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Measuring credit risk: The relation between CDS Spreads, the modified Merton model and credit ratings

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Abstract

Prior articles and reports have named Credit Default Swap (CDS) spreads as a plausible indicator of default risk. In this report, the authors present a significant correlation between CDS spreads and two other more acknowledged methods of measuring default risk probabilities; the modified Merton model and credit ratings from the rating institute Moody's. The tests are implemented by Spearman's rank correlation with data obtained between the years 2008 to 2011. The sample is based on 30 firms in Europe and America, respectively, and is chosen after the number of outstanding CDS contracts in November 2012. In order to get as accurate results as possible, the selection of firms are separated into financial and non-financial sectors: five financial and 25 non-financial firms, respectively for each continent. The CDS spreads are obtained from 5-year maturity contracts and are taken from Thomson Reuters DataStream. The variables needed to calculate the modified Merton are obtained from the same source as well as from comprehensive Excel files provided by professor Aswath Damodaran at NY University.

Keywords: Credit Default Swaps, CDS spreads, credit ratings, Moody's, the modified Merton model, risk assessment, measuring credit risk

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1. Introduction

A financial actor's exposures to systematic and nonsystematic risks have to be taken into account when investing in the financial markets.

Systematic risk is the type of risk that cannot be diversified away; it depends on the return from the whole financial market (Hull 2012). For instance, a portfolio of stocks with different types of volatility can be diversified in order to reach a minimum level of risk but cannot erase other forces such as bank solvency, interest rates and economic shocks which are a part of systematic risk (Schwarcz 2008).

Nonsystematic risk is the risk that is confined only to a certain asset, firm or industry and can be diversified away, unlike macroeconomic risk (systematic). Examples of nonsystematic risk could be union related strikes or management risk (Franklin Templeton Investments 2012).

In our thesis, we will put the emphasis on the latter, i.e. nonsystematic risk. Credit risk, or default risk, which is a type of nonsystematic risk, is an important risk for financial institutions to measure and manage (Hull 2012). Credit risk derives from the likelihood that a firm, which could work as a borrower and a counterparty, often in transactions with derivatives, will default (Hull 2012). For instance, the risk that a firm issuing a bond not will be able to pay back the par value and interest, i.e. not be able to pay back their debts, is defined as default risk (Garlappi, Shu & Yan 2008).

The attention for credit risk in the financial markets has increased during the last years due to the unstable financial climate that have been seen since the start of the financial crisis in 2007 and today's debt crisis in Europe. The assessment of the credit risk linked to different financial actors – irrespectively if they are sovereign states or individual firms – has become an increasingly important and complex issue in the financial market. In order to get an estimate of the exposure to credit risk, there are some methods that can be applicable.

The credit risk is measured and classified in rating systems that are managed by different ratings agencies acting on different levels and parts of the markets both on local level as well as worldwide.

On a global level there are three main rating agencies in the world today: Moody's, Standard & Poor's and Fitch (Christiansen et al. 2004). These agencies all have their own way of defining the ratings, although having a similar approach (Christiansen et al. 2004).

The purpose of these types of ratings is to independently and objectively inform about issuers ability to meet their financial commitments in the future. With the ratings in mind investment decisions can more reliably be made and investors become more protected, since they bring better transparency in the capital markets (Christiansen et al. 2004).

Investors, savers, governments, issuers and borrowers, for instance, are the typical users of credit ratings. Regarding issuers, they benchmark pricing against ratings, and investors use ratings in the decision to invest in a security. Investors have a consensus that a minimum credit rate must be used in investment to debt (Christiansen et al. 2004).

Credit ratings also facilitate communication of creditworthiness between counterparties and are working as instruments for investors in portfolio management (Christiansen et al. 2004).

1.1 Risk assessment and reduction

Different financial activities usually have an immediate exposure to credit risk. Measuring such risk is therefore crucial to forecast the losses that could occur if a, for example, counterparty does not fulfill its financial commitments (Byström 2005).

