Aalto University
School of Business

Credit spread discrepancies between European rated and unrated corporate bonds

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Abstract of master's thesis

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OBJECTIVES OF THE STUDY

As the increasing regulation in the banking industry is pushing Europe towards more vivid capital markets, also an increasing portion of mid-cap companies without official credit ratings are extending their funding sources towards the bond markets. In this thesis, I study whether credit risk is equally well depicted in the prices of European unrated and rated bonds, or whether credit spread discrepancies between the two occur.

DATA AND METHODOLOGY

In the study, I calculate implied credit ratings for a sample of unrated bonds using three different credit risk models: a shadow rating model provided by Moody's, Altman's Z-Score and the Merton DD model. To assess the accuracy and biasedness of the three models, implied credit ratings are also calculated for a sample of rated bonds. On the basis of the assessment calculations, I conclude that the shadow rating model is unbiased in estimating implied credit ratings, whereas the Merton DD model is somewhat biased to estimate excessively high ratings. The Altman's Z-Score model is completely dismissed due to extremely high inconsistency in rating predictions. After assigning the unrated bonds an implied credit rating, I assess whether their credit spreads are comparatively equal to those of rated bonds with the same level of credit risk and other characteristics. For this, I use simple regression analysis, separately controlling for bond liquidity. The bond samples consist of 237 unrated and 594 rated bonds issued by European listed, non-financial companies during the time period ranging from January 2001 to December 2013.

FINDINGS OF THE STUDY

The results of the study indicate that the credit spreads of unrated bonds differ from those of rated bonds, i.e. credit risk is not equally accounted for in the prices of these bonds. Interestingly, the results also suggest that unrated bonds with high credit quality, i.e. high implied ratings, have larger credit spreads with regard to their rated counterparts than bonds with lower credit quality, i.e. low implied ratings, do with regard to theirs. In other words, the results imply that investors perceive unrated bonds with high credit quality to be relatively riskier than unrated bonds with low credit quality.

Keywords Credit risk, credit rating, credit spread, yield spread, unrated, corporate bond

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TUTKIELMAN TAVOITTEET

Euroopan joukkovelkakirjamarkkinat ovat kasvaneet viime vuosina merkittävästi, ja lisääntyneestä pankkiregulaatiosta johtuen myös pienemmät yhtiöt, joilla ei ole virallista luottoluokitusta, ovat laajentaneet rahoituslähteitään kyseisille markkinoille. Tutkin Pro gradu -tutkielmassani, onko luottoriski yhtäläisesti hinnoiteltu luottoluokiteltujen ja -luokittelemattomien joukkovelkakirjojen luottoriskipreemioihin.

DATA JA METODOLOGIA

Tutkielmassani lasken implisiittiset luottoluokitukset otokselle luokittelemattomia joukkovelkakirjoja kolmea eri luottoriskimallia käyttäen. Nämä mallit ovat Moody’sin varjoluokitusmalli, Altman Z-Score sekä Merton DD -malli. Arvioidakseni mallien toimivuutta luottoluokitusten arvioimisessa, lasken implisiittiset luottoluokitukset myös otokselle luokiteltuja joukkovelkakirjoja. Arvioinnin perusteella varjoluokitusmalli todetaan toimivaksi arvioimaan todellisia luottoluokituksia, kun taas Merton DD -malli arvioi luottoluokitukset hieman korkeammaksi kuin mitä ne ovat todellisuudessa. Altman Z-Score jätetään seuraavista tarkasteluista pois kokonaan suurista virhearvioista johtuen. Implisiittisten luottoluokitusten laskemisen jälkeen tarkastelen, ovatko luottoriskiprofiililtaan ja muilta ominaisuuksiltaan yhtäläisten luokittelemattomien ja luokiteltujen joukkovelkakirjojen luottoriskipreemiot yhtä suuret. Otokset koostuvat 237 luokittelemattomasta sekä 594 luokitellusta joukkovelkakirjasta, jotka ovat laskettu liikkeelle 2001 tammikuun ja 2013 joulukuun välisenä aikana eurooppalaisten, listattujen yhtiöiden toimesta. Liikkeeseenlaskijat eivät ole rahoitusalan yhtiöitä.

TUTKIELMAN TULOKSET

Tutkielman tulosten mukaan luokittelemattomien ja luokiteltujen joukkovelkakirjojen luottoriskipreemiot eroavat toisistaan, eli luottoriski ei ole yhtäläisellä tavalla hinnoiteltu luokiteltuihin ja luokittelemattomiin joukkovelkakirjoihin. Lisäksi, hyvän luottoriskiprofiilin omaavien luokittelemattomien joukkovelkakirjojen luottoriskipreemiot ovat suhteellisesti katsottuna korkeammat luokiteltuihin vastineisiinsa verrattuna, kuin matalan luottoriskiprofiilin omaavien joukkovelkakirjojen luottoriskipreemiot niiden luokiteltuihin vastineisiin verrattuna. Toisin sanoen, tutkimustulosten mukaan sijoittajat mieltävät hyvän luottoriskiprofiilin omaavat luokittelemattomat yhtiöt suhteellisesti katsottuna korkeariskisemmiksi kuin huonon luottoriskiprofiilin omaavat luokittelemattomat yhtiöt.

Keywords Luottoriski, luottoluokitus, luottoriskipreemio, luokittelematon, joukkovelkakirja

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1. Introduction

The European corporate bond market has grown substantially during the past decades. Van Landschoot (2004) reports that the number and market value of Euro-denominated corporate bonds more than doubled during the years between 1993 and 2003, with especially the A and BBB rated segment growing substantially to account for nearly half of individual bond issues outstanding at the time of writing. In recent years, the increasing regulation in the banking industry has been pushing Europe towards even more vivid capital markets and away from the traditional reliance on bank financing. With Basel III Accord and Solvency II to be implemented in the near future, bank financing can be expected to become more expensive as well as its terms and conditions more restrictive, causing corporates to seek an increasingly large portion of their debt financing through the capital markets[1]. Further, a growing number of mid-cap companies often without an official credit rating by one of the major credit rating agencies are extending their funding sources towards the bond markets, while traditionally bonds have mostly been issued by large rated companies.

As a result of the increasing activity in the European bond markets, the understanding of credit risk has become essential. Numerous research papers have addressed questions regarding credit risk measurement (see Altman and Saunders, 1998, for a comprehensive review on the developments of credit risk measurement) as well as specific credit spread determinants (e.g. Elton et al., 2001; Collin-Dufresne et al., 2001). The credit rating industry naturally also plays an important role in this part of the capital markets, and has thus also been subject to vast economic research. A number of papers have studied, for example, the role, information value and security pricing effects of credit ratings (see, e.g., Hand et al., 1992; Liu et al., 1993; Liu and Moore, 1999; and Kliger and Sarig, 2000).

The amount of bonds and other securities outstanding that do not have official credit ratings already make up a sizeable portion of the European capital markets. According to the Financial Times, there was USD 58 billion worth of unrated bond sales in 2013, and issuance has continued at roughly the same pace in 2014[2]. Generally speaking, unrated bond issues have reportedly accounted for around 10 % of the European bond market in recent years. Although credit risk has been an extensively studied topic for some time now, this unrated

[1]See: Why Basel III And Solvency II Will Hurt Corporate Borrowing In Europe More Than In The U.S. A report published by Standard and Poor’s, September 11. 2011

[2] ”’Dash for trash’ lifts unrated debt sales”, Financial Times, May 19, 2014

part of the markets has been somewhat neglected in economic literature discussing credit risk, credit ratings and securities pricing. As the European bond markets are constantly growing, and the credit risk of unrated securities is arguably not as straightforward for investors to assess, it is of interest to study how credit risk is accounted for in the prices of these unrated securities. This thesis aims to shed light on whether credit risk is similarly priced in European unrated bond issues as it is in rated issues, or if pricing (i.e. credit spread) discrepancies occur. Effectively, this paper also addresses the question of what the effects of lacking a credit rating are for a company and its bonds.

In the study, I utilize three models with different theoretical underpinnings to measure the credit risk of a sample of unrated bonds. These credit risk measurements are then used to map the unrated bonds into implied credit rating classes. The motivation for using three alternate models is to find one that is as unbiased in the credit risk estimations as possible. That is, the study aims to utilize a credit risk model that is able to map the unrated bonds as correctly as possible into the credit rating classes they would belong to if they had official credit ratings. Thus, in order to assess the accuracy of the conducted credit risk measurements and credit rating mappings, the same calculations are performed for a sample of rated bonds. After mapping the unrated bond issues into implied credit rating classes, I assess whether their credit spreads are comparatively equal to those of rated bonds with corresponding levels of credit risk, i.e. credit ratings, and otherwise similar characteristics. If credit risk is equally well accounted for in the prices of both rated and unrated bonds, and other relevant factors affecting credit spreads are controlled for, then theoretically the credit spreads of these two bond categories should not differ from each other. If, on the other hand, credit risk is not priced in an equal manner in unrated and rated bond issues, systematic yield spread differences will occur.

The structure of the study is as follows. Section 2 elaborates on the definition of credit risk as well as the determinants of credit spreads to lay a theoretical ground for the study. Section 3 introduces credit risk measurement on a general level and discusses the special role of credit ratings in the bond markets. In Section 4, the credit risk measurement models used in this thesis are presented in more detail. Section 5 provides a description of the data used for the study, and in Section 6 the study's results and their implications are discussed. Section 7 concludes.

2. Credit risk

The value of a particular issue of corporate debt depends essentially on three factors: 1) the required return on riskless debt, 2) the various provisions and restrictions of the bond (e.g. maturity, coupons, seniority in the event of default, call terms, sinking funds etc.) and 3) the probability that the firm will be unable to satisfy some or all of the bond indenture requirements, i.e. the probability of default (Merton, 1974). The third factor, namely the probability of default, is often viewed as the main determinant of credit risk. In fact, some even define credit risk as default risk alone. Duffie and Singleton (2003), for example, define credit risk to be the risk of default or the risk of reductions in market value caused by changes in the credit quality of issuers or counterparties. In line with the latter part of the this definition, Fabbozzi (2000) suggests that investors are in fact more concerned with the changes in perceived default risk, i.e. changes in the yield spreads demanded by investors for a given level of default risk, and/or the costs associated with a given level of default risk, than with the actual event of default. Fabozzi (2000) specifies the reason for this to be that the change in perceived default risk, i.e. in demanded yield spreads, can have an immediate effect on the value of the bond, even though the actual default event may be highly unlikely. As the spreads investors demand for investing in bond issues are the key ingredient of study when examining credit risk as well as the pricing behavior of investors in the bond markets, their determinants are elaborated on in more detail below.

2.1 Credit spreads

The market value of credit risk is often measured as the yield spread between a credit-risky instrument and an otherwise identical Treasury (risk-free) security. As this yield spread is indeed in large part due to the credit risk of corporate bonds, it is often referred to as the credit spread, and can be thought of as the compensation to investors for bearing the risks inherent in corporate bond issues. (Sundaresan, 2002)

Much of the research conducted on corporate bond pricing and credit spreads is based on so-called structural or contingent-claim models, initiated by Black & Scholes (1973) and Merton (1974). Structural models relate default events (credit risk) to the issuing firm's asset value and capital structure in an intuitively simple manner: default occurs if the firm's asset value falls below the firm's debt value. Thus, structural models also provide a meaningful way to assess what affects the price of credit risk, and define corporate yield spreads to be determined by the following factors: the prevailing spot rate and slope of the yield curve, the value and volatility of the issuer company's assets, the possibility of downward jumps, as well as the prevalent business climate. These determinants are described in more detail under Section 2.2.

Although the credit spread determinants of structural models are widely acknowledged by academics, research has found that various other factors are also likely to explain credit spreads (see, e.g., Collin-Dufresne et al., 2001). For example, bond liquidity, taxes and risk premia for systematic risk have also been suggested to account for variations in credit spreads. Also these determinants are elaborated on in Section 2.3.

2.2 Structural determinants of credit spreads

Structural models commonly identify six key determinants affecting the probability of default and thus credit spreads. These determinants are presented below.

Spot rate

A negative relation between credit spreads and the spot rate, i.e. the prevailing risk-free rate, has been found to persist for corporate bonds (Collin-Dufresne et al., 2001; Van Lanschoot, 2004). The logic behind this negative relation is that an increase in the spot rate suggests an increase in the expected growth rate of a firm's asset value. In the structural framework, a higher growth rate reduces the probability that the value of a firm's assets will fall below the value of its liabilities, meaning a lower probability of default. A lower default probability again implies that investors will demand lower credit spreads for investing in the firm's bonds (Longstaff and Schwartz, 1995). Put the other way around, a low spot rate implies a low growth rate of assets, which means that there is a higher probability that the value of a firm's assets will fall below the value of its debt. Again, this implies a higher probability of default and thus higher credit spreads.

Furthermore, as Van Landschoot (2004) points out, low interest rates are often associated with a weakening economy. A negative outlook for the economy translates into lower risk-appetite in the capital markets, meaning that higher spreads are demanded to compensate for credit risk. Also, studies suggest that the sensitivity to the spot rates varies with bond characteristics. For example, Collin-Dufresne et al. (2001) find that the sensitivity to interest rates is higher for lower rated bonds, which means that high-risk bonds react to changes in the spot rate more aggressively than low-risk bonds. In addition, Van Landschoot (2004) reports that the significance of the spot rate as a credit spread determinant depends on the maturity of the bond, first increasing and then slightly decreasing with maturity.

Slope of the yield curve

As, for example, Litterman and Scheinkman (1991) report, most variations in the term structure of interest rates, i.e. the yield curve, are driven by the level and slope of the yield curve. If an increase in the slope of the yield curve implies an increase in the expected short rate, then the same argument as in the section above advocates a decrease in credit spreads. That is, a higher short rate implies a higher asset growth rate, which translates to lower default risk and lower credit spreads. Furthermore, the slope of the yield curve is often linked to future business cycle conditions. An increase in the slope is then considered to be an indication of a strengthening economy, implying lower default rates and lower credit spreads (Van Lanschoot, 2004).

Mixed results on the significance of the slope of the yield curve as a credit spread determinant are reported. Van Landschoot (2004) studies the European bond market, and reports the slope of the yield curve to be an important determinant of credit spreads. Collin-Dufresne et al. (2001) study the US bond market and gather contradictory findings, reporting that the slope of the term structure is not of large significance when determining credit spreads.

