflects the ability to generate capital, which improves the proper functioning of a company. The total assets also appeared to have a small positive influence on the ratings obtained by the banks. The size of a bank therefore appears to improve the rating it is assigned. The liquidity ratio used in this paper influenced the ratings assigned to the banks in a negative way. This result, although counter-intuitive, is in line with the findings of Shen et al. (2011). They explain this results by the fact that banks which suffer from economic unrest need more capital and liquidity. The coverage ratio, the leverage ratio and the tier 1 capital ratio appeared had no significant role in the methodology used by S&P and Moody's to compute credit ratings.

The results of the OLS regressions with the probabilities of survival of the banks were less convincing than the results obtained with the simple numeric ratings. However, the outcomes are consistent with what was found previously as the non-performing loans and the ROE had a big impact on Moody's ratings. For S&P, only the non-performing loans ratio gave statistically significant results.

The third set of computations were OLS regressions with the most relevant financial variables and three non-financial variables. The results displayed that the rating of the country in which a bank is located has a positive impact on the ratings it is assigned by Moody's and S&P. This means that a bank operating in economically strong country will obtain a better rating than a bank located in a badly rated country, everything else remaining the same. Moody's appeared to give more weight to the country rating than S&P. In addition, Moody's applies a penalty to systematic banks by reducing the ratings they obtain by almost two notches.

The last set of computations was the computation of the Shapley values. The Shapley values were computed for Moody's and S&P for the years 2013 and 2016, in order to analyze a possible evolution of the methodologies over time. Following the outcomes of the OLS regressions and the results of simple linear regressions, the variables included in the models used to compute the Shapley values were the ROE, the non-performing loans ratio and the tier 1 capital ratio. The ROE reduced the precision of the model in 2013 for Moody's and in 2016 for both Moody's and S&P. Therefore, it was excluded in these 3 cases. The explanatory power of the three-variable model was significantly high (more than 68% in 2013) but decreased between 2013 and 2016, especially for Moody's. This might be due to the increased importance of other financial variables in the methodologies used by S&P and Moody's. An alternative answer is that this loss of prediction power is explained by the increasing reliance of the CRAs on qualitative aspects. The non-performing loans ratio is once more the variable with the largest impact on the ratings obtained by banks. In 2016, the non-performing loans ratio could be used to predict 38.55% of S&P's rating decisions while it could explain 29.13% of Moody's rating decision.

It seems relevant to conclude this paper by pointing out the several flaws of the methodologies used, and by making some recommendations for the studies to come. The first limitation of this paper is that a small sample of banks was used to do the statistical research. More insightful results could possibly be obtained by using a bigger sample. As a matter of fact, as information on banks is very difficult to access, the final sample ended up being significantly smaller than the initial sample. As the coverage ratios, the leverage ratios and the tier 1 capital ratios were very homogeneous in the sample, more observations would maybe improve the outcomes of the calculations. Including more banks in the sample could however change the results significantly. Indeed, as the banks used in this paper were among 61th biggest European banks, the additional banks would necessarily be smaller banks. It could nevertheless be interesting to analyze if the methodologies and the weights assigned the financial variables are the same for big banks and small banks. Another way to increase the sample could be to extend the time span analyzed. Including more years would indeed increase the number of observations. However, as methodologies evolve over the years, the period analyzed should not be too long either. The second main flaw of this paper is the use of the current ratio. The liquidity coverage ratio is believed to be a better indicator of a banks' liquidity and different results could be obtained if the current ratio is replaced by the liquidity coverage ratio. As the qualitative aspects seem to have a growing impact on the ratings assigned by the CRAs, it could be interesting to try to shed light on how CRAs take these aspects into account.