Investing in credit derivatives can be helpful for investors to manage and reduce credit risk (Byström 2005). In theory, the higher risk you take, the higher the pay-off from your investment and at the same time, a higher risk of losing a large part of your investment, all depending on the creditworthiness of the counterparty in the financial contract (Hull 2012).

The most commonly traded credit derivative is a credit default swap (CDS) (Hull 2012). Briefly, a CDS is a credit derivative that can be defined as an insurance contract between two parties, the protection buyer/holder and the protection seller/issuer of the contract, against a credit event involving a reference entity (Byström 2005). The reference entity's credit status therefore helps to determine the value on the CDS (Jacobs et al. 2010). Such a reference entity can be a bond or a loan of a financial institution (firm) or of a sovereign institution (state) (Giglio 2010). So-called single-name CDSs are the most frequently used when trading with credit derivatives (Hull 2012).

The CDS contract includes a periodic CDS premium, often called “spread”, which is the cost of insuring against a firm’s probability of default. The CDS spread is a (often) quarterly serial of payments that the buyer pays the seller in case of a default by the reference entity (Hull 2012).

An increase in the CDS spread implies that the risk of default of institutions increases (Giglio 2010). Since a CDS contract includes counterparty risk, the spread indicates both the likelihood of default of the reference entity (a specific firm) and the correlation between its default and the default of the protection seller (Giglio 2010). Consequently, this information is valuable for how financial markets identify the default risk on corporate or sovereign debt (Noeth & Sengupta 2012).

Spreads have two main areas of importance; CDS spreads can be used as a good pricing estimator of default risk of the underlying reference entity since it is often traded on standardized conditions on specific maturities (Zhang, Zhou & Zhu 2005). However, in general, the contracts are traded Over the Counter (OTC) (Giglio 2010). CDS spreads also have the trait that they respond more quickly to anomalies in credit conditions in the short run compared to, for instance, bond spreads (Zhang, Zhou & Zhu 2005).

An alternative way to estimate credit risk to CDS spreads is to find credit risk information directly from the market. If there is credit risk in the market, market prices could include risk information and by calculating on basis of this information there are ways to measure credit risk. Byström (2006) presents a modified “spread sheet” model of Merton’s (1974) default probability model. Merton (1974) examines a firm’s equity and debt relative to its underlying assets. In order to calculate this, Merton (1974) extract figures and volatilities from stock prices resulting in specific probabilities of default. Compared to the traditional Merton model, the modified model takes some assumptions that makes the model more easily calculated, and results in a firm’s “*distance-to-default*” probability.

1.2 Our task related to the calculation of credit risks

The aim of this thesis is to give a contribution to an in-scientific explanatory discussion by comparing different credit risk indicators to estimate the level of default risk. Generally speaking, we want to show how different risk methodologies "behave" in relation to some common parameters in the credit risks environment.

In order to succeed with this ambition, we have collected a mass of empirical material consisting of data from 30 American and 30 European firms. The size of the empirical material allows us to carry out statistical tests in order to investigate into different types of risk indicators.

This empirical approach and a statistical calculation give us the opportunity to accomplish the main purpose of this Bachelor Thesis to compare and examine

- Credit Default Swap (CDS) spreads
- Credit ratings from Moody's credit rating agency
- The modified Merton model.

Our objective is to explain the meaning of these three measures, find whether there is any correlation between them, call attention to which differences there are, and on basis of the results achieved, draw conclusions for the benefit of an improved discussion on risk assessment. Credit ratings from Moody´s credit rating institute are acknowledged by the market as an accepted measure of default risk (Daniels & Jensen 2005) and the modified Merton model is based on a well-used traditional estimator of default risk (Byström 2006). Therefore, we are using them as a benchmark in relation to CDS spreads in order to analyze if CDS spreads are plausible indicators of default risk. This can be summarized into our main purpose:

"Are CDS spreads a statistical significant indicator of credit risk compared to acknowledged credit risk measurements?"

A rise in CDS spreads implies that the risk of default of institutions increases (Giglio 2010). We are therefore hoping that our results will show that when CDS spreads rise, there is a downfall in *distance-to-default* (the modified Merton model) and Moody´s credit ratings and by that find a correlation between these two acknowledged methods of measuring default risk and CDS spreads.