Asset value / Leverage

As previously mentioned, in the framework of structural models, default is triggered if a firm's asset value falls below the value of its debt. This means that firms with asset values high above debt values, in other words firms with low leverage ratios, are less likely to default. Lower leverage ratios thus imply lower credit spreads, which is quite intuitive. Collin-Dufresne et al. (2001) report that leverage is a significant factor in determining credit spreads, and that the sensitivity of credit spreads to changes in the leverage ratio tends to increase with leverage. That is, the higher the value of debt with regard to the value of assets, the more sensitive credit spreads are to changes in leverage. Furthermore, Van Landschoot (2004) reports that changes in asset value have a stronger effect on bonds with a short term to maturity. The credit spreads of bonds with less time to repayment are thus more sensitive to changes in the leverage ratio.

Asset volatility & downward jump

In the structural framework, equity is viewed as a call option on a firm's assets with a strike price equal to the value of its debt. The logic here is that due to the limited liability feature of equity, equity holders have the right, but not the obligation, to pay off the firm's debt holders and take over the remaining assets of the firm[3]. This means that if the value of the firm's assets is less than the value of its debt, i.e. the strike price, the call option will not be exercised and default will occur. With put-call parity, debt claims can then be viewed as containing a short position on a put option on the firm's assets. As option value increases with volatility, it follows that credit spreads should increase with volatility (Collin-Dufresne et al., 2001). This relationship is quite intuitive. As Van Landschoot (2004) points out, higher asset volatility corresponds to a higher likelihood that a firm's asset value will fall below the value of its debt, i.e. that the firm will default with a higher likelihood. Again, this translates to higher credit spreads. Both Collin-Dufresne et al. (2001) and Van Landschoot (2004) find that the effect of volatility is significant in determining credit spreads, but clearly asymmetric: increases in implied volatility strongly affect credit spreads, whereas decreases do not.

Following the logic of asset volatility indicating higher credit spreads, increases in either the probability or the magnitude of a downward jump in asset value should also increase credit spreads. This is supported by Collin-Dufresne et al. (2001), who report that an increase in the markets' expected probability of a downward jump triggers an increase in credit spreads homogenously across bond groups.

Business climate

Many structural models consider the so-called recovery rate to be a partial explanation as to why credit spreads exist. The recovery rate can be defined as the portion of promised payments the bondholder receives in the event of default (see, e.g., Collin-Dufresne et al., 2001). Collin-Dufresne et al. (2001) suggest that even if a firm's probability of default remains constant, changes in credit spreads can occur due to changes in the expected recovery rate, which in turn should be a function of the overall business climate. When the business climate is good, recovery rates should be comparatively better and credit spreads smaller. This relation is confirmed to prevail by the results of their study.

[3] The framework of structural models is discussed in more detail in Section 4.3.

2.3 Other determinants of credit spreads

Although structural models are widely used in credit spread estimations, it has been recognized that the credit risk determinants of structural models only explain a part of the observed credit spreads. For example, Collin-Dufresne et al. (2001) find that the traditional factors of structural models presented under Section 2.2 only explain about 25 % of the variation in credit spreads. Also Elton et al. (2001) conclude that default risk accounts for no more than 25 % of credit spreads. The remaining fraction of credit spreads has been suggested to be the result of factors related to liquidity, taxes and systematic risk. These factors are introduced in more detail below.

Liquidity

Amihud and Mendelson (1986) suggest that investors aim at maximizing expected returns net of transaction or liquidity costs, with the bid-ask spread being a natural measure of these costs. High liquidity implies that bonds are traded frequently and easily, which implies lower bid-ask spreads. Low liquidity, on the other hand, implies that the bond is not as easily tradable, resulting in higher bid-ask spreads. Also Van Landschoot (2004) suggests that investors are only willing to invest in less liquid assets compared to similar liquid assets at a higher premium. Van Landschoot (2004) argues that, as government bond markets are larger and more liquid than corporate bond markets, investors may expect some compensation for the lower liquidity when investing in corporate bonds.

Chen et al. (2007) use three alternate proxy measures for liquidity risk and find a significant association between liquidity and bond yield spreads. The authors conclude that liquidity alone can explain as much as 7 % of the cross-sectional variation in bond yields for investment grade bonds, and as much as 22 % for speculative grade bonds. Also Van Lanschoot (2004) reports the level of liquidity, measured as the bid-ask spread, to be a significant determinant of credit spread changes on bonds of all rating categories considered in the study.

Taxes

Elton et al. (2001) suggest differences between corporate and government bond taxation to be one of the main reasons for why the demanded spreads for these two bond classes differ. Elton et al. (2001) claim that, as corporate bonds are subject to state and local taxes on interest payments in the US, whereas government bonds are not, corporate bonds have to offer a higher pre-tax return to yield the same after-tax return. The results of the study indicate that taxes account for an even larger portion of the spreads between corporate and treasury bonds than do expected default losses. Of course, these results do not directly imply taxes to be a determinant of credit spreads in the European bond market. Furthermore, taxes most likely cannot explain possible differences in the credit spreads of different corporate bonds.

Systematic risk

Elton et al. (2001) advocate that if corporate bond returns vary systematically with other assets in the market, whereas government bonds, which are often perceived risk-free, do not, then corporate bonds should carry a risk premium to compensate for the non-diversifiable risk, just like any other asset. The study concludes that as much as 85 % of credit spreads not accounted for by taxes and expected default losses can be explained by systematic risk premia. Elton et al. (2001) state this risk premium to be affected by the same influences that affect systematic risks in the stock market.

3. Measuring credit risk

Credit risk measurement has been a popular topic of research for decades, and a large variety of measurement methods and models have been developed. This section introduces three key classes of credit risk measurement prevalent in academic literature: 1) accounting based credit scoring models, 2) structural credit risk models and 3) reduced form models. After these introductions, the special role of credit ratings in credit risk measurement is discussed by elaborating on the information value of credit ratings and the effect that credit ratings have been suggested to have on the pricing of corporate bonds. The credit risk measurement models utilized in this study, i.e. the shadow rating model, the Altman's Z-Score model and the Merton DD-model, are discussed in more detail in Section 4.

3.1 General classes for credit risk measurement

Measuring a company's default risk is a central problem of credit risk analysis, and various approaches to modeling default probabilities have been pursued. One of the main classes of credit risk measurement are so-called multivariate accounting based credit scoring models, in which key accounting variables are combined and weighted to produce either a credit risk score or a probability of default (Altman and Saunders, 1998). Altman and

Saunders (1998) list four methodological approaches to developing multivariate credit-scoring models: 1) the linear probability model, 2) the logit model, 3) the probit model and 4) the discriminant analysis model. According to the abovementioned authors, the by far most commonly used approach is the fourth one, which uses discriminant analysis as a statistical technique. Discriminant analysis models seek to find a linear function of accounting (and sometimes market) variables that best distinguishes between two classes: default and no default. The pioneering and arguably most recognized model of this kind is the Altman‘s Z-Score, which is also used for credit risk measurement in this thesis, and is thus elaborated on more closely in Section 4.

While multivariate accounting based credit-scoring models have been shown to perform quite well in assessing the probability of default, they have been subject to at least three key kinds of criticism. First, book value accounting data fails to pick up more subtle and fast-moving factors affecting bond issuers and their credit risk. These kinds of factors are much more efficiently picked up by market variables. Thus, the prediction power and accuracy of book value based credit risk models is limited by definition. The second set of criticism relates to the fact that multivariate accounting based models are often based on an assumption of linearity. The real world is, however, by no means linear. Thus, multivariate accounting based models are not able to forecast default as accurately as models that relax the linearity assumption among explanatory variables. The third set of criticism often targeted at these models is that they are often only tenuously linked to any theoretical underpinnings, for example when choosing which variables to include in the model. This has in part led to the development of other more theory based approaches to estimating the probability of default. (Altman and Saunders, 1998)

One class of default prediction models with stronger theoretical underpinnings are so-called structural models, introduced partly already under Section 2.1. In structural models, an issuer’s inability to pay is explicitly modeled as the default-triggering event, which means that it can be predicted. Structural models are often also referred to as market based models, as they incorporate market based variables, such as the market value of equity and the market value of leverage, into the default estimations. One key model belonging to this category is the classic structural model of Merton (1974), in which default occurs at the maturity date of debt in the event that the value of the issuer’s assets is less than the face value of its debt (Duffie and Singleton, 2003). In this model, equity is viewed as a call option on the issuer’s assets, which links the prediction of default to the option pricing theory of Black and Scholes

(1973). The classic Merton model has been extended in a number of ways.[4] One innovative and widely acknowledged model used by both academics and practitioners is the Moody's KMV model (also known as the Vasicek-Kealhofer / VK model or the Expected-Default-Frequency / EDF model). The Moody's KMV model was originally developed by the KMV Corporation, which was later on acquired by Moody's (see, e.g., Bharath and Shumway, 2008). The Moody's KMV model builds on insights collected from modifications to the classical Merton model applied by various research papers. Also, the model uses an empirically constructed distribution of distance-to-default, i.e. the number of standard deviations the firm is away from default, to generate an Expected Default Frequency credit risk measure, instead of using the normal distribution (Arora et al., 2005). The distance-to-default distribution is only in Moody's proprietary use, which means that practitioners often use a simpler variant of the Moody's KMV model in default estimations. A variant of the model is also used in this thesis, and will thus be discussed in more detail under Section 4.

A third broad category of default prediction models are so called reduced-form models. In contrast to structural models, the reduced-form approach does not attempt to model the asset value and capital structure of the issuer. Instead, reduced-form models treat default as an unexpected event, the likelihood of which depends on a default intensity (or hazard rate) process (Duffie and Singleton, 2003; Van Landschoot, 2004). Mathematically, these models are more adaptable, which means that they are more suitable for, for example, credit derivatives pricing (Van Landschoot, 2004).[5] However, Arora et al. (2005) comment that this flexibility may result in reduced-form models with strong in-sample fitting properties, but poor out-of-sample predictive ability. Furthermore, reduced-form models represent a characterization of default risk that is generally less grounded in the economics driving default, and more in mathematical tractability, which makes it more challenging to diagnose how model performance could be improved (Arora et al., 2005). As reduced-form models are mathematically quite complex and often intuitively less informative, the models were not considered suitable for the purposes of this thesis.

[4] See Arora et al. (2005) for a brief summary of these various extensions.
[5] See Arora et al. (2005) for a more thorough comparison of reduced form and structural models.

3.2 Credit ratings

As Fabozzi (2001) points out, few individual investors and institutional bond investors rely solely on their own credit analysis to estimate the ability of bond issuers living up to their future contractual obligations. Instead, investors utilize public credit ratings produced by commercial rating companies, such as Moody's, Standard & Poor's and Fitch, to assess a bond's attractiveness. Standard & Poor's (2012) define an issue credit rating to be "a forward-looking opinion about the creditworthiness of an obligor with respect to a specific financial obligation, a specific class of financial obligations, or a specific financial program", and emphasize the likelihood of default, encompassing both the capacity and willingness to pay, to be the single most important factor in their assessment of the creditworthiness of an issuer or an obligation. Although credit ratings are in fact just opinions issued by commercial companies, investors often rely on them to incorporate practically all relevant information on a bond issuer's or issue's risk profile, and thus perceive credit ratings to be comprehensive measures of credit risk. Virtually all public corporate bond issues in the U.S. have been assigned a credit rating by at least one of the major credit rating agencies, which highlights the credit rating industry's importance in the financial markets. Additionally, many institutional investors have placed restrictions on ratings classes in which they are allowed to invest in, as well as on the size of their allocations in each ratings class. This feature of pegging investment decisions to official credit ratings adds to the important role credit ratings have in today's capital markets, and will be discussed in more detail in the chapters below.

Numerous papers in economic literature have studied the value credit ratings incorporate and provide to investors in the capital markets. A common question under dispute is whether credit ratings encompass incremental information with regard to public bond issuer information available from other sources, and whether they thus can independently affect security prices or not. Research reports somewhat mixed results. Amongst others, Katz (1974), Hand et al. (1992) and Ingram et al. (1983) study the effects credit rating changes have on securities prices, and find significant price adjustments following ratings change announcements. This supports the argument of credit ratings having an independent effect on investors' pricing behavior. Weinstein (1977), on the other hand, has the same idea of study, and finds no evidence of price reactions as a result of announcements on rating changes, providing contradictory support. Ederington et al. (1987) examine whether bond yields are related to rating information and conclude, not surprisingly, that they are. However, the authors also find that market yields vary with ratings independently of the financial accounting variables considered in the study, and conclude that ratings must thus incorporate non-public, price-sensitive information. Additionally, studying the price effects of Moody's rating refinement (in which the number modifiers 1, 2 and 3 were added to the original rating symbols Aaa, Aa…D), Kliger and Sarig (2000) as well as Liu et al. (1999) find that bond prices adjust to the implications provided by the new modifiers. The rating refinement studies arguably enable an even better measurement of the informational content of ratings than the other aforementioned studies, as the actual credit quality of the companies remained completely unchanged during the refinement announcement. This makes the results of the studies increasingly plausible, and leads the aforementioned authors to conclude that credit ratings must incorporate incremental pricing relevant information. Furthermore, Kliger and Sarig (2000) argue that the reason that companies are willing to pay for official credit ratings is that they are able to incorporate valuable inside information into the ratings without fully disclosing any underlying details to the public.

Boot et al. (2006), on the other hand, argue that credit ratings derive their value primarily from two institutional features: the monitoring role of credit rating agencies, depicted in principle by their credit watch procedures, and the role credit ratings play in the investment decisions of institutional investors. Regarding the first feature, if market and/or company developments threaten to deteriorate the credit rating of a company, the credit rating agency takes action and puts the company on credit watch. In the credit watch procedure, the credit rating agency enters an implicit contract with the rated company, in which the company promises to undertake specific actions to mitigate the possible deterioration of its credit rating. The procedure thus adds value to investors, as credit rating agencies act as outside overseers of a company's performance, and give it concrete incentives to prevent its credit quality from sinking.

The second value adding institutional feature of Boot et al. (2006) relates to the fact that many institutional investors often stipulate that investments are only allowed in issues with an investment grade rating, which effectively conditions investors' investment decisions on the assigned ratings. The authors show that if a sizeable proportion of institutional investors (such as pension funds) base investment decisions on credit ratings, other investors will rationally follow. As a result, the authors argue that credit ratings serve as problem solvers for situations where multiple equilibria situations regarding required rates of return could arise. If investors anticipate a high-risk investment, they will demand a high premium, and vice versa if they anticipate a low-risk investment. When confronted with a high funding cost, a company is induced to choose a high-risk project as opposed to a low-risk one, as it is forced to pay the higher cost in either case. As the authors suggest, however, if the majority of investors rationally follow the sizeable proportion of institutional investors using credit ratings to determine required returns, these multiple equilibria situations will not arise. Investors will perceive the firm’s investment to be as risky as its assigned rating implies. The study by Boot et al. (2006) thus implies that for unrated bond issues, it is more likely that multiple equilibria situations will arise, which could cause larger variations in demanded rates of return, i.e. credit spreads.