Appendix

Appendix I: Symbols used to represent ratings by the 2 main CRAs

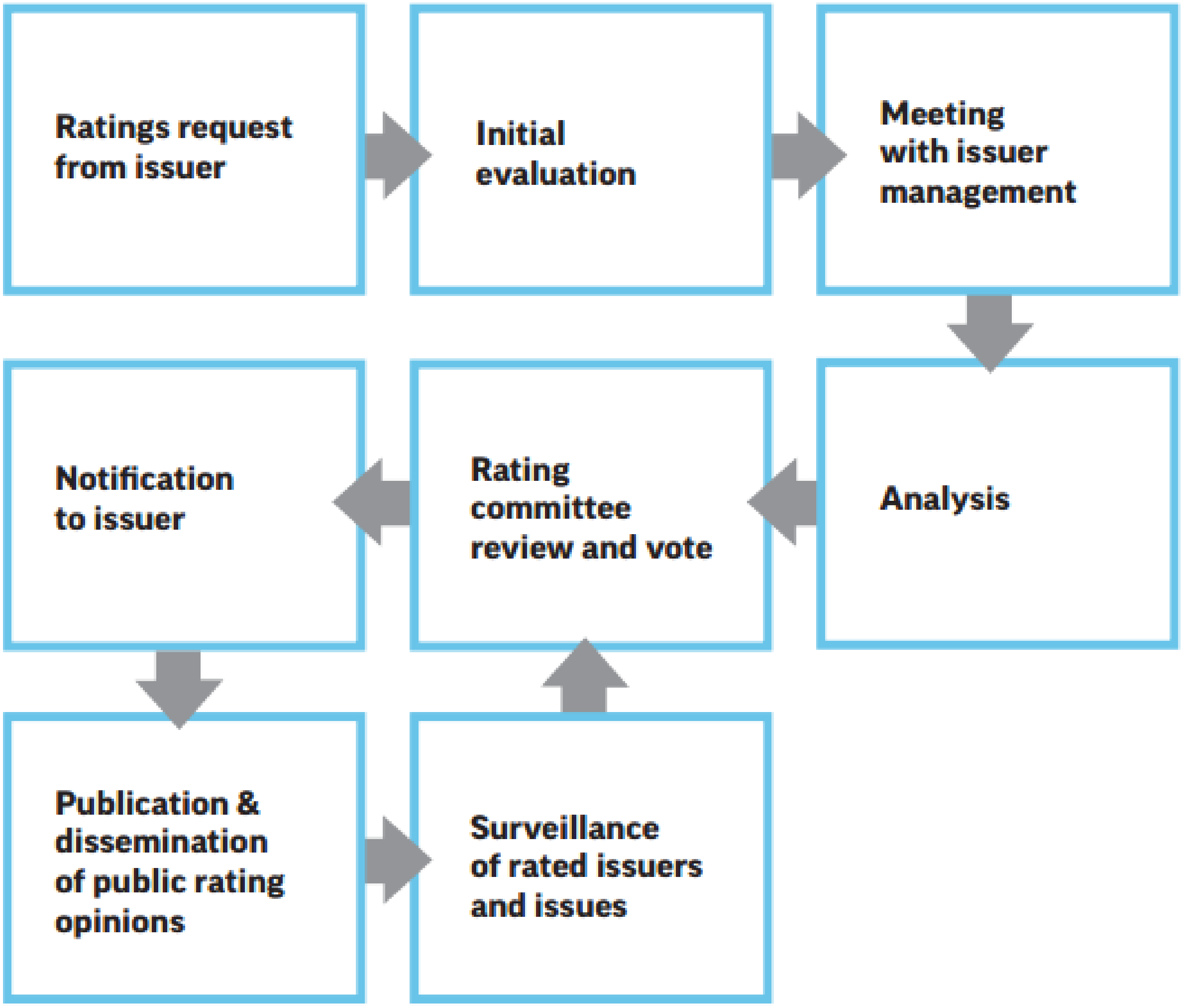
Table 1: Rating Scales/Grades Used by Moody's and S&P alongwith their Respective Interpretations