The rationale behind our chosen topic is that we personally have been increasingly interested in credit risk in the last years due to the tremulous financial climate in the financial markets.

The thesis is structured in the following way: Chapter 2 highlights which studies that already exist on this topic, Chapter 3 explains the theory behind the credit risk indicators we are using, Chapter 4 presents our data, Chapter 5 describes the methodology in our calculations, Chapter 6 the results, Chapter 7 the analysis, and finally Chapter 8 contains the conclusion.

2. Previous research

Measuring credit risk has been a topic – not unsurprisingly – in numerous scientific papers during last years. For instance, Jacobs et al. (2010) have written a paper that examines the relationship between CDS spreads and credit ratings in order to clarify how market participants recognize and price credit risk. While Berndt et al. (2008) investigates the price variation over time when being exposed to U.S. corporate default risk, based on Moody's and CDS market rates as measures of probability of default.

Jacobs et al. (2010) implement a similar survey, yet a bit more extensive than ours, by examine 391 5-year CDS contracts using Bloomberg as the data source over a time period from 2003 to 2008. They model the CDS spreads and also the variation between CDS spreads and credit ratings. Also, they study the scope of spreads for every rating and what happens to the variation scope of spreads if the credit quality gets worse (Jacobs et al. 2010).

Furthermore, Jacobs et al. (2010) investigates the dependent factors that affect the variation scope of spreads. Similar to our thesis, they also give examples of methodologies on how to valuate CDSs. With the dependent factors, they seek to find an explanation of the variation scope of spreads of reference entities that have equal ratings.

Jacobs et al (2010) find that there is a broad variation in the observed CDS spreads for firms compared to their given credit rating, although CDS spreads are related to credit ratings.

Concerning Berndt et al. (2008), they provide a survey on 93 firms and can present a strong explanatory degree between actual and risk-neutral default probabilities. When examining CDS rates, they see variations over time in spreads for a certain default probability. Berndt et al. (2008) concludes that CDS spreads are highly dependent on volatilities in the stock market when they examine this on firms' specific volatility on probabilities of default.

When it comes to modeling default risk by the Merton model, Byström (2006) is, in his paper "Merton Unraveled: A Flexible Way of Modeling Default Risk", presenting a simplified version of this model of which we are using as the main source when describing and calculating on the modified Merton measure.

Information on CDSs, credit rating agencies and the Merton model are in general well documented in earlier papers and publications. Moreover, as described above, studies concerning the relation between CDS spreads and credit ratings have also been done. However, to our knowledge, there is no previous work on examining the statistical relationship between CDS spreads, credit ratings and Merton's *distance-to-default* measure.

3. Theory

3.1 Credit Default Swaps and CDS Spreads

As mentioned in the introduction, the credit derivative CDS is a financial contract which objective is to protect against the risk that a reference entity (a firm) will not be able to meet its financial obligations; and consequently defaults. If a default occurs, it is called a credit event (Hull 2012, Byström 2005).

A CDS means trading with pure credit risk since it is not linked with other likely risks, for example interest rate risk or foreign exchange risk. By not transferring the underlying asset, a CDS trades the credit risk from one actor to another (Byström 2005). CDS contracts are usually traded Over The Counter (OTC) and could therefore be customized by the issuer and the holder of the contract (Giglio 2010). However, standardized contracts, concentrated around specific maturities, are commonly used as well (Byström 2005). According to Giglio (2010), a contract with a maturity of 5 years is relatively standardized.