The conditioning of investment decisions on assigned ratings discussed in Boot et al. (2006) relates closely to what is known as credit rating migration risk. Changes in credit ratings may lead to certain bonds no longer being acceptable in the bond portfolios of investors subject to rating restrictions, such as those of many institutional investors, and may thus even lead to mandatory termination of financial contracts. Changes in credit ratings can also have an effect on many other factors, such as the coupons of so called step-up bonds, where coupons are dependent on explicit ratings, as well as rating based regulatory capital for banks and credit derivatives, which sometimes have provisions for contingent payments based on credit ratings. As a result, specific models for measuring the credit rating migration risk have been developed. (Duffie and Singleton, 2003) Also rating agencies themselves produce information about the probabilities of a firm migrating from one rating category to another (Sundaresan, 2002).

The factors discussed above demonstrate how widely credit ratings are used in the capital markets, and how they can thus affect the demand and prices of securities. This makes studying the unrated bond market increasingly interesting. If credit ratings in fact have an independent effect on the prices of bonds, and/or if credit ratings are able to provide value through the monitoring role of credit rating agencies and the investment decisions of institutional investors, it is intuitive to expect the pricing of unrated bond issues to differ from that of rated bonds. What makes this pricing discrepancy even more likely is the fact that unrated bond issues often automatically fall into the speculative grade category, even if their credit quality would actually be of investment grade. If an unrated bond with good credit quality, for example an implied rating level Aa, automatically falls into the speculative grade category, one could expect its bond’s credit spread to be higher than what would be advocated by its actual credit risk. This again raises the question of why a company would rather choose to be unrated rather than acquire an official rating, if being unrated negatively affects the value of its bonds. Reuters reports Fitch Ratings to have stated in a special report that credit quality is unlikely to be the key driver for the lack of assigned ratings, i.e. the reason for choosing to remain unrated is not that the company would be assigned a low quality rating if they acquired one. This is for example depicted by the choices of strong unrated issuers; among the largest unrated companies are prominent names such as Neste Oil, Finnair and SAP AG[6]. Rather, it has been suggested that the companies that choose to issue unrated bonds tend to be ones that do not issue bonds that often and, therefore, do not want to go through the workload and costs of getting and maintaining a credit rating for infrequent borrowing.[7] That is, companies assess the costs of acquiring credit ratings to overweigh the benefits provided by them.

4. Credit risk measurement models

This thesis studies the role of credit risk in the pricing of European bonds without official credit ratings. In the study, possible credit spread discrepancies between rated and unrated bonds with similar credit risk levels and other characteristics are measured. The idea behind the study is that if credit risk is equally well accounted for in the prices of both unrated and rated bond issues, and possessing a credit rating does not in itself affect the credit spreads of bonds, then no significant credit spread differences should occur. Of course, this assumption is made given that other relevant factors affecting the level of credit spreads, like the business climate around the time of issuance, are also accounted for. In order to be able to compare the credit spreads of these unrated and rated bonds with similar credit risk profiles, a method for measuring the credit risk of unrated bonds and mapping them to implied rating classes is needed. As discussed in Section 3 above, numerous methods for credit risk measurement have been developed, which differ both in the explanatory variables included in the model and the mathematical / statistical methods used in the calculations. In order to make the results of this thesis more viable as well as informative, three different models with somewhat different theoretical underpinnings are tested. The goal with estimating credit risk with three alternate models is to find a model that is able to map the bond into its implied rating category in a way that is as unbiased as possible. That is, the aim is to map the unrated bonds into the rating classes that they would actually belong to if they had official ratings. To examine the unbiasedness of the models, the credit risk calculations are also performed for a sample of

[6] "RPT-Fitch: Unrated corporate bond issuance in EMEA", www.reuters.com, Jul 31, 2013.
[7] "'Dash for trash' lifts unrated debt sales", Financial Times, May 19, 2014

bonds that have official credit ratings. For these bonds, the implied ratings and official ratings are then compared and the accuracy of the estimations is assessed.

The three models chosen for the study are presented below. The first of the models provides a credit risk estimate, i.e. an implied credit rating, which is directly comparable to official credit ratings. The other two models produce default probability estimates, which are converted into implied credit ratings using a historical cumulative default rate distribution provided by Moody's. Details on the default distribution can be found in Appendix 2.

4.1 Shadow credit ratings

The value and implications of credit ratings discussed in Section 3.2 highlight how widely credit ratings affect today's capital markets. They also bring about the question of what the effects of lacking a credit rating are for companies and their individual bond issues. If credit ratings in fact affect securities pricing, then it simply follows that securities lacking a credit rating should be priced differently, all else equal. This is one of the prime motivations behind this thesis, and explains why shadow, or reference, credit ratings were chosen as one of the three models for measuring credit risk.

Shadow credit ratings aim at measuring credit risk in a very similar manner to how credit rating agencies themselves do with official credit ratings. As simple measures credit risk, proprietary shadow ratings are also applied widely in practice. For example, on the sales side, investment banks often produce shadow credit ratings to give their clients a proprietary opinion on a bond issue's credit profile. On the debt origination side, on the other hand, investment banks use shadow credit ratings for estimating the spreads that will be demanded by investors when new bonds are issued. In this study, shadow ratings are derived for each bond issue in the study sample by using a credit rating grid for global manufacturing companies published by Moody's Investors Service (2010). The grid is a simplified version of one of Moody's own credit rating methodologies, and includes factors which Moody's states to be generally most important in assigning ratings to industrial companies. The shadow rating model thus provides an intuitive way of measuring an unrated bond issue's credit risk, and is easily comparable to rated bonds. However, as pointed out by Moody's, the grid does not incorporate all rating considerations that Moody's official credit ratings do. Thus, the calculated implied credit rating is not expected to perfectly match the actual rating each company would have. As pointed out previously, shadow ratings are also calculated for a sample of rated bonds to assess the accuracy of the calculated grid-indicated ratings.

Moody's provides specific credit rating grids for a vast variety of industry types, ranging from telecommunications to auto leasing. The global manufacturing grid was chosen here as it is the most general of the models, and concentrates on firm-specific quantitative information that is available and applicable across most industries. The grid officially also includes a set of qualitative variables, but due to limited availability of qualitative data, only quantitative variables are included in this study. Although dismissing the qualitative factors admittedly makes the rating process less accurate, it also makes the incorporation of a larger sample of companies into the research possible. This improves the informational value of the research results as a whole. Additionally, it is not uncommon for rating agencies themselves to make use of credit scoring models that only concentrate on quantitative data.

When stripped of its qualitative factors, the global manufacturing rating grid examines a company's credit risk profile on three main dimensions: 1) size and profitability, 2) financial policy and 3) financial strength. These factors are further divided into nine sub-factors, which are weighted according to their importance, as determined by Moody's, in producing accurate credit risk estimates.[8] Table 1 depicts all of the rating factors considered as well as their individual weightings.

[8] The qualitative factors stripped were related to business profile, the sub-categories being product diversity and regional diversity. The total weighting of qualitative factors was 20%.

Table 1: Grid rating factors

The table depicts the specific rating factors and their weightings used to calculate implied credit ratings for the sample bonds using the shadow rating model. The factors are based on Moody's grid for the global manufacturing industry. The grid contains three key factors (situated on the left side of the table), which are divided into nine sub-factors (situated in the middle of the table). The right hand's side of the table depicts the factor weightings. Qualitative business profile factors, which the original grid incorporates, are not included in the study.

Rating Factor	Factor Weighting		Relevant Sub-factor	Sub-factor Weighting
1.) Size and Profitablility	37,50 %	a)	Revenues	18,75 %
		b)	EBITA	12,50 %
		c)	Return on Average Assets (ROAA)	6,25 %
2.) Financial Policy	18,75 %	a)	Debt / Book Capital	6,25 %
		b)	Gross Debt / EBITDA	12,50 %
3.) Financial Strength	43,75 %	a)	EBITA / Interest Expense	18,75 %
		b)	Funds from Operations (FFO) / Gross Debt	12,50 %
		c)	Funds from Operations (FFO) Less Dividends / Net Debt	6,25 %
		d)	Free Cash Flow (FCF) / Gross Debt	6,25 %
Total	100,00 %			100,00 %

All factor estimates for the individual bonds are measured using averages for the past three fiscal years prior to bond issuance, except for revenues for which the most recent annual figure is used. More detailed information on calculating the rating factors can be found in Appendix 1. After measuring the rating factor estimates, the outcomes are mapped to a set of numerical values ranging from 1 to 21. The numerical values each represent one of the alphanumerical ratings in Moody's rating category (Aaa, Aa, A, Baa, Ba, B, Caa, Ca). The higher the numerical value of the sub-factor estimate, the lower the implied rating category is for that specific factor estimate. Table 2 illustrates the mapping procedure.

Table 2: Mapping the outcomes of grid sub-categories

The table illustrates how the potential outcomes for all nine sub-categories used to calculate an implied credit rating for the sample bonds are mapped into a specific rating category (first row of table), and then converted into a numerical value to calculate the overall rating score (second row of table).

Global Manufacturing Grid

	Implied Rating	Aaa	Aa	A	Baa	Ba	B	Caa	Ca
	Score	1	3	6	9	12	15	18	21
Size and profitability	Revenues	> 24 940	12 470 - 24 940	4 157 - 12 470	1 663 - 4157	831 - 1 663	416 - 831	208 - 416	< 208
	EBITA	> 2 494	1 870 - 2 494	1 247 - 1 870	831 - 1 247	208 - 831	0 - 208	-83 - 0	< -83
	ROAA	> 25%	20% - 25%	15% - 20%	10% - 15%	5% - 10%	2% - 5%	0% - 2%	< 0%
Financial policy	Debt / Book capital	< 10%	10% - 20%	20% - 35%	35% - 50%	50% - 60%	60% - 70%	70% - 80%	> 80%
	Gross debt / EBITDA	< 0.5x	0.5x - 1.0x	1.0x - 2.0x	2.0x - 3.0x	3.0x - 4.5x	4.5x - 6.0x	6.0x - 7.5x	> 7.5x
Financial strength	EBITA / Interest expense	> 13x	10x - 13x	7x - 10x	4x - 7x	3x - 4x	2x - 3x	1x - 2x	< 1x
	FFO / Gross debt	> 100%	80% - 100%	50 % - 80%	25% - 50%	15% - 25%	5% - 15%	0% - 5%	< 0%
	FFO less div / Net debt	> 60%	45% - 60%	30% - 45%	20% - 30%	10% - 20%	5% - 10%	0% - 5%	< 0%
	FCF / Gross debt	> 40%	30% - 40%	20% - 30%	10% - 20%	5% - 10%	0% - 5%	-5% - 0%	< -5%

The total rating score of the bond is then obtained by adding up each sub-category score multiplied by its weight (see weights from Table 1). Lastly, the final implied rating is obtained by mapping the total rating score back to an alphanumeric rating based on Table 3.

Table 3: Mapping the total rating scores

The table describes how the total rating scores obtained for the bond samples are mapped to an alphanumeric rating.

Grid-Indicated Rating	Weighted Total Rating Score
Aaa	x < 1.5
Aa1	1.5 ≤ x < 2.5
Aa2	2.5 ≤ x < 3.5
Aa3	3.5 ≤ x < 4.5
A1	4.5 ≤ x < 5.5
A2	5.5 < x ≤ 6.5
A3	6.5 ≤ x < 7.5
Baa1	7.5 ≤ x < 8.5
Baa2	8.5 ≤ x < 9.5
Baa3	9.5 ≤ x < 10.5
Ba1	10.5 ≤ x < 11.5
Ba2	11.5 ≤ x < 12.5
Ba3	12.5. ≤ x < 13.5
B1	13.5 ≤ x < 14.5
B2	14.5 ≤ x < 15.5
B3	15.5 ≤ x < 16.5
Caa1	16.5 ≤ x < 17.5
Caa2	17.5 ≤ x < 18.5
Caa3	18.5 ≤ x < 19.5
Ca	x ≥ 19.5

Although consisting of many different measuring and mapping phases, the shadow rating process is ultimately quite simple: value-weighted financial ratios are combined to produce a credit risk score, which is mapped to an implied credit rating. The deficiency of the model is that Moody's does not provide detailed explanations for how, for example, the factor weightings or the individual sub-factors have been chosen. However, the shadow-rating model provides an effective way to measure a bond's credit risk, for practitioners as well as for this study, as it provides a simple yet comprehensive risk estimate that is very easily comparable to actual credit ratings.

4.2 Altman's Z-Score

Another model for estimating default risk that is widely used by practitioners but also highly acknowledged by economic researchers is the so-called Altman's Z-score model. The model was developed by Edward Altman already in 1968, and it has since become undoubtedly one of the most recognized methodologies used for default prediction. As briefly presented in Section 3.1, the Altman's Z-Score model can be classified into the category of multivariate accounting based default prediction models, where a set of key financial ratios are weighted and combined to produce a measure for the probability of default.

According to Altman (1968), studies conducted already in the 1930's concluded that firms on the verge of default exhibit significantly different financial ratio measurements than continuing ones. Altman (1968) argues that these early studies and several other studies of the like conducted in later time periods (e.g. the study by Beaver, 1966) imply a definite potential of financial ratios as predictors of default, but that adopting the results of the studies is questionable due to their univariate research methodologies and excessively high emphasis on individual signals of impending problems. Using this as motivation, Altman (1968) develops a model where multiple ratios are combined to provide a meaningful predictive model.