No.	Moody's Ratings	Standard and Poor's Ratings	Interpretation		
			Grading	Credit Risk	Capacity to meet Financial Commitment
1	Aaa	AAA	Highest quality	Minimal	Extremely Strong
2	Aa1	AA+	High quality	Very Low	Very strong
3	Aa2	AA			
4	Aa3	AA-			
5	A1	A+	Upper-Medium	Low	Still strong
6	A2	A			
7	A3	A-			
		Speculative Grade			
8	Baa1	BBB+	Medium	Moderate	Weakened
9	Baa2	BBB			
10	Baa3	BBB-			
11	Ba1	BB+	Lower-Medium	Substantial	Inadequate
12	Ba2	BB			
13	Ba3	BB-			
14	B1	B+	Low	High	Impaired
15	B2	B			
16	B3	B-			
17	Caa1	CCC+	Poor	Very high	Not likely
18	Caa2	CCC			
19	Caa3	CCC-			
20	Ca1	CC+	Very low	Very near default	Vulnerable to non-payment
21	Ca2	CC			
22	Ca3	CC-			
23	C1	C+	Lowest	In default	Highly vulnerable to non-payment
24	C2	C			
25	C3	C-			

Moody's use numeric 1, 2 & 3 and Standard and Poor's use (+) and (-) sign for generic rating classification to show relative standing in major rating categories.

Source: Iyengar (2012)

Appendix II: S&P's credit rating process



Source: S&P's (2016)

Appendix III: Moody's BCA computation framework

Example BCA Scorecard

Baseline Credit Assessment

Banking Group ABC Inc
Country XYZ

Macro Factors

	Country / Region	Macro Profile	Weight
Country 1	Country 1	Very Strong	60%
Country 2	Country 2	Strong	20%
Country 3	Country 3	Moderate +	20%
Weighted Macro Profile		Strong +	100%

Financial Profile

	Historic Ratio	Initial Score	Expected trend	Assigned Score	Key driver #1	Key driver #2
Solvency						
Asset Risk						
Problem Loans / Gross Loans	2.0%	a1	↓↓	baa2	Geographical diversification	Capital market risk
Capital						
Tanigble Common Equity / RWA	8.5%	ba2	↔	b1	Risk-weighted capitalisation	Nominal leverage
Profitability						
Net Income / Tangible Assets	0.5%	baa2	↔	a3	Loan loss charge coverage	
Combined Solvency Score				baa3		
Liquidity						
Funding Structure						
Market Funds / Tangible Banking Assets	15.0%	a2	↔	baa2	Term structure	
Liquid Resources						
Liquid Banking Assets / Tangible Banking Assets	20.0%	baa1	↑	baa1	Expected trend	Intragroup restrictions
Combined Liquidity Score		a3		baa2		
Financial Profile				baa3		

Qualitative Adjustments

	Adjustment	Comment
Business Diversification	0	Highly complex organisation
Opacity and Complexity	-1	
Corporate Behavior	0	
Total Qualitative Adjustments	-1	

		Comment
Sovereign or Affiliate constraint	Aaa	Government rating
BCA range	baa3 - ba2	
		Rationale
Assigned BCA	ba1	Appropriate position vs peers

Source: Moody's Investors Service

Source: Moody's Investors Service (2016)

Appendix IV: weights assigned to each rating category by the Basel Committee

Counterparty category	Ratings					
	AAA to AA-	A+ to A-	BBB+ to BBB-	BB+ to B-	Less than B-	Unrated
Sovereigns and central banks	0%	20%	50%	100%	150%	100%
Banks under option 1*	20%	50%	100%	100%	150%	100%
Long-term claims on Banks under option 2** (> 3months)	20%	50%	50%	100%	150%	50%
Short-term claims on banks under option 2 (< 3months)	20%	20%	20%	50%	150%	20%

* Banks under the option 1 are assigned a risk-weight one category less favorable than the risk-weight obtained by its country. Banks located in countries which have lower ratings than BBB- obtain the same risk-weight as the bank

** The second option is to assign the banks a risk-weight base on their own external credit ratings as presented in the table