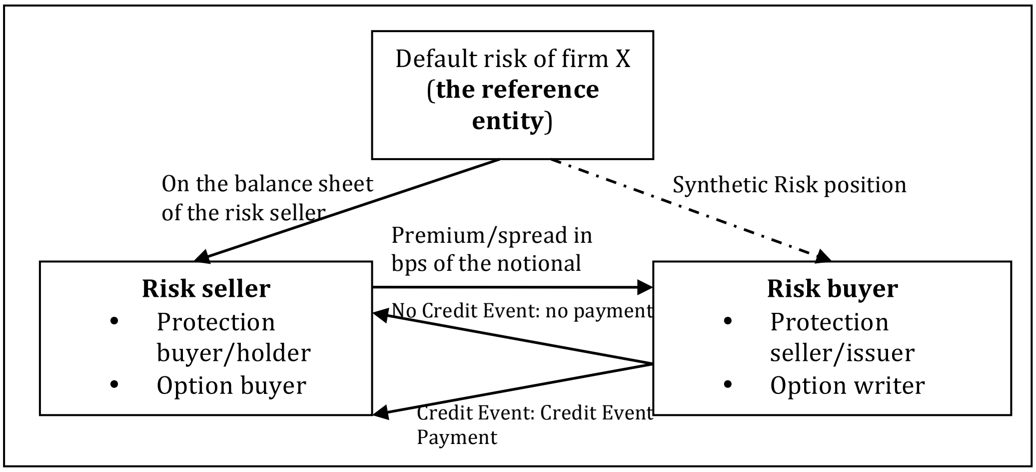
In case of a credit event the seller is forced to compensate the buyer. The compensation is often designed in two ways; either by physical settlement or by cash settlement. The first term means that the holder of the CDS can give the issuer of the CDS the defaulted bond in exchange of the par value of the bond (Noeth & Sengupta

2012). The CDS could in this case be seen as a contingent put option, it is only activated if the reference entity defaults (Skora 1998).

The second term implies that the issuer can pay the holder the difference between the bond's par value and its current market price of the reference entity that it still holds (Noeth & Sengupta 2012).

If a credit event does not happen, the holder pays a fee, or spread, based on the value insured to the issuer until the financial contract expires (Noeth & Sengupta 2012). The spread, also called premium, is quoted as a percentage of the notional value that is insured (Giglio 2010). The CDS spread percentage is normally expressed in basis points (bps), where one percent is 100 basis points (Zhang, Zhou & Zhu 2005).

Figure 3.1. Illustration of a CDS[1]



For instance, if the seller is insuring 1 million dollars to the buyer on a defaultable bond and the annual spread is 400 basis points, then the buyer has to pay the seller 100 basis points of the 1 million dollars, which is 10 000 dollars, four times per year (if there are quarterly payments). The buyer of the swap is obliged to pay the seller this annual premium for protection from credit risk (Bodie, Kane & Marcus 2011).

One important aspect of CDSs is that the contract can help the buyer to increase its creditworthiness on the outstanding loan. For instance, if the issuer of the CDS has a credit rating of Aaa (top ranking); the insured debt would obtain the same rating. If a Baa-rated bond were to be incorporated with insurance on a CDS contract making it equivalent to an Aaa-rated bond, the premium/spread on the swap would be the yield

[1] Based on professor Ian H. Giddy's, New York University, diagram introduced at the seminar on "Risk Management in Financial Institutions" at Sogang University, Seoul, October 2011.

spread between the Aaa-rated bond and the Baa-rated bond (Bodie, Kane & Marcus 2011).

Tang & Yan (2012) write that changes in CDS spreads, according to the Merton model, are mainly driven by "leverage, asset volatility, and market conditions such as interest rates". Another factor in CDS spread changes is risk aversion of investors in the market, making the spreads potentially increase when investors becoming more risk averse (Tang & Yan 2012).

To determine the price on a CDS, it is significant to look at the exposure of credit risk on the reference entity. To calculate this, three main methods can be used. The first method is to look at different credit institutes' (e.g. Moody's) rating for an individual firm, concerning its capability to meet its financial commitments. The second is to use accounting information to measure credit risk. The third method is to find information of the credit risk from the stock market, using the earlier mentioned modified Merton model (Byström 2005).