Altman (1968) uses multiple discriminant analysis (MDA) as a statistical technique in developing his default prediction model. MDA classifies observations into one of several a priori groupings dependent upon the observations' individual characteristics. The analysis technique is often used to make predictions in cases where the dependent variable appears in qualitative form (e.g. male or female). The first step in MDA is to establish explicit group classifications, after which a linear combination of characteristics that best discriminates between the established groups is derived. Altman's model discriminates between two groups, namely default and no default, and, therefore, the analysis is transformed into a simple one-dimensional form instead of a more complicated multi-dimensional matrix. The discriminant function that transforms individual variable values into a single discriminant score (i.e. a Z-score), which is used to make the classification between default and no default, is as follows:

$$Z = v_1x_1 + v_2x_2 + ... + v_nx_n, \quad (1)$$

where v_1, v_2, ... v_n are the discriminant coefficients and x_1, x_2, ... x_n are the independent variable values. The discriminant coefficients are computed by Altman through the MDA method, while the independent variables are observed characteristic values of companies. (Altman, 1968)

The original sample of the Altman study (1968) consists of 66 manufacturing companies with 33 firms in each discriminant group. The defaulted group consists of firms that filed for bankruptcy during the period 1946-1965, with asset size ranging from USD 0,7 million to

USD 25,9 million. The non-defaulted group consists of corporations with matching asset size and other characteristics[9]. As for the financial ratios chosen as variables for Equation (1), Altman (1968) chooses 22 different variables for evaluation based on their popularity in existing economic literature and their perceived potential relevancy for default prediction. The variables can be classified into five ratio categories: liquidity, profitability, leverage, solvency and activity. From the original list of variables Altman (1968) selects five variables that have the best overall predictive power based on the following iterative procedures: 1) observation of the statistical significance of various alternative functions, including determination of the relative contributions of each independent variable, 2) evaluations of inter-correlations between the variables, 3) observation of the predictive accuracy of the various combinations and 4) judgment of the analyst. The final discriminant function arrived at is as follows:

$$Z = 0{,}012X_1 + 0{,}014X_2 + 0{,}033X_3 + 0{,}006X_4 + 0{,}999\,X_5, \qquad (2)$$

where

X_1 = Working capital / Total assets,

X_2 = Retained earnings / Total assets,

X_3 = Earnings before interest and taxes / Total assets,

X_4 = Market value of equity / Book value of total debt,

X_5 = Sales / Total assets and

Z = Overall index.

Altman (1968) attempts so generalize the results of the study so that the default prediction model can be used in a more simplified manner, and concludes that all corporations yielding a Z-score of greater than 2,99 clearly fall into the non-bankrupt category, whereas corporations that have a Z-score of less than 1,81 are all in the bankrupt category. Altman (1968) refers to the area between 1,81 and 2,99 as the “zone of ignorance” or “grey area” because of the susceptibility to error classification. Following Hillegeist et al. (2004), the Z-score is in this thesis further transformed into a more accurate default probability measure through a logistic

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[9] Due to large heterogeneity in the defaulted group, careful selection was attempted when forming the non-defaulted group. The latter consists of a paired sample of firms stratified by industry and size, asset size restricted to USD 1 – USD 23 million. All of these firms were still existent in 1966. (Altman, 1968)

transformation[10]. In more detail, the logistic cumulative distribution function is used so that the probability of default can be calculated as follows:

$$\textit{Probability of default} = e^{Z\text{-}score} / (1 + e^{Z\text{-}score}) \qquad (3)$$

As with the shadow-rating model, Altman's Z-scores are calculated for each sample bond. Again following Hillegeist et al. (2004), year-end financial data from the year prior to issuance is used for the calculations. The Z-score is converted into a default probability measure using Equation (3), and the probability measure is further mapped to an implied credit rating class using the cumulative historical default probability distribution provided by Moody's (see Appendix 2).

4.2.1 Applications and criticism regarding Altman's Z-score

A study by Grice and Ingram (2001) states that Altman's Z-score has been widely used by economic researchers to evaluate the financial conditions of firms in a variety of industries and time periods. In addition, the authors state that the model has also been applied by practitioners in a variety of business situations involving the prediction of bankruptcy and other financial stress conditions. For example, the Grice and Ingram (2001) specify that commercial banks often use the model as part of their periodic loan review processes, and investment bankers use the model in security and portfolio analysis. Also Brealey et al. (2006) comment that refined versions of Altman's Z-score are regularly used by banks and finance companies in default estimations. As the model and its variants are in fact so widely acknowledged and used in practice, its inclusion for default probability measurement in this study seems viable as well.

Altman's Z-score is in many ways similar to the shadow credit rating model presented in Section 3.3.1. As widely utilized and practical models, both combine a set of accounting based financial ratios with predetermined weightings to produce a credit score, which can be mapped into a default probability measure and further into an implied credit rating class. The mapping procedures differ in that the shadow rating model directly produces an implied rating, whereas the Altman's Z-Score measures are first converted into default probabilities through the logistic transformation, and then mapped to implied ratings through a historical default rate distribution. Although the underlying idea of two models is the same, the factors

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[10] Hillegeist et al. (2004) state that while the logistic transformation is not strictly correct for the original Z-score estimated using MDA, it has been shown that the MDA and logit approaches are closely related under normality assumptions, which makes the logistic transformation viable.

examined in the models differ from each other quite remarkably. In fact, the models do not incorporate any of the same financial ratios in the estimations. This is most likely due to the fact that the shadow rating model has been published very recently (in 2010) by a company specialized in credit analysis, whereas the Altman's Z-score model was developed back in 1968 with a smaller data sample and less advanced techniques. It is reasonable to expect the risk factors and factor weightings in the shadow rating model to be more up to date, and thus for the shadow rating model to able to produce more accurate default probability estimates than the Altman's Z-score model. As stated earlier, however, Moody's does not provide accurate information on how the factors and their weightings have in fact been determined in the shadow rating model. Altman's Z-score thus also adds to the theoretical validity of the shadow rating model by pointing out their many similarities.

Although a widely acknowledged model, Altman's Z-score has also been subject to criticism. For example, Hillegeist et al. (2004) point out that Altman's Z-Score may be less viable when used in more recent time periods. This is due to the fact that the Altman Z-score coefficients were estimated with data from the time period between 1946 and 1965, and there may be ample reasons for why the associations between these accounting variables and the probability of bankruptcy may have changed since these original sample periods. The same question is addressed by Grice and Ingram (2001), who also ask whether the model is useful for predicting other financial stress conditions than bankruptcy, and whether the model is applicable for non-manufacturing industries as well. The results of the study by Grice and Ingram (2001) indicate that the Altman's Z-score model is in fact useful for predicting financial distress conditions other than bankruptcy, but that prediction accuracy is significantly lower in other more recent time periods than in that of the Altman (1968) study. Additionally, the authors report that better predictive accuracy can be achieved by re-estimating model coefficients, and that accuracy decreases significantly when non-manufacturing firms are included in the sample. Hillegeist et al. (2004), however, report contradictory results regarding the use of updated coefficients, as they find that using Z-score coefficients estimated with more recent data does not improve measuring probability of default.

Another set of criticism towards Altman's Z-score relates to the problem of a potential search bias in the chosen variables. Scott (1980) notes that multidimensional approaches, such as that of Altman's Z-Score, can suffer from statistical overfitting: when searching for the best set of default predicting financial variables, researchers are neither guided nor restricted by theory, which means that they face an unlimited number of possible variables. Since many of these financial variables are highly correlated, the choices are often made on the basis of slight differences in predictive power. Researchers attempt to minimize this problem by testing the model on a different set of data, but while such tests are useful, they do not change the fact that the model itself is a result of an empirical search. (Scott, 1980)

Furthermore, models based on accounting data are often criticized for using backward-looking accounting data to produce forward-looking probability estimates. As Hillegeist et al. (2004) point out, financial statements are formulated under the going concern principle, i.e. under the assumption that the company will not go bankrupt. Thus, the ability of accounting data to accurately and reliably assess the true probability of default will by design be limited. Additionally, financial statements often understate asset values relative to their market values, causing accounting based leverage measures to be overstated (Hillegeist et al., 2004). Overstated leverage measures can be expected to produce excessively high probability measures. The Altman's Z-score model does incorporate one market based metric measuring the market value of equity to the book value of debt, but together with the shadow rating model still incorporates another common deficiency of accounting based models: their failure to incorporate a measure of asset volatility. In the so-called structural framework, greater volatility translates into higher default risk simply because there is a larger chance that a company's asset values will fall below the values of their liabilities (Hamilton et al., 2012). This implies that there is a higher probability that a company cannot repay its liabilities, and default will occur. Thus, a further model incorporating both market value measures and volatility measures is included in the study.

4.3 Merton DD model

The third model utilized in this thesis is a variant of the well-known structural default prediction model developed by Merton (1974). As introduced briefly in Section 3.1, under the structural framework of the original Merton model, default occurs at the maturity of debt in the event that the value of the issuer's assets is less than the face value of its debt. Equity is viewed as a call option on the issuer's assets with a strike price equal to the face value of the issuer's debt. The logic behind this framework is as follows: the limited liability feature of equity means that equity holders have the right, but not the obligation, to pay off debt holders and take over the remaining assets of the firm. This means that the debt holders essentially own the firm until the equity holders pay off the debt in full. Thus, in the simplest case, equity is the same as a call option on the firm's assets with a strike price equal to the book value of the firm's debt. (Crosbie and Bohn, 2003)

The original Merton model has been extended in a number of ways, one of the most famous and advanced extensions being the Moody's KMV model (also known as the Vasicek-Kealhofer / VK model, or Moody's Expected Default Frequency / EDF model). As an example of its extensions, whereas the classic Merton model only allows for a single class of debt and a single class of equity, the Moody's KMV model is extended to include a more detailed specification of liabilities: short-term, long-term and convertible debt, as well as preferred and common equity (Crosbie and Bohn, 2003). In addition, the Moody's KMV model relaxes the assumption of a company's assets being normally distributed by using proprietary default distribution data to determine the final default probability estimate, which makes it a more accurate model for the real world. The partially proprietary nature of the Moody's KMV model has lead researchers to apply a somewhat simplified variant of the model in economic literature, which incorporates some but not all of the model's advanced elements[11]. The most important difference between the models is the application of normality assumptions. The model applied by researchers is often referred to as the Merton Distance-to-Default model (the Merton DD model), as the Moody's KMV model uses the term distance-to-default (DD) for the number standard deviations a firm is away from defaulting. The Merton DD model will also be applied in this thesis.

Regardless of their methodological differences, all applications of the Merton models are premised on the assumption that there is a causal, economically motivated reason for why companies default. According to the framework of the Merton models, the two determining factors for default are a company's financial risk and its business risk. The models thus take a very similar approach to measuring credit risk as does fundamental, financial statement based credit analysis. However, the Merton models distinguish themselves by using market based valuations instead of book valuations. Namely, the models measure financial risk (or leverage) by the difference between the market value of assets and the book value of liabilities, and business risk by asset volatility. As asset values and asset volatilities are not directly observable, they are estimated using the market value and volatility of equity. (Hamilton et al., 2012)

[11] The model is discussed for instance in Duffie and Singleton (2003), and applied by Vassalou and Xing (2004), Duffie et al. (2007) and Bharath and Shumway (2008) among others.

Following the classic Merton model and the Moody's KMV model, the Merton DD model assumes that the value of a firm's assets evolves according to a geometric Brownian motion of the following form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW, \tag{4}$$

where V_A is the value of the firm's assets, μ is the expected return on V_A, σ_A is the instantaneous volatility of assets and W is a standard Wiener process. Viewing equity (V_E) as a call option on the firm's assets (V_A), the model makes use of the Black and Scholes (1973) formula for valuing call options:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2), \tag{5}$$

where X is the strike price of the call option, i.e. the book value of debt at time t with a maturity equal to T. $N(.)$ is the cumulative standard normal distribution function. With r being the risk free rate, d_1 is given by

$$d_1 = \frac{ln\left(\frac{V_A}{X}\right) + \left(r + \frac{1}{2}\sigma_A^2\right)T}{\sigma_A\sqrt{T}}, \tag{6}$$

and d_2 is given by

$$d_2 = d_1 - \sigma_A\sqrt{T}. \tag{7}$$

Equation (5) clearly states that the value of a firm's equity (V_E) is directly connected to the value of a firm's assets (V_A), and indirectly to the volatility of a firm's assets (σ_A). Unlike in a typical option valuation case, in which the value of the underlying asset is known and the value of the option is calculated, in the Merton DD model the value of the option (the value of a firm's equity) is observable and one aims to solve the value and volatility of the underlying asset (a company's assets).

In principle, the volatility of a company's assets relates to the volatility of its equity through Ito's lemma:

$$\sigma_E = \left(\frac{V_A}{V_E}\right) \frac{\partial V_E}{\partial V_A} \ \sigma_A. \tag{8}$$

As reported by Bharath and Shumway (2008), in the Black-Scholes model, it can be shown that $\frac{\partial V_E}{\partial V_A} = N(d_1)\,\sigma_A$, so that under the Merton model's assumptions, the volatilities of the firm and its equity are related by

$$\sigma_E = \left(\frac{V_A}{V_E}\right) N(d_1)\ \sigma_A. \tag{9}$$

Thus, by simultaneously solving equations (5) and (9) one can derive the values for V_A and σ_A. However, Crosbie and Bohn (2003) point out that Equation (8) holds only instantaneously, as in practice market leverage moves around too much for the equation to provide reasonable results. Thus, the Moody's KMV and the Merton DD models use a more complex iterative procedure to calculate σ_A[12]. The procedure first uses an initial guess of volatility to determine asset value. For example, Vassalou and Xing (2004) use σ_E calculated from daily stock returns from the past 12 months as the initial estimate for σ_A[13]. Using the Black-Scholes formula, V_A is then calculated for each trading day for the past 12 months using V_E as market value of equity of that day. Through this process, daily data of V_A is obtained. The following step is to calculate the volatility of V_A, and this measure is then used as input to the next iteration, which determines a new set of V_A and hence σ_A. This procedure is repeated until the values of σ_A converge. Once the converged value of σ_A is obtained, it is used to back out V_A through Equation (5).

Once asset values and asset volatilities have been obtained, the probability of default can be estimated using the so-called distance-to-default measure (DD-measure). As stated earlier, in the Moody's KMV model, the distance-to-default is simply the number of standard deviations that the firm is away from default. In the Black-Scholes world, this is given by

$$DD = \frac{ln\,\frac{V_A}{X_t} + \left(\mu - \frac{\sigma_A^2}{2}\right)t}{\sigma_A\sqrt{t}}, \tag{10}$$

where the drift (μ) is computed as the mean of the change in $\ln(V_A)$. Moody's KMV relaxes normality assumptions and uses proprietary empirical default data to acquire the final default

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[12] Moody's KMV model also incorporates Bayesian adjustments in asset volatility calculations with respect to the country, industry and size of the firm. (Crosbie & Bohn, 2003)

[13] Another option would be to use option-implied volatility measures or CDS implied volatility measures.

probability from this DD-measure. In the Merton DD model, however, normality is assumed, and the probability of default is given by

$$P_{default} = N\left[-\frac{ln\ \frac{V_A}{X_t} + \left(\mu - \frac{\sigma_A^2}{2}\right)t}{\sigma_A\sqrt{t}}\right]. \tag{11}$$

In line with the shadow rating and Altman's Z-score models, the default probability as implied by the Merton DD model is calculated for each sample bond. Following the methodology of Vassalou and Xing (2004), the issuer's stock return data from 12 months prior to the bond's issue date is used to calculate the volatility of equity (σ_E), which is used for the iterative procedure of solving the volatility of assets (σ_A) and the value of assets (V_A). A tolerance level of 99 % is used for convergence. In the final probability calculations, the bond issuer's short-term debt and 50 % of its long-term debt from the most recent financial statement prior to issuance is used as the book value of debt (X). The forecasting horizon (T) is one, and for the risk-free rate (r) in equation (6) I use the issue date's one-year swap rate. With these parameters, the result obtained is a 1-year default probability for each sample bond. As with Altman's Z-score, the final probability measures are mapped to implied credit ratings using a cumulative 1-year historical default probability distribution provided by Moody's (see Appendix 2).