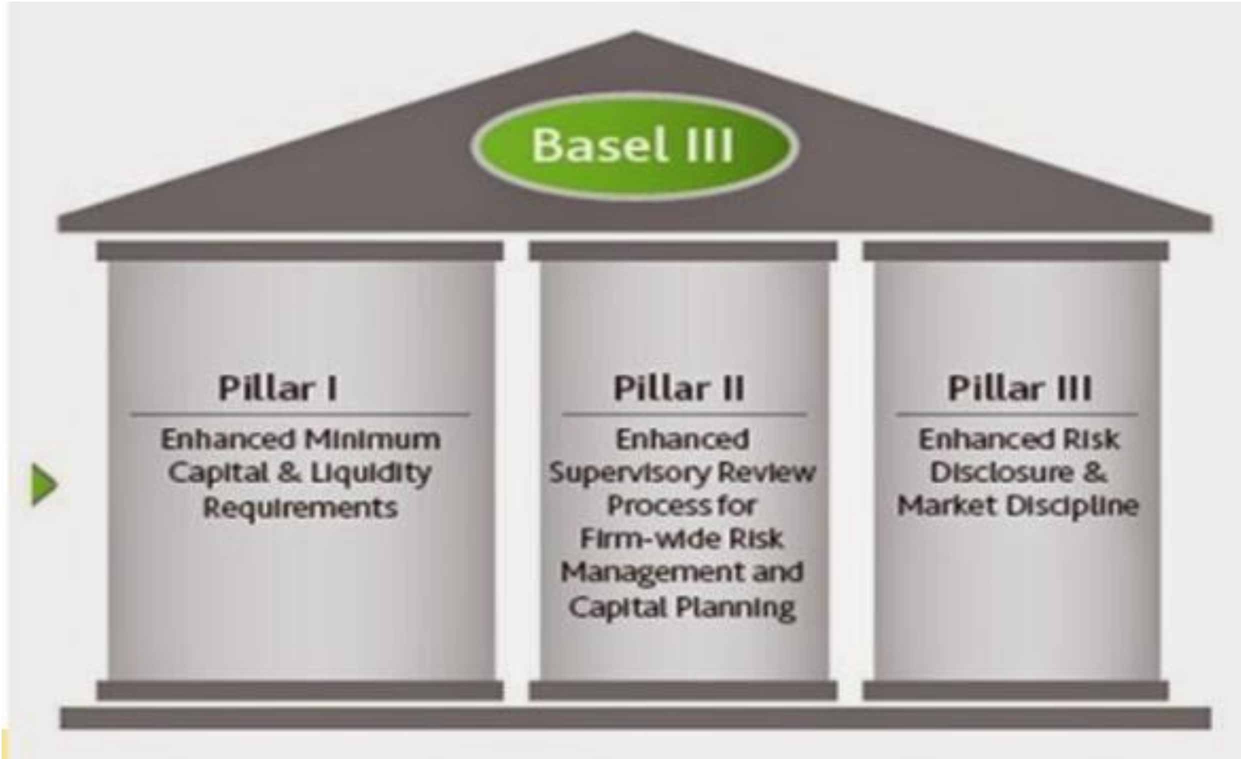
Source: Basel Committee on Banking Supervision (2015)

Appendix V: SEC's list of NRSROs and initial year of entrance

Name of the CRA	Year of entrance
Moody's Investor Service	1975
Standard & Poor's	1975
Fitch Rating	1975
Dominion Bond Rating Service Ltd.	2007
A.M. Best Company	2007
Japan Credit Rating Agency Ltd.	2007
Egan-Jones Rating Company	2007
Kroll Bond Rating Agency	2008
Morningstar Inc.	2008
HR Ratings de Mexico	2012

Source: U.S. Securities and Exchange Commission (2016)

Appendix VI: Basel II and Basel III pillars



Source: Bank exams today (2014)

Appendix VII: Evolution of the Basel III requirements

Basel Committee on Banking Supervision

BANK FOR INTERNATIONAL SETTLEMENTS

Basel III phase-in arrangements

(All dates are as of 1 January)