4.3.1 Applications and criticism regarding the Merton DD model

The Moody's KMV model has been the industry leading default probability model since its introduction in the 1990's. Moody's Analytics provides default probability measures for over 30 000 entities globally on a daily basis, and provides these probability measures to customers through various platforms. Moody's has a long tradition of validating the model, and reports that the model has been performing consistently over different stages of the credit cycle, including the financial crisis of 2008 (Hamilton et al., 2012). Although the Moody's KMV model has been widely recognized to provide reliable default measures, the Merton DD model is not quite as viable as it is in many ways somewhat more simplified. For example, the Merton DD model often only considers two classes of liabilities: short-term debt and common stock. The Moody's KMV model, on the other hand, also considers long-term debt, preferred stock and convertible stock. In this study, common stock, short-term debt and 50 % of long-term debt is used. Furthermore, the Merton DD model does not take cash payouts into consideration, and presumes that default occurs only at debt maturity. The Moody's KMV model in turn takes both coupons and dividends into consideration and presumes that default can occur at any time. The Moody's KMV model also determines the so-called default point with empirical data, whereas the Merton DD model often assumes the default point to be the book value of total debt.

Even though the Merton DD model is not as accurate in predicting default as the Moody's KMV model, it is still in many ways more advanced than many accounting based models. For example, Hillegeist et al. (2012) report that the Merton DD model succeeds significantly better in providing information about default probabilities than does the accounting based Altman's Z-Score model. The study's conclusion is even robust to various modifications of the Z-Score, including updated coefficients and industry effect adjustments. One can expect that incorporating market based value measures and volatility considerations into the calculations enables a model to better capture valuable changes in fast paced environments. Thus, market based models might better reflect the level of perceived credit risk, i.e. credit spreads.

5. Description of data

The data used in this study consists of a sample of fixed- and floating-rate bonds issued by European listed, non-financial companies during the time period ranging from January 2001 to December 2013. All bonds are euro-denominated, senior-ranking, unsecured bonds with no callability, convertibility, sinking fund and/or other optionality characteristics. To enhance the homogeneity of the sample even further, bond maturity is restricted between one and ten years, and the minimum issue amount is restricted to EUR 50 million.

Table 4 describes the characteristics of the unrated and rated bond samples used in the study in more detail. The final unrated bond sample consists of 237 bonds with an average issue size of 240 mEUR (median 160 mEUR) and average maturity of 5,6 years (median 5,0 years). The rated bond sample used for assessing the accuracy of the calculated implied credit ratings is larger and consists of 594 bonds. All bonds in the rated bond sample have an assigned credit rating by at least one of the major credit rating agencies (Moody's, Standard &

Poor's and Fitch) at the time of data collection[14], and are those which were assigned to the bonds at issuance. The average issue amount of the rated bond sample is 639 mEUR (median 600 mEUR), which is significantly larger than that of the rated bond sample. This is not surprising, as unrated bonds are often issued by smaller companies. The average maturity of the rated sample is 6,8 years (median 7,0 years), which is also somewhat longer than that of the unrated bond sample. Roughly 80 % of the bonds in both samples were issued during or after 2008. All bond and issuer specific financial data used for the credit risk calculations was collected from Bloomberg.

Table 4: Description of bond samples

The table depicts the characteristics of the unrated and rated bond samples. The rated bond sample is used for assessing the accuracy of the credit risk models by which the implied credit ratings are calculated for the unrated bond sample.

	Rated bond sample	**Unrated bond sample**
Issued prior to 2008	120	53
Issued during / after 2008	474	184
Total number of bonds	**594**	**237**
Average issue amount (mEUR)	639	240
Median issue amount (mEUR)	600	160
Highest issue amount (mEUR)	3269	1000
Lowest issue amount (mEUR)	50	50
Average maturity (years)	6,84	5,62
Median maturity (years)	7,01	5,01

The unrated bonds' yield spreads at issuance are compared to the issue date's average yield spread of rated bonds with the same level of credit risk (i.e. credit rating). Issuance spreads of unrated bonds are used for the comparison as they are able to depict the credit risk investors actually perceive the bond to carry in an intuitive way. Namely, right before a bond is issued investors analyze the bond and assess its riskiness and attractiveness in practice. They also receive topical marketing material on the issuer and the bond at this time. These perceptions of the investors are then directly reflected in the market prices of the bonds when they are issued, i.e. in their credit spreads at issuance. The average yield spreads to which the issuance spreads of unrated bonds are compared to are calculated using iBoxx indices, which are rated bond indices for European non-financial companies provided by Markit. The ideal

[14] Some bonds might have had an assigned credit rating at time of issuance, but which has then later on been withdrawn.

case would of course be to compare individual unrated bonds' issuance spreads to the issuance spreads of individual rated bonds, instead of using average index spreads, to make the credit risk comparisons more accurate. However, comparing individual spreads would in practice be next to impossible, as it is extremely unlikely that one could fine a large enough sample of rated and unrated bonds with corresponding credit risk profiles, issue dates and maturities to make the comparisons viable. Also, using indices is good in that indices report the average pricing for a given category of credit risk, meaning that indices even out any irregularities present in individual rated bonds due to, for example, bond covenants. For investment grade bonds (ratings classes between Aaa and Baa), the iBoxx indices are divided by rating class (Aaa, Aa, A and Baa) and maturity (1 - 3, 3 - 5, 5 - 7 and 7 - 10 years) into 16 different indices. The fact that the indices are as specific as this makes the yield spread comparisons increasingly reliable - the indices even out irregularities of individual bonds while still keeping the sample quite homogenous. For speculative grade bonds (bonds with ratings between BB and D), however, only one index is available, which does not specify further differences in rating class or maturity. The fact that there is only one index for speculative grade bonds available is most likely due to the fact that there simply are not enough speculative grade bonds outstanding for further divisions to be reasonable. The credit spreads of speculative grade bonds are subject to large dispersion, which makes the speculative grade index somewhat less viable for comparisons. However, it is even more unlikely that one could find individual matching speculative grade unrated and rated bonds for the yield spread comparisons than it would be to find matching investment grade bonds, which supports the use of the speculative grade index in any case.

As for the yield spread calculations: for the rated bond indices, index asset swap margins are directly used when reported for the respective iBoxx index. Otherwise, the yield spread is calculated by subtracting the corresponding maturity's swap rate from the reported index yield on matching dates. For all floating rate unrated bonds, yield spreads at issuance are directly collected from Bloomberg. For fixed rate unrated bonds, Bloomberg reported yield spreads at issuance are used when available, and otherwise are calculated by subtracting the issue date's swap rate of corresponding maturity from the bond's coupon rate. Using coupon rates here leads to insignificant inaccuracy as each sample bond has been issued at or very close to its par value.

6. Results

This thesis studies the pricing discrepancies between European rated and unrated bonds. The study begins with estimating the credit risk of an unrated bond sample utilizing three different credit risk models: the shadow rating model, the Altman's Z-Score model and the Merton DD model. The credit risk measurements are used to map the sample bonds to implied credit rating classes. The shadow rating model produces an implied credit rating directly, while Altman's Z-Score and the Merton DD model produce probabilities of default, which are mapped to implied ratings using historical default probability distributions by ratings class as reported by Moody's. In order to assess the accuracy of the conducted credit risk assessments and implied ratings, the same estimations are performed for a sample of bonds with official credit ratings. After mapping the unrated bond issues to a specific credit rating class, I assess whether the credit spreads of unrated bonds are comparatively equal to the credit spreads of rated bonds with corresponding rating classes and other characteristics. Note that all implied ratings are calculated bond-specifically to account for timing related factors affecting credit spreads. An issuer company can thus have more than one implied credit rating. This section first discusses the results regarding the implied credit ratings obtained as well as the three credit risk models' accuracy in the estimations. Then, the central findings regarding the examined credit spread discrepancies are examined.

6.1 Implied credit ratings

Out of the total unrated sample of 237 bonds, implied credit ratings are calculated for 179 unrated bonds using the shadow rating model. For the remaining sample, the calculations could not be performed due to insufficient data. The calculated shadow credit ratings range from Aa3 to Caa1, which means that no ratings from the best or worst rating classes (Aaa & Ca) are scored.[15] 59 % of the calculated shadow ratings are investment grade (Aaa - Baa3) and 41 % speculative grade (Ba1 - Ca). By examining the calculated implied ratings for the sample of rated bonds, one can conclude that the shadow rating model works well. Implied credit ratings are calculated for 534 rated bonds out of the total sample of 594 bonds using the shadow rating model, with 75 % of the implied ratings being two or less modifiers away from the bond's actual credit rating (for example, Baa1 is two modifiers away from Baa3). That is, the vast majority of rated bonds landed into the correct rating category when ignoring the

[15] See Appendix 3 for a more detailed description of Moody's, S&P and Fitch ratings classes.

specific numerical modifiers. Out of these, 18 % of the shadow ratings scored the exact same rating as actually assigned to the bond at issuance (14 % out of total sample). In total, as much as 85 % of the implied ratings calculated with the shadow rating model predicted correctly whether the bond is investment grade or speculative grade. The results presented show that the shadow rating model is reliable and unbiased in estimating the credit risk of unrated bonds and mapping them into correct rating categories, which also makes the yield spread comparisons between unrated and rated bonds with corresponding implied and official credit ratings viable using the results of this model.

Using the Merton DD model, implied credit ratings are calculated for 163 unrated bonds out of the total sample of 237 bonds. The distribution of the Merton DD model's implied ratings differs from that of the shadow rating model, especially in the higher rating classes. In the Merton DD model, the majority of implied ratings (64 %) scored the highest or second highest rating class (Aaa / Aa)[16], whereas in the shadow rating model only 21 % of the implied ratings scored these categories. However, the distributions between investment grade ratings and high yield ratings do not differ as remarkably between the two models. In total, 72 % of the implied ratings calculated with the Merton DD model scored an investment grade rating and 28 % a high yield rating, the corresponding distribution in the shadow rating model being 59 % and 41 % respectively.

One can quickly conclude that the Merton DD model's accuracy in calculating implied credit ratings is not as good as that of the shadow rating model. Merton DD implied ratings are calculated for 421 rated bonds out of the total sample 594 bonds. Only 32 % of the calculated implied ratings were two or less modifiers away from the bonds' actual rating, out of which 18 % scored the exactly correct rating (6 % of total sample). These misspecifications can largely be attributed to the characteristics of the historical default rate distribution by which the Merton DD default probabilities are mapped to implied ratings. Namely, for all rating classes ranging from Aaa to A3, Moody's reports historical 1-year default probabilities to have been very close to zero (see Appendix 2 for details). That is, if the Merton DD model yields a 1-year default probability of less than about 1 %, it is difficult to specify whether the bond should be rated Aaa, Aa or A. Thus, the accuracy of the implied ratings is better only when examining the better half of the rating spectrum (Aaa – A3) as a whole, and not by

[16] Due to the characteristics of the historical default rates used to convert the default probabilities of the Merton DD model to ratings, these two best rating classes cannot be separated. See more about the historical default rates in Appendix 2.

rating class. This is supported by the fact that as much as 78 % of the Merton DD implied ratings predicted correctly whether the bond possesses an investment grade or a speculative grade rating. It is also possible, however, that the Merton DD model simply does not fit the bond sample examined, or would work better in estimating default probabilities for a longer time period, for example five years. Although the Merton DD model is not as accurate in producing implied ratings as the shadow rating model, it is included in the yield spread comparisons. Due to the nature of the calculation method, the Merton DD implied ratings can be expected to better capture time-sensitive factors affecting investors' perceptions on credit risk, and thus the level of credit spreads, which are depicted in market data. That is, the Merton DD implied ratings in a sense provide a more instantaneous figure on how investors view the credit risk of a bond at time of issuance, as Merton DD default probabilities are calculated using market variables right up to the time of bond issuance, whereas shadow ratings are based on historical financial statement data. Even if this was the case, however, one must bear in mind the lower accuracy of the model in predicting implied ratings when looking at the yield spread comparisons conducted using the Merton DD implied ratings.

As for the Altman Z-Score model, it is alarmingly apparent that the model does not provide unbiased credit risk estimates. Out of the total unrated sample of 237 unrated bonds, Altman Z-Score implied ratings are calculated for 185 bonds. Each of these implied ratings land in the speculative grade category, which is highly unrealistic. Furthermore, out of the calculated sample more than 70 % were rated Caa or lower, implying that the vast majority of these unrated bonds are of very high credit risk. Obviously, it is not likely that this be the case in reality. When calculated for the rated bond sample (492 rated bonds out of total sample 594) only two of the implied ratings scored two or less modifiers away from the bond's actual rating – an extremely low number compared to the other two models. Furthermore, only six implied ratings predicted correctly whether the bond was high yield or investment grade, out of which only one predicted an investment grade rating. The Altman's Z-Score model is clearly biased to predict excessively high default probabilities, which makes the inclusion of the model to the yield spread comparisons unfeasible. The biasedness of the model may be due to the fact that the model variables as well as their coefficients were estimated using a fairly small sample, and they may well be outdated to fit the sample of this study. Altman's Z-Score is thus dropped out of the analysis at this point.

A more detailed description of the implied rating distributions is depicted in Table 5 and a summary of model accuracies is provided in Table 6.

Table 5: Detailed distribution of implied credit ratings

The table depicts a detailed distribution of the implied credit ratings calculated for the sample of unrated bonds using three different credit risk models: the shadow rating model, the Merton DD model and the Altman's Z-Score model. The shadow rating model automatically yields an implied rating class, whereas Merton DD and Altman's Z-Score implied ratings are obtained by converting the default probabilities yielded by the models into ratings using historical default rates provided by Moody's. See Appendix 3 for the historical default rates.

	Shadow rating model		Merton DD Model		Altman Z-Score Model	
Implied credit rating	**Number of bonds**	**%**	**Number of bonds**	**%**	**Number of bonds**	**%**
Aaa / Aa	11	6.15 %	104	63.80 %	0	0.00 %
A	26	14.53 %	2	1.23 %	0	0.00 %
Baa	69	38.55 %	12	7.36 %	0	0.00 %
Ba	48	26.82 %	13	7.98 %	8	4.32 %
B	23	12.85 %	12	7.36 %	26	14.05 %
Caa	2	1.12 %	16	9.82 %	136	73.51 %
Ca	0	0.00 %	4	2.45 %	15	8.11 %
Total	179	100.00 %	163	100.00 %	185	100.00 %
Investment grade	106	59.22 %	118	72.39 %	0	0.00 %
High yield	73	40.78 %	45	27.61 %	185	100.00 %
Total	179	100.00 %	163	100.00 %	185	100.00 %

Table 6: Accuracy of implied credit ratings

The table depicts the accuracy of the implied ratings calculated with the three credit risk models for a sample of rated bonds. The first row, "≤ 2 modifiers", shows how many of the implied ratings scored two or less modifiers away from the bond's actual rating (for example, Baa1 is two modifiers away from Baa3). The second row, "Actual rating", specifies how many implied ratings scored the exactly same rating the bond has been assigned in reality. The third row, "IG / HY", shows how many of the implied ratings correctly predicted whether the bond is investment grade or high yield. The percentages are from the total sample unless specified otherwise.

	Shadow rating model		**Merton DD Model**		**Altman Z-Score Model**	
Implied credit rating	**Number of bonds**	**%**	**Number of bonds**	**%**	**Number of bonds**	**%**
≤ 2 modifiers	398	74.53 %	135	32.07 %	2	0.40 %
Actual rating	73		24		0	
Out of total sample		13.67 %		5.70 %		0.00 %
Out of ≤ 2 modifiers		18.34 %		17.78 %		0.00 %
IG / HY	456	85.39 %	329	78.15 %	6	1.21 %
Calculation sample	534		421		496	

6.2 Credit spread discrepancies

In estimating the pricing relationship between the unrated bonds and the rated bond indices, I use simple regression analysis:

$$BCS_{t,m,cr}^{i} = \beta_1 + \beta_2 ICS_{t,m,cr}^{i} + \beta_3 IS^{i} + \varepsilon_{t,m,cr}^{i}, \qquad (12)$$

where the dependent variable $BCS_{t,m,cr}^{i}$ is the credit spread of an unrated bond *i* at a given issue date *t*, with maturity *m* and an implied credit rating *cr*. The explanatory variable $ICS_{t,m,cr}^{i}$ represents the rated index spread on the corresponding date *t*, with the corresponding maturity *m* and credit rating *cr*. IS^{i} is a liquidity proxy representing the issue size of bond *i*.

The index credit spread coefficient (β_2) is therefore a simple measure of the relationship between the credit spreads of rated bonds and unrated bonds. According to the hypothesis of the study, if credit risk is equally well accounted for in the prices of both rated and unrated bonds, and other relevant factors affecting credit spreads are either equal or controlled for, then theoretically the credit spreads of these two categories should not significantly differ from each other. It follows that, according to the hypothesis, the coefficient β_2 should equal 1: bonds with an equal degree of credit risk should theoretically have equal credit spreads.

H_1: Credit risk is equally well accounted for in the pricing of unrated and rated bonds. Thus, the credit spreads between the two bond classes do not differ from each other significantly, ceteris paribus.

Furthermore, if the hypothesis includes the assumption that credit ratings do not independently affect credit spreads, i.e. that the lack of an official credit rating does not in itself have an impact on a bond's credit spread, it follows that the constant term (β_1) is also expected to be zero. The credit spread of an unrated bond should equal that of a rated bond, if credit risk and other factors related to the bond's spread are accounted for equally, and if lacking a credit rating does not independently affect the credit spread of a bond.

In the reported regression results, the t-values of the index spread coefficients are adjusted according to the hypothesis of β_2 equaling one, and are calculated as follows:

$$t = \frac{b_2 - \beta_2^0}{s.e.(b_2)} \tag{13}$$

Heteroscedasticity is controlled for in the regression analysis with the White-test, which generally looks for evidence on an association between the variance of the disturbance term and the regressors. The results imply the regressions to be homoscedastic with the Chi-squares in principle being quite low.

Timing related factors affecting credit spreads, such as the prevailing spot rate, slope of the yield curve and business climate, are automatically accounted for in the regressions, as the yield spreads of unrated bonds are compared to the average spreads of rated bonds on the corresponding day. Liquidity is another factor which has been shown to affect credit spreads (Chen et al., 2007; Van Landschoot, 2004), and is controlled for separately. The issue size of a bond is often assumed to give an indication of its liquidity, and along with many other research papers it is also used here as a proxy for bond liquidity (see, e.g., Houweling et al., 2005). The correlation coefficient of the issue size, *IS*, is expected to be negative: bonds with a larger issue size are generally more liquid and thus have lower yield spreads. Put the other way around, bonds with a smaller issue size are less liquid, and thus carry a liquidity premium, which increases the bond's spread.

As discussed in Section 2.1., also other factors, such as taxes and systematic risk, have been suggested to affect credit spreads. These other credit spread determinants could on their part lead the coefficient β_2 measuring the relationship between the unrated and rated credit spreads to be something different than one. It is reasonable to assume that unrated and rated corporate bonds are taxed in an equal manner, but the systematic risk component might provide some explanation for possible credit spread differences. For example, if the index yield spread coefficient estimate is larger than one, the difference can be interpreted to at least partly be a result of greater systematic risk. Alternatively, the constant term (β_1) could be lead to be something other than zero. Additionally, asset volatility, which is only accounted for by the Merton DD model, has been suggested to affect credit spreads. This might lead the regression results run separately for the Merton DD implied ratings and the shadow rating model implied ratings to differ from each other. Of course, the models differ also in other respects, as in how they account for leverage, which in addition to explaining some of the mismatches in the implied rating calculations could explain some of the discrepancies between the regression results.

To test the functioning of the regression model as well as the use of rated bonds indices, i.e. the average yield spreads rated bonds, as a comparison point, a regression is run for the original rated bond sample against the indices. The results are depicted in Table 7. When run for the all rated bonds, the regression model works poorly. The index yield spread coefficient is below its hypothesized value of one at the 0,1 % significance level, and the constant coefficient is above its hypothesized value of zero at the 0,1 % significance level. The issue size of the bonds proxying for liquidity returns a coefficient estimate close to zero, implying that liquidity does not seem to account for much variation in credit spreads. However, this result can be expected because, as stated previously, investment grade issues are generally quite liquid. Thus, one would not expect a liquidity premium to be a strong explanatory factor for their yield spreads.

When performing the regressions separately for investment and speculative grade bonds, however, the regression model improves significantly. As depicted in Table 7 below, the accuracy of the regression model is very good for investment grade bonds. In line with the hypothesis of the thesis, the yield spread coefficient is very close to one and the constant coefficient is very close to zero. For speculative grade bonds, however, the model seems to be less accurate with both the yield spread coefficient and the constant coefficient being below their hypothesized values. This is most likely due to the fact that there is often by default more dispersion in the credit spreads of high yield bonds, which is caused simply by their more diverse nature, higher level of risk as well as the lower amount of high yield issues outstanding. To recall, there is also only one index available for measuring the average yield spreads of speculative grade issues, which does not distinguish between bond maturities or rating classes within the speculative grade rating spectrum. This is also likely to be a reason for the regression model being less accurate for high yield issues. The coefficients cannot be attributed to any so-called new issue premia or announcement effects, as these would cause bond spreads to be higher – not lower – than average. The use of issuance spreads against average yield spreads does thus not seem to distort the results. The differences in the regression model's accuracy are also depicted by the R-squares, i.e. the goodness of fit measures, of the regressions. For the investment grade sample, the regression model is able to explain as much as 74 % of the yield spreads of the individual rated bonds against the rated

Table 7: Regression results for rated bonds

The table depicts the regression results for the sample of rated bonds against the rated bond indices. The regressions are run separately for all rated bonds, investment grade rated bonds and speculative grade rated bonds. [17]

Rated bonds	All bonds			Investment grade bonds			Speculative grade bonds		
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	0,631	0,021	-17,57***	0,962	0,039	-0,97	0,784	0,070	-3,09**
Amount issued	0,014	0,006	2,33*	0,007	0,008	0,88	0,027	0,045	0,60
Constant	0,362	0,082	4,41***	-0,089	0,080	-1,11	-0,581	0,447	-1,30
n		591			507			84	
R-square		0,530			0,741			0,450	
Chi-square		7,62			3,78			7,09	

[17] ***, ** and * denote significance at the 0,1%, 1% and 5% levels respectively

bond indices. For the speculative grade sample, however, the goodness of fit is much lower, only 45 %. The differences in the accuracy of these two regressions also explain why the regression run for all rated bonds did not provide the hypothesized results. As for the bond liquidity proxies, the sizes of the bond issues again do not seem to account for much variation in rated bond yield spreads, which is to be expected.

As for the yield spread analyses of the unrated bonds, the regressions are performed separately using the implied ratings obtained from the shadow rating model and the Merton DD model. To recall, the Altman's Z-Score implied ratings are dismissed from further analysis due to the model's extremely high inaccuracy in credit rating calculations. As depicted by Table 8 below, when performed for the whole implied rating spectrum, the regression results indicate that the credit spreads of unrated bonds differ significantly from those of rated bonds with the index yield spread coefficients being 0,358 for the shadow rating model and 0,230 for the Merton DD model, and the constant coefficients being 1,164 and 1,893 respectively. However, the regression results for the rated bond sample implied errors in the regression model when used for the whole rating spectrum, and thus, the results of the unrated sample are more difficult to interpret. The yield spread coefficients being below one is in line with the rated bond sample, but the effects seem to be much larger for the unrated bond sample, as the yield spread coefficients are even further away from their hypothesized value. This indicates that the credit spread component as represented by β_2 is lower for unrated bonds relative to rated bonds. The constant coefficients for the unrated bond sample are, however, much larger than zero, and statistically significant at the 0,1 % level, which is inconsistent with the rated bond sample for which also the constant coefficient was below one. In contrast with the index yield spread coefficients, the extremely high constants suggest that the credit spreads of unrated bonds are by default higher than those of rated bonds.

In line with the rated bond regressions, the coefficients for bond liquidity are very low and not of statistical significance (0,015 and -0,048 for the shadow rating and Merton DD models respectively). This is somewhat surprising, as liquidity has been shown to be relatively significant determinant of yield spreads (e.g. Van Landschoot, 2004), and unrated bond issues are generally known to be smaller. What is also interesting about the bond liquidity results is that the signs of the coefficients for the two models differ from each other, being negative for the Merton DD model but positive for the shadow rating model. This implies that yield spreads can either increase or decrease with issue size, which is somewhat counterintuitive.

However, getting both negative and positive signs for the coefficient estimate is actually consistent with other studies that proxy corporate bond liquidity with issue size, and report mixed results (see, e.g., Gehr and Martell, 1992; Mullineaux and Roten, 2002). As issue size is only a proxy for liquidity, it might be the case that some large bonds are illiquid while some small bonds are liquid. Changing the liquidity proxy to for example the bid-ask spread could perhaps provide improvement to the regression model, but for unrated bonds this data is rarely available. Also, the inaccuracy apparent in the regression model when used for the whole rating spectrum most likely affects the liquidity coefficients as well.

As said, the regressions performed for the rated bond sample implied inaccuracy in the regression model when used for examining the whole rating spectrum, as depicted for example by the relatively low measure for goodness of fit (0,53). The R-squares of both regressions examining all unrated bonds are also low (0,252 and 0,167 for the shadow rating and Merton DD models respectively), which implies that there are differences in credit spread dispersion between rating classes - one can expect, for instance, that there is higher dispersion in the credit spreads of speculative grade bonds than there is in the credit spreads of investment grade bonds. This would provide an explanation for the constant coefficients jumping to high levels in the unrated bond regressions, as high constants even out the dispersion of speculative grade bonds when all bonds are examined together. However, by comparing the R-squares of the rated and unrated bond regression, there also appears to be differences between the credit spread dispersion of rated and unrated bonds, as the R-squared is relatively much higher for the rated bond sample. Higher dispersion in the spreads of unrated bonds is, however, not very surprising as the unrated bond market is smaller, less liquid and thus also less transparent. These issues will be discussed later on in section 6.3.

In order to be able to examine the credit spread discrepancies more accurately, the regressions are again run separately for bonds with an investment grade implied rating and for bonds with a speculative grade implied rating. The results are depicted in Table 8. As with the rated bond sample, goodness of fit improves remarkably for the shadow rating model when the bond sample is restricted to investment grade bonds only, but only moderately for the shadow rating model's group of speculative grade bonds. This supports the view that credit spread dispersion is in fact lower for bonds in higher rating classes than for bonds in lower ones. For the Merton DD model, goodness of fit changes only moderately for both rating categories, and actually decreases for the bonds with implied investment grade ratings. This suggests that there are misspecifications in the implied rating calculations of the Merton DD model, which is discussed more later on in this section. When compared to the R-squares of the rated bond sample, it again seems that, overall, there is somewhat more dispersion in the credit spreads of unrated bonds. The coefficients for bond liquidity remain mixed for the unrated sample, but are statistically significant for the shadow rating model's investment grade implied bonds. However, the sign of the coefficient is still counterintuitive, suggesting that credit spreads increase with bond liquidity. For speculative grade implied bonds, on the other hand, the liquidity coefficient has a negative sign implying higher spreads for low liquidity. The fact that liquidity does not seem to be a significant determinant of credit spreads even for the speculative grade bonds is unexpected. Namely, research has found that liquidity alone can explain as much as 22 % of yield variations for speculative grade bonds (Chen et al., 2007). As mentioned earlier, it might be the case that the liquidity proxy used in this study does not function well in capturing the effects of liquidity of credit spreads.