	Phases	2013	2014	2015	2016	2017	2018	2019
Capital	Leverage Ratio		Parallel run 1 Jan 2013 – 1 Jan 2017 Disclosure starts 1 Jan 2015				Migration to Pillar 1	
Capital	Minimum Common Equity Capital Ratio	3.5%	4.0%	4.5%				**4.5%**
Capital	Capital Conservation Buffer				0.625%	1.25%	1.875%	**2.5%**
Capital	Minimum common equity plus capital conservation buffer	3.5%	4.0%	4.5%	5.125%	5.75%	6.375%	**7.0%**
Capital	Phase-in of deductions from CET1*		20%	40%	60%	80%	100%	**100%**
Capital	Minimum Tier 1 Capital	4.5%	5.5%	6.0%				**6.0%**
Capital	Minimum Total Capital		8.0%					**8.0%**
Capital	Minimum Total Capital plus conservation buffer		8.0%		8.625%	9.25%	9.875%	**10.5%**
Capital	Capital instruments that no longer qualify as non-core Tier 1 capital or Tier 2 capital		Phased out over 10 year horizon beginning 2013					
Liquidity	Liquidity coverage ratio – minimum requirement			60%	70%	80%	90%	**100%**
Liquidity	Net stable funding ratio						Introduce minimum standard	

Source: The Basel Committee on Banking Supervision (n.d)

Appendix VIII: Table of the 61 biggest European banks

Rank	Bank	Country	Total Assets, US$b (December 31, 2016)
1	HSBC Holdings	UK	2,374.99
2	BNP Paribas	France	2,196.45
3	Credit Agricole Group	France	1,821.96
4	Deutsche Bank	Germany	1,682.05
5	Barclays PLC	UK	1,490.69
6	Societe Generale	France	1,461.76
7	Banco Santander	Spain	1,416.16
8	Groupe BPCE	France	1,306.30
9	Lloyds Banking Group	UK	1,004.91
10	Royal Bank of Scotland	UK	981.391
11	UBS Group AG	Switzerland	919.296
12	UniCredit S.p.A.	Italy	908.982
13	ING Group	Netherlands	893.698
14	Credit Suisse Group	Switzerland	806.050
15	Credit Mutuel Group *	France	782.370
16	BBVA	Spain	773.959
17	Intesa Sanpaolo	Italy	766.815
18	Rabobank Group	Netherlands	700.439
19	Nordea Bank	Sweden	651.078
20	Standard Chartered Plc	UK	646.692
21	European Investment Bank	Luxembourg	606.209
22	DZ Bank Group	Germany	538.706
23	KfW Group	Germany	536.168
24	Commerzbank AG	Germany	507.614
25	Danske Bank	Denmark	495.517
26	Cassa Depositi e Prestiti (CDP) **	Italy	445.897
27	Sberbank Rossii	Russia	420.417
28	ABN AMRO Group	Netherlands	417.176
29	CaixaBank	Spain	367.943
30	DNB Group	Norway	308.918
31	KBC Group NV	Belgium	291.032
32	Svenska Handelsbanken	Sweden	289.824
33	Skandinaviska Enskilda Banken	Sweden	289.060
34	Nationwide Building Society	UK	276.358
35	Landesbank Baden-Wurttemberg	Germany	257.635

36	La Banque Postale	France	242.785
37	Swedbank	Sweden	237.611
38	Dexia Group	Belgium	225.012
39	Banco Sabadell	Spain	224.734
40	Bayerische Landesbank	Germany	224.355
41	Erste Group Bank AG	Austria	220.206
42	Raiffeisen Schweiz	Switzerland	214.886
43	Bank VTB	Russia	208.572
44	Bankia	Spain	201.107
45	Nykredit Realkredit Group	Denmark	199.222
46	Belfius Bank	Belgium	186.888
47	Norddeutsche Landesbank (NORD/LB)	Germany	184.853
48	Banco Bpm SpA	Italy	177.935
49	Landesbank Hessen-Thuringen (Helaba)	Germany	174.704
50	BNG Bank	Netherlands	162.860
51	Banca Monte dei Paschi di Siena	Italy	161.942
52	Banco Popular Espanol	Spain	156.436
53	Zurich Cantonal Bank	Switzerland	155.329
54	NRW.Bank	Germany	150.275
55	RZB Group	Austria	142.605
56	OP Financial Group	Finland	141.441
57	Bank of Ireland	Ireland	130.213
58	UBI Banca	Italy	118.849
59	Allied Irish Banks (AIB)	Ireland	101.123
60	NWB Bank (Nederlandse Waterschapsbank NV)	Netherlands	99.846
61	Caixa Geral de Depositos	Portugal	98.929

Source: Banks around the world (2016)

Appendix IX: Remaining banks in the sample

Allied Irish Bank	BPCE	KBC
Banco Bilbao Vizcaya	CaixaBank	Kreditanstalt für Wiederaufbau
Banca Montei dei Paschi di Siena	Cassa Depositi e Prestiti	Landwirtschaftliche Rentenbank
Banco Popular Espanol	Commerzbank	Nationwide Building Society
Banco de Sabadell SA	Credit agricole	Nykredit Realkredit
Banco Santander	Credit Suisse	Rabobank
Bank Neederlandse gemeetnen	Danske Bank	Raiffeisen Bank International
Bank of Ireland	Deutsche Bank	Royal Bank of Scotland Group
Bankia SA	DZ Bank Deutsche Zentral-Genossen	Sberbank of Russia
Banque du crédit mutuel	Erste Group Bank	Société générale
Barclays	European Investment Bank	Standard Chartered
Belfius	HSBC Holdings PLC	Svenska Handelsbanken
BNP Paribas	Intesa Sanpaolo	Unione di Banche Italiane

Appendix X: List of European systemic banks

G-SIBs	Designated authority[1]	Competent authority[2]
BNP Paribas	Autorité de contrôle prudentiel et de résolution (ACPR)/ECB	ECB
Deutsche Bank	BAFIN/ECB	ECB
HSBC	Bank of England -Prudential Regulation Authority (PRA)	PRA
Barclays	PRA	PRA
BPCE	ACPR/ECB	ECB
Crédit Agricole	ACPR/ECB	ECB
ING Bank	De Nederlandsche Bank (DNB)/ECB	ECB
Nordea	Finansinspektionen (FI)	FI
Royal Bank of Scotland	PRA	PRA
Santander	Banco de Espana/ECB	ECB
Société Générale	ACPR/ECB	ECB
Standard Chartered	PRA	PRA
Unicredit Group	Banca d'Italia/ECB	ECB

Source: European Parliament (2017)

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Executive summary

Following the 2007 subprime crisis, interest rates dropped dramatically, making savings accounts look unattractive. Therefore, investors should consider acquiring risky assets if they expect moderate or high returns. The creditworthiness of risky assets should be examined wisely, in order to make sure risk are taken consciously. Due to the increasing complexity of financial instruments we observed in the last two decades, assessing a firm's creditworthiness with a large scope has become very difficult. For these reasons the relevance of credit rating agencies (CRAs) increased. Credit rating agencies assign an easy to interpret credit ratings to firms after having evaluated its creditworthiness. Credit ratings are displayed in the form of a letter grade. The letter A is assigned to the most creditworthy firms, while C is assigned to the least creditworthy firms.

This thesis presents the history of the CRA market, the importance of CRAs, what is known about the rating methodologies and why they started to be criticized in the recent years. One of the reasons presented is that CRAs use intransparent methodologies to compute credit ratings. Moody's Investors Service (2016) states that in order to compute a bank's credit rating, macro-economic features, individual financial characteristics and qualitative information are analyzed. In this paper, several financial and accounting characteristics of major European banks are analyzed in the empirical study. In order to make the computations, a sample composed of 32 of the 61 biggest European banks is used. Various calculations have been conducted to identify the influence of banks' financial characteristics on the credit ratings emitted by Moody's and Standard and Poor's (S&P), the two biggest CRAs.

The main results of the empirical research showed that non-performing loans and the return on equity had the biggest influence on the ratings emitted by Moody's and S&P. As the non-performing loans lowers the rating assigned to the banks, the return on equity has a positive impact on the credit ratings. In addition, computations indicated that by analyzing the non-performing loans and the tier 1 capital of a bank, Moody's and S&P's rating decision can be explained at 60%. This amount is decreasing, which may imply an increase in the importance of qualitative data in the rating decisions.

Key Words: Credit Rating Agencies - credit ratings - creditworthiness - Moody's - S&P - Financial characteristics - European banks