Although the results demonstrate there to be significant differences in the yield spreads of unrated and rated bonds, the more interesting phenomenon apparent for both models is that both the index yield spread coefficients and the constants indicate that unrated bonds with investment grade implied ratings carry higher credit spreads with regard to their rated counterparts than do speculative grade bonds with regard to theirs. For the shadow rating model, the results indicate that unrated bonds with an investment grade implied rating are in fact priced at a clear credit spread premium when compared to bonds with official investment grade ratings. This is depicted by an index yield spread coefficient that is higher than one (1,194) as well as a constant coefficient above zero (0,122). Also, to recall, the coefficient estimates for the rated bond sample's investment grade bonds were 0,962 and -0,089 respectively. The fact that the index yield spread coefficient is higher than one proposes that these unrated bonds are priced to be of higher credit risk than their rated counterparts, and also the positive constant suggests an additional compensation demanded for investing in low or moderate risk unrated bonds. Unrated bonds with a speculative grade implied rating from the shadow rating model, on the other hand, have an index yield coefficient lower than one (0,716) and a largely negative constant (-0,720), which implies that they are perceived to be of lower credit risk and thus carry a lower credit spread with regard to rated bonds with official speculative grade ratings. The coefficients are also lower than the ones obtained from the rated bond regression (0,784 and -0,581 respectively), which supports this implication, although in part mitigating its significance. As for the Merton DD model, the results are different in that even though the index yield spread coefficient is higher for investment grade implied bonds than for speculative grade ones, both index yield coefficients are less than one (0,731 and 0,397 for investment and speculative grade implied bonds respectively). Also, in contrast with the shadow rating model, the constant coefficients for the Merton DD model's investment and speculative grade bonds are both positive (1,765 and 0,485 respectively). However, in line with the shadow rating model, the constant coefficient is higher for the investment grade implied issues than for the speculative grade ones, and in fact statistically significant at the 0,1 % level. In total, the results for the Merton DD model again indicate that investment grade bonds have relatively higher credit spreads than speculative grade implied bonds when compared to their rated peers. The results demonstrated above depict that the credit spreads of unrated bonds differ from those of rated bonds irrespective of their credit quality, implying that there are differences in how investors account for the credit risk of unrated versus rated bond issues.

The credit spreads of shorter maturity bonds have been suggested to be more sensitive to short run changes in the issuing company, for example the leverage ratio (Van Landschoot, 2004), which effectively makes these bonds prone to greater credit spread fluctuations. It is thus of interest to study the relationship between the relative spreads of investment grade and speculative grade bonds with a more stable sample group. Thus, the regressions are performed for a bond sample with maturity restricted between 5 and 10 years. The regression results, which are presented in Table 9, are in principal consistent with the results discussed in the paragraphs above, although they seem to even out somewhat. For example, the constant coefficient of the Merton DD model's speculative grade implied bonds moves closer to that of investment grade implied bonds with the index yield spread coefficients remaining roughly the same, implying a smaller difference between investment and speculative grade bonds. For both models, however, the index yield spread coefficients as well as the constant coefficients are still higher for bonds with investment grade implied ratings than for bonds with speculative grade implied ratings, suggesting that investment grade unrated bonds carry higher yield spreads relative to their rated peers than are speculative grade unrated bonds relative to theirs. The regression results for rated bonds are also reported for comparative purposes, although they remain to a high extent the same as when reported for all rated bonds with investment grade ratings.

Table 8: Regression results for unrated bonds

The table depicts the regression results for all unrated bonds, for unrated bonds with an implied investment grade rating and for bonds with an implied speculative grade rating. The regressions are performed separately for the two sets of implied ratings obtained using the shadow rating model and the Merton DD model.

	All bonds			Investment grade bonds			Speculative grade bonds		
Shadow rating									
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	0,358	0,047	-13,66***	1,194	0,118	1,63	0,716	0,138	-2,06*
Amount issued	0,015	0,044	0,34	0,079	0,036	2,19*	-0,078	0,077	-1,01
Constant	1,164	0,210	5,54***	0,122	0,202	0,60	-0,720	0,761	-0,95
n		179			106			73	
R-square		0,252			0,499			0,288	
Chi-square		8,31			2,91			6,53	
Merton DD									
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	0,230	0,041	-18,78***	0,731	0,246	-1,09	0,397	0,111	-5,43***
Amount issued	-0,048	0,054	-0,89	-0,076	0,062	-1,23	0,029	0,089	0,33
Constant	1,893	0,184	10,29***	1,765	0,215	8,21***	0,485	0,765	0,63
n		163			118			45	
R-square		0,167			0,086			0,234	
Chi-square		5,74			2,93			6,38	

Table 9: Regression results for bonds with maturities ranging from 5 to 10 years

The table depicts the regression results for unrated and rated bonds with maturities ranging from five to ten years. The regression results are reported separately for bonds with investment grade implied ratings and for bonds with speculative grade implied ratings. The regressions for the unrated bonds are performed separately for the two sets of implied ratings obtained using the shadow rating model and the Merton DD model.

	Investment grade bonds, maturity 5 - 10 years			Speculative grade bonds, maturity 5 - 10 years		
Rated bonds						
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	1,003	0,046	0,07	0,775	0,120	-1,88
Amount issued	0,012	0,009	1,33	-0,026	0,090	-0,29
Constant	-0,121	0,093	-1,30	-0,359	0,529	-0,68
n		302			84	
R-square		0,702			0,450	
Chi-square		3,62			7,09	
Shadow rating						
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	0,949	0,123	-0,42	0,571	0,15	-2,86**
Amount issued	0,132	0,043	3,05**	-0,043	0,076	-0,57
Constant	0,258	0,218	1,18	-0,236	0,769	-0,31
n		84			59	
R-square		0,446			0,207	
Chi-square		1,21			4,41	
Merton DD						
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	0,606	0,324	-1,22	0,244	0,109	-6,97***
Amount issued	-0,031	0,082	-0,38	0,049	0,080	0,62
Constant	1,756	0,246	7,17***	1,090	0,753	1,45
n		101			32	
R-square		0,035			0,153	
Chi-square		3,98			2,61	

The phenomenon of unrated bonds with investment grade implied credit ratings having relatively higher credit spreads than bonds with speculative grade implied credit ratings becomes even more evident and interesting when the index yield spread coefficients are examined by rating class. Namely, as Table 10 depicts, the coefficient estimates decline steadily by ratings class, which implies that the higher the credit risk of the unrated bond, the higher its credit spread discount is relative to its rated counterpart. The declining coefficients are evident for both the shadow rating and the Merton DD model, although the Merton model is somewhat less consistent when examining the constant coefficients as well. In the shadow rating model, also the constant coefficients decline steadily with rating class, whereas in the Merton DD model the constant first declines, then increases and finally jumps to a very high level. In the shadow rating model, the best rating classes (Aa - A) are priced at a clear premium relative to rated bonds with both the index yield spread coefficient and the constant being positive. When moving to the speculative grade categories, the index yield spread coefficients drop below one and the constant coefficients turn negative. The coefficients are lowest for bonds rated B1 - B3. Caa rated bonds were not examined due to an excessively small sample size. Figure 1 depicts the decline in the index credit spread coefficients.

Figure 1

The figure depicts the index yield spread coefficients by rating class for the shadow rating model and Merton DD model.

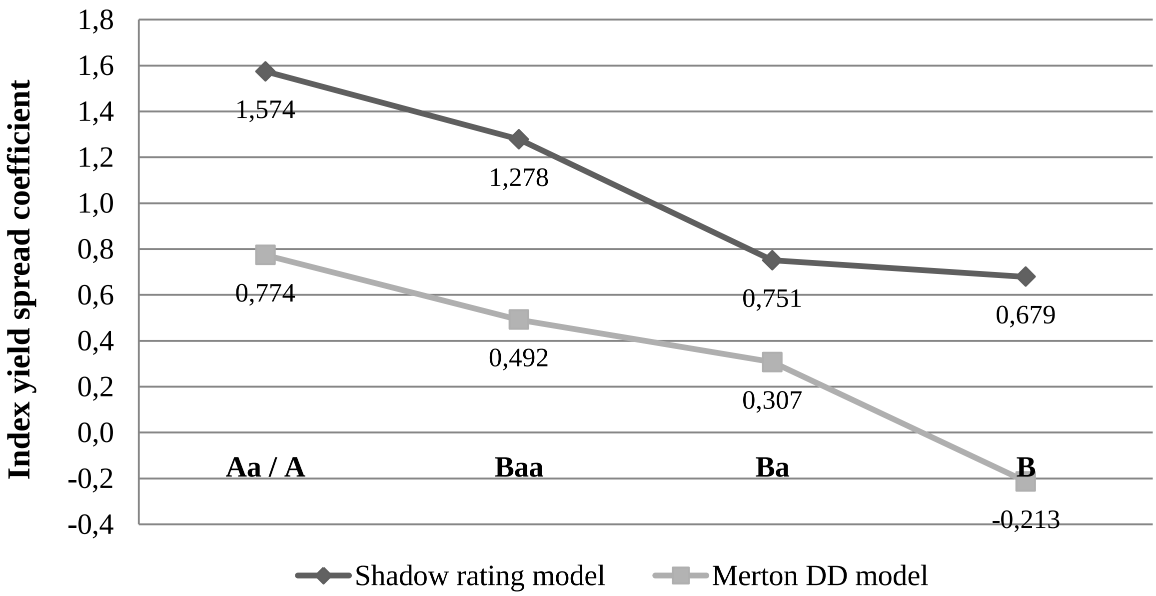

Table 10: Regression results unrated bonds by rating class

The table depicts the regression results for unrated bonds by implied rating class. The regressions are performed separately for the two sets of implied ratings obtained using the shadow rating model and the Merton DD model.

	Shadow rating model			**Merton DD model**		
	Aa1 - A3			Aa1 - A3		
Independent variable	Est. Coef.	S.e.	t-value	Est. Coef.	S.e.	t-value
Index yield spread	1,574	0,274	2,09*	0,774	0,565	-0,40
Amount issued	0,032	0,055	0,58	-0,080	0,059	-1,37
Constant	0,161	0,300	0,54	1,693	0,250	6,77***
n		37			106	
R-square		0,517			0,04	
Chi-square		11,45			1,08	
	Baa1 - Baa3			Baa1 - Baa3		
Independent variable	Est. Coef.	S.e.	t-value	Est. Coef.	S.e.	t-value
Index yield spread	1,278	0,169	1,64	0,492	0,570	-0,89
Amount issued	0,097	0,061	1,58	0,469	0,320	1,46
Constant	-0,110	0,305	-0,36	0,885	1,403	0,63
n		69			12	
R-square		0,473			0,208	
Chi-square		3,16			5,95	
	Ba1 - Ba3			Ba1 - Ba3		
Independent variable	Est. Coef.	S.e.	t-value	Est. Coef.	S.e.	t-value
Index yield spread	0,751	0,154	-1,62	0,307	0,294	-2,36*
Amount issued	-0,008	0,084	-0,10	-0,037	0,179	-0,21
Constant	-1,356	0,830	-1,63	1,111	1,828	0,61
n		48			13	
R-square		0,347			0,108	
Chi-square		5,12			5,47	
	B1 - B3			B1 - B3		
Independent variable	Est. Coef.	S.e.	t-value	Est. Coef.	S.e.	t-value
Index yield spread	0,679	0,247	-1,30	-0,213	0,341	-3,56**
Amount issued	-0,104	0,138	-0,76	-0,283	0,278	-1,02
Constant	-0,123	1,370	-0,09	5,942	3,247	1,83
n		23			12	
R-square		0,311			0,110	
Chi-square		3,11			10,31	

Of course, one must bear in mind that the regression model was earlier shown to be less accurate for speculative grade bonds. The declining trend also in the investment grade classes is, however, a quite interesting phenomenon. In order to verify that the declining yield spread coefficients especially in the higher rating classes is not a model misspecification, the same regressions are performed for the sample of rated bonds by rating category Aa/A, Baa and Ba. B rated bonds were not available in the bond sample. As depicted by the regression results in Table 11, the coefficient estimates do not decline in a similar manner for bonds with official investment grade credit ratings. For both Aa/A and Baa rated bonds, the yield spread coefficient stays very close to its hypothetical value of one and the constant coefficient stays very close to zero. For bonds with official speculative grade ratings both coefficients are, however, quite in line with the results obtained using the shadow rating model. In fact, both the index yield spread coefficient and the constant coefficient are roughly in the middle of the values obtained for speculative grade bonds from of the shadow rating model. Again, the Merton DD model's results are less comparable.

It is noteworthy that the goodness of fit for the Merton DD model's regressions by rating class are extremely low, especially for the best rating classes Aa - A for which R-squared is only 0,04. This points to very large dispersion in the examined credit spreads. To recall, the Merton DD model's implied rating calculations are most likely erred at least in the investment grade rating classes. As stated in Section 6.1, the misspecifications in the higher rating classes are caused by the historical default rate distribution used for mapping the Merton DD default probabilities into implied credit ratings, which then also causes inconsistencies in the regression analyses. Also, it seems that the Merton DD model is to some extent biased to estimate excessively high ratings, as depicted by the large amount of bonds that scored a high investment grade rating. As can be recalled from Table 5, 64 % out of the Merton DD model's total sample of unrated bonds scored an Aaa / Aa rating, which is unlikely to reflect the true level of the unrated bonds' credit risk. As a result, also the regression results in these rating categories can be expected to be distorted, as depicted by the low measured for goodness of fit. Furthermore, the fact that most bonds in the Merton DD model scored the highest rating classes makes the sample sizes for the other rating classes significantly smaller, again leading to somewhat unreliable regression results. Thus, it is perhaps better to concentrate on larger bond / credit rating groupings when examining the Merton DD model's regression results. Most likely a part of the Merton DD implied Aa or Aaa rated bonds are in reality worthy of an A or Baa rating.

Table 11: Regression results for rated bonds by rating class

The table depicts the regression results for the sample of rated bonds against the rated bond indices. The regressions are run separately by ratings class.

	Aa1 - A3			Baa1 - Baa3			Ba1 - Ba3		
Rated bonds									
	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value	Est. Coef.	s.e.	t-value
Index yield spread	1,002	0,061	0,03	0,974	0,064	-0,41	0,784	0,070	-3,09**
Amount issued	0,019	0,008	2,38*	-0,006	0,014	-0,44	0,027	0,045	0,60
Constant	-0,106	0,070	-1,51	-0,048	0,155	-0,31	-0,581	0,447	-1,30
n		207			294			84	
R-square		0,720			0,690			0,450	
Chi-square		4,02			5,11			7,09	

6.3 Implications of credit spread discrepancies

Regardless of the certain issues regarding the regression analyses, the results clearly indicate that pricing discrepancies between unrated and rated bonds prevail. One possible explanation for these discrepancies supported by earlier literature is simply that the unrated issues lack a public credit rating: if credit ratings independently offer value to investors and affect their pricing behavior, the prices of unrated bonds should rationally differ from those of rated bonds with otherwise equal characteristics. For example, it has been suggested that the reason that companies are willing to pay for credit ratings is that they can incorporate price-sensitive inside information into them and thus the market prices of their securities, i.e. credit spreads, without fully disclosing the information to the public (Kliger and Sarig, 2000). The inside information included in credit ratings would make the ratings a valuable pricing tool for investors, the lack of which would then lead to wider differences in demanded credit spreads. Another quite plausible suggestion for credit ratings providing incremental value to investors is the monitoring role provided by credit ratings agencies (Boot et al., 2006). Namely, if a company's credit rating is in threat of deterioration, the credit rating agency can place the issuer company on so-called "Credit Watch". The "Credit-Watch" procedure incentivizes the company to take action towards improving its credit quality, which again offers value to bond investors and drives down the demanded credit spread. The lack of a credit rating and an outside overseer of the company should thus increase the credit spreads demanded for investing in unrated issues, which would suggest the credit spreads of unrated bonds to be higher than those of rated bonds.

This theory of unrated bonds having higher credit spreads is, however, only weakly supported by the study results. Namely, as can be seen from the different regression analyses, the credit spreads of unrated bonds relative to rated bonds are not only different, but seem to vary with the level of credit risk. The phenomenon of unrated investment grade bonds carrying relatively higher credit spreads than unrated speculative grade bonds, as reported by this study, can certainly be called an anomaly, especially since the coefficient estimates decline with rating class (although this effect isn't completely reliable when examining the speculative grade classes). The possible additional value component of credit ratings and rating agencies can perhaps explain some of the overall discrepancies between the credit spreads of unrated and rated bonds, but it fails to provide an explanation for the declining yield spread and constant coefficients. One factor which provides support for both the overall credit spread discrepancies and the declining credit spread coefficients is the fact that unrated bond issues often automatically fall into the speculative grade category when examined by institutional investors. If it were the case that institutional investors would demand higher credit spreads for all unrated bonds regardless of their actual credit quality, it would simply follow that those unrated bonds that would in reality be of high credit quality would be priced at higher spreads than advocated by their level of credit risk. This would support the declining yield spread and constant coefficients of unrated bonds with investment grade implied ratings. Namely, the higher the actual credit quality and implied rating of the unrated bond and the lower the credit spread of the similar rated bond, the larger the additional spread is that the unrated bond must carry.

Ignoring the fact that unrated bonds often are directly categorized as speculative grade, simply the higher opacity in the unrated bond market when compared to the rated bond market can cause differences in investors' pricing behavior in these markets. Unrated bonds are often issued by smaller companies, for which there is less information publicly available. Furthermore, institutional investors often stipulate that investments in unrated securities is restricted or not allowed at all. The smaller amount of information available in the markets and the restrictions large investors pose upon themselves effectively make the unrated market less transparent and less traded, prohibiting efficient price formation and leading to credit spread illogicalities. The restricted presence of institutional investors in the unrated market also affects smaller investors. For example, the guidelines that many institutional investors have pegged to credit ratings provide common ground when trading securities in the secondary markets of rated bonds. As an article by Financial Risk Management News and Analysis points out, without a rating that investors can use for comparative purposes, unrated bonds become harder to trade on[18]. The lack of a credit rating and the lower amount of information available in the unrated market makes it difficult for investors to compare the attractiveness of unrated bonds. These factors leave smaller investors more room for error, which again causes the spreads of unrated securities to differ from those of rated ones, and also explains why the credit spreads of unrated bonds may be subject to higher dispersion than the spreads of rated bonds. Supporting the framework of higher opacity in the unrated market, Morgan (2002) studies the risk assessments conducted by credit rating agencies for securities issued by the opaque bank industry, and for securities issued by other, less-opaque

[18] ”Unrated bonds: Borrowers go at it alone”, Financial Risk Management News and Analysis, 10 December 2009.

industries, such as e.g. the manufacturing and mining industries. The study uses disagreements between bond raters as a proxy for the uncertainty and information asymmetry associated with increased opaqueness, and reports, not surprisingly, that the risk of more opaque companies is harder to assess, making them more subject to rater disagreement. Furthermore, Morgan (2002) reports that rater disagreements decrease with issue size, and presumes this to be the result of smaller issues being issued by smaller, more opaque firms, which is also relatable to the unrated bond market.

The opacity issue in the unrated bond market supports a hypothetical framework that could explain the declining credit spread coefficients in both the implied investment grade and speculative grade rating classes, assuming that the phenomenon is also present in the speculative grade classes when using a more sophisticated model. The idea of the framework is that, if there was very little information available on a company, investors would most likely have highly differing estimations on the level of its credit risk. If investors anticipate the company to be of high risk, they will demand a higher credit spread, whereas if they anticipate a low risk company, the will demand a lower credit spread. The differing anticipations would result in a wide range of credit spread demands, causing the final level of the credit spread to amount to some kind of a weighted average of the range of demanded spreads. If the company was in reality of high credit quality, the average spread demanded would most likely force the company to pay a higher premium than required by its level of risk. This is consistent with the yield spread coefficients declining for the unrated bonds with implied investment grade ratings. If on the other hand the company was actually of low credit quality, the average spread demanded by investors would benefit the company, enabling it to pay a smaller premium than required by its level of risk. This would again be constant with the declining yield spread coefficients for the unrated bonds with speculative grade ratings: the lower the actual credit quality, the lower the index yield spread coefficient and the larger the benefit of increased opaqueness.

Although various theories can be built around the interesting phenomenon of declining credit spreads, much of the unrated bond market is still dominated by practical factors. The presence of institutional investors in the unrated bond market is smaller than in the rated market, which decreases the unrated market’s transparency and efficiency, and leaving more room for smaller investors to make errors. Unrated issuers tend to be small companies often prone to a “home bias”. That is, unrated issuers tend to be companies which investors feel they know and are in a sense emotionally attached to. This psychological bias leads investors to be less rational and objective when valuing their investments, often overestimating the issuers' financial stability and creditworthiness, leading to "erred" price formations and credit spreads. The home bias of these unrated issuers also causes high demand for the bonds and credit-linked notes of these companies. Larger demand naturally translates to a higher price and thus a lower credit spread, in this case seemingly in an excessive amount.

7. Conclusion

This thesis aims to provide insight into the pricing of European bonds without official credit ratings. More specifically, the goal is to study whether credit risk is similarly accounted for in the credit spreads of unrated and rated bonds, or whether discrepancies between the two classes occur. Utilizing three credit risk measurement models with different theoretical underpinnings, I measure the credit risk of a sample of European unrated bonds, and map them into implied credit rating categories. The credit risk measurement models used are a shadow rating model provided by Moody's, which is a simplified version of one of Moody's own rating methodologies, the classic Altman's Z-Score model, which weighs a set of financial ratios to provide a standardized credit score, and the Merton DD model, which draws its theoretical underpinnings from Black-Scholes-Merton option pricing theory. To assess the biasedness of the three models, the implied ratings are also calculated for a sample of rated bonds. On the basis of the assessment calculations, it is concluded that the shadow rating model is unbiased in estimating implied credit ratings, whereas the Merton DD model seems to be somewhat biased to estimate excessively high ratings. The Altman's Z-Score model is completely dismissed from further analysis due to extremely high inconsistency in rating predictions. After assigning the unrated bonds an implied credit rating based on the credit risk estimates of the shadow rating and the Merton DD model, I assess whether their credit spreads are comparatively equal to those of rated bonds with similar credit risk profiles (i.e. credit ratings) and other characteristics.

The hypothesis of the study is that if credit risk is accounted for equally in the prices of unrated and rated bonds, and other factors affecting credit spreads are taken into account, then theoretically the credit spreads of unrated bonds and rated bonds with the same level of credit risk should be equal. That is, the correlation coefficient measuring the relationship between the yield spreads of the unrated bond and the rated bond benchmark, which have similar credit risk profiles, should equal one. Furthermore, the constant coefficient should equal zero.

Liquidity, measured as the issue size of the bond, is controlled for separately. The expectation is that the correlation coefficient for liquidity is negative: higher liquidity is expected to imply a lower credit spread. The empirical results of the study provide support for rejecting the hypothesis of credit spreads between unrated bonds and rated bonds being equal. Using the implied ratings of both credit risk models, both the yield spread coefficients and the constant coefficients differ significantly from their hypothesized values, with the yield spread coefficient being much lower than one and the constant being much higher than zero. The coefficients for liquidity, on the other hand, are insignificant. The results are obtained when examining the whole implied rating spectrum are difficult to interpret, as the yield spread coefficients being lower than one indicate that the credit spreads of unrated bonds are lower than those of rated bonds with the same level of credit risk, but the extremely high constants imply otherwise. The results are plagued by high dispersion of credit spreads in the different rating classes, as depicted by fairly low measures of goodness of fit. Also, the regression model is shown to work properly only for investment grade issues, due to the nature of the high yield bond market. Thus, the study concentrates on examining these rating classes separately.

Although the economic significance of the results diminishes, an interesting phenomenon appears when credit spreads are analyzed separately for investment grade and speculative grade bonds. For both the shadow rating and the Merton DD models, the yield spread coefficients as well as the constants are higher for unrated bonds with investment grade implied ratings than for bonds with speculative grade implied ratings. This suggests that unrated bonds with higher credit quality, i.e. higher implied ratings, have larger credit spreads with regard to their rated counterparts than bonds with lower credit quality do with regard to theirs. In other words, the results imply that investors perceive unrated bonds with high credit quality to be relatively riskier than unrated bonds with low credit quality, which is quite counterintuitive. The phenomenon becomes even more intriguing when examining the yield spread coefficients by rating class. Namely, for both credit risk models, the yield spread coefficients decline steadily with rating class, implying that the lower the credit quality of the unrated bond, the higher the discount on its credit spread is with regard to its rated peers. In the shadow rating model, also the constant coefficients decline steadily, and the best rating classes (Aa - A) are even priced at a credit spread premium relative to rated bonds with the index yield spread coefficient being higher than one and the constant higher than zero. When moving to the speculative grade categories, the index yield spread coefficients drop below one and the constant coefficients turn negative. The results provided by the Merton DD model are not as consistent, as although the yield spreads decline, the movements of the constant coefficient vary.

The differences in the credit spreads of rated and unrated bonds can be suggested to be the result of various factors. For example, earlier literature suggests that credit ratings provide informational value for investors in the form of inside information and the supervising role of credit rating agencies, thus affecting the way they price credit securities. However, it is with high likelihood that the credit spread discrepancies found in this thesis are simply a result of practical issues in the unrated bond market. For instance, institutional investors, which drive price formation in most if not all financial markets, are less present in the unrated bond market due to various restrictions regarding unrated bonds. This reduces the transparency of the unrated market and makes it more difficult for smaller investors to follow the rationale of sophisticated investors. Without the guiding role of institutional investors and credit ratings providing a simple means of comparison in assessing a bond’s attractiveness, there is more room for errors and illogicalities in the prices of unrated bonds, resulting in a higher dispersion of credit spreads. Furthermore, as unrated bond issuers are generally smaller companies, investors often have psychological and emotional biases towards them in the form of over optimism regarding the issuer’s financial stability and creditworthiness. Summing up these factors, it is not surprising that the credit spreads of rated bonds and unrated bonds differ from each other, and it is also reasonable to assume that the effects are the largest for the unrated bonds with the highest and lowest credit risk profiles, leading to a declining pattern in the coefficient estimates.

My research focuses solely on a homogeneous sample of unrated and rated bonds to study the credit spread discrepancies in the European markets. However, the results of the study suggest there to be ample interesting topics for further research in the unrated securities markets on the whole. One interesting possibility for further research would be to expand the study to account for a wider set of geographical areas. For example, as the bond market is both larger and more developed in the US than in Europe, performing a similar study in the US bond market could provide more insight into how exactly the prices of unrated bonds behave with regard to their rated counterparts, or whether the phenomena even prevail in larger bond markets. Another interesting topic would be to expand the research sample to include a wider range of unrated securities. For example, studying whether the prices of stocks issued by unrated companies behave differently from the stocks of rated companies would reveal whether the same phenomena hold in other market segments as well. Furthermore, it would be interesting to perform a more accurate study on how the pricing discrepancies between unrated and rated securities evolve over time, especially since the market for unrated debt securities is constantly becoming larger and gaining influence.

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Appendix 1

Rating factor		Factor weighting		Sub-factor	Sub-factor weighting
1.)	Size and profitability	37,50 %	a.)	Revenues	18,75 %
			b.)	EBITA	12,50 %
			c.)	Return on average assets	6,25 %
				→ EBITA / Average total assets	
2.)	Financial policy	18,75 %	a.)	Debt / Book capital	6,25 %
			b.)	Gross debt / EBITDA	12,50 %
3.)	Financial strength	43,75 %	a.)	EBITDA / Interest expense	18,75 %
			b.)	FFO / Gross debt	12,50 %
				→ FFO = Cash from operations - change in working capital - change in non-cash working capital	
			c.)	FFO less dividends / Net debt	6,25 %
			d.)	FCF / Gross debt	6,25 %
				→ FCF = Cash from operations - dividends paid - capital expenditure	
Total		**100,00 %**			**100,00 %**

All figures are three year averages except revenues, which is the most recent annual figure.

All gross debt figures are adjusted according to Moody's standards:

Gross debt = short- and long term debt + 0,5 x pension reserves + future minimum operative lease obligations.

Appendix 2

Annual Default Study by Moody's Investors Service

Average Cumulative Issuer-Weighted Global Default Rates by Alphanumeric Rating, 1983-2012*

Rating	1-year default rate
Aaa	0,000
Aa1	0,000
Aa2	0,000
Aa3	0,052
A1	0,084
A2	0,070
A3	0,062
Baa1	0,151
Baa2	0,177
Baa3	0,273
Ba1	0,660
Ba2	0,767
Ba3	1,754
B1	2,381
B2	3,668
B3	6,372
Caa1	8,258
Caa2	17,858
Caa3	28,029
Ca_C	41,400
Investment Grade	0,101
Speculative Grade	4,721
All rated	1,858

* Data in percent

Appendix 3

Moody's	Fitch	S&P	Rating description (Moody's)	
AAA	AAA	Aaa	Investment grade	Minimal credit risk
AA+ AA AA-	AA+ AA AA-	Aa1 Aa2 Aa3		Very low credit risk
A+ A A-	A+ A A-	A1 A2 A3		Low credit risk
BBB+ BBB BBB-	BBB+ BBB BBB-	Baa1 Baa2 Baa3		Moderate credit risk
BB+ BB BB-	BB+ BB BB.	Ba1 Ba2 Ba3	Speculative grade	Substantial credit risk
B+ B B-	B+ B B-	B1 B2 B3		High credit risk
CCC+ CCC CCC-	CCC+ CCC CCC-	Caa1 Caa2 Caa3		Very high credit risk
CC C	CC C	Ca		In or near default, with possibility of recovery
DDD DD D	SD D	C		In default, with little chance of recovery