3.1.1 Credit ratings impact on CDS pricing

Credit ratings are the most significant informants on credit risk, and they have a great impact on CDS prices when an announcement of a rating agency is made (Batta 2011). They calculate different rating levels on an individual firm's ability to meet its financial commitments (e.g. repayment of loans) (Byström 2005). Credit ratings are important guidelines for credit quality of financial institutions and different reference entities (Daniels & Jensen 2005). A significant part of the spread on a CDS is reflected in the rating of a reference entity, thus, this rating stands for the compensation required to insure against the pure credit risk of a firm. If this is true, CDS spreads and credit ratings of the reference entity should correlate to a certain degree (Jacobs et al. 2010).

3.1.2 Accounting information's impact on CDS pricing

Another determinant when pricing CDSs is accounting information. Batta (2011) writes that it has been documented that prices on CDSs react to quarterly reports by firms. When adding accounting information to market models it increases their predictive relevance for the prices on CDSs.

Some criticisms regarding accounting information are that this information is not updated contemporary with the market and is also updated with too large time spaces.

Moreover, accounting information is only based on historical information, and do not take the market's anticipation of the future into account. There is also a risk that it has been manipulations with the accountancy (Byström 2006).

It is however not clear if the CDS market integrates the information directly from accounting reports, or just uses some of the accounting information to look at the debt and equity security prices, and the credit ratings (Batta 2011). The Merton (1974) model, for example, relies on the firm's equities, debts, volatility, and stock prices. These variables may already be included in the firm's accounting reports (Batta 2011).

Regarding credit ratings, they are less costly and time consuming than examine accounting reports in a regular way, since accounting information is often already included in the ratings (Batta 2011).

3.2 Moody's credit ratings and rating methodology

Rating agencies purpose is to give reliable ratings on issuers' creditworthiness in the financial market (Hull 2012). We have decided to use Moody's credit ratings in this thesis. The motivation for using Moody's is that when researching for our thesis, we found that many of the previous research reports and papers indeed were using Moody's as the main benchmark. Moreover, it was easy to gain access to the ratings.

Moody's uses a rating classification – highest to lowest – of Aaa, Aa, A, Baa, Ba, B, Caa, Ca and C. The rating Aaa indicates that the (for example) bond has a small risk of defaulting. Bonds with ratings better than Baa are seen as the boundary for investment grade (Hull 2012).

There are also subcategories, Moody's uses Aa1, Aa2, and Aa3 for its Aa category, and A1, A2 and A3 for its A category etc. The highest rating along with the two of the lowest ratings is normally not divided into subcategories (Hull 2012). Bonds that have large risk of defaulting are denoted as non-investment grades, that is, below Baa3 (Daniels & Jensen 2005).

Some general criticisms that rating agencies have received are that they are updating the ratings too infrequently (Byström 2006) and only react to actual events, instead of forecasting them (Christiansen et al. 2004). Though, it is the management of the firm that is the basis of their analysis, consequently, the management could be able to conceal bad financial status (Christiansen et al. 2004).

3.2.1 Moody's rating method

Moody's uses both a qualitative and a quantitative approach to determine its credit ratings. Moody's examines the macroeconomic situation (the setting of politics, economy and industry), then assesses each firm's operating situation, and concludes with evaluating the firm's financial strategy. Emphasis is put on financial protection in the future, not only on historical information. These approaches are almost the same for all of the industries (Christiansen et. al. 2004).

In terms of qualitative factors, Moody's examines a firm's management, financial pliability etc. (Christiansen et. al 2004). And concerning the quantitative factors, Moody's looks at, for instance, a firm's capital sufficiency, its profitability, its investment/asset risk, and solvency and liquidity (Christiansen et al. 2004). Likewise Standard & Poor's, Moody's gives the different variables a rating and then calculates an average value as the final grade.

For banks, Moody's is using a different rating classification system, namely Bank Financial Strength Ratings (BFSR). The difference from the rating system explained above is that BFSR are not evaluating the probability of banks' failure of meeting their timely payments (creditworthiness). BFSR rather measure the probability that a certain bank will need help from third parties, for instance from the management or official institutions (Moody's Investors Service, Inc. 2012).

BFSR consider factors of risk in the bank's business settings, such as the status of the economy, the financial system, and how the bank's regulations and supervision is working (Moody's Investors Service, Inc. 2012).

The rating scale in this case goes from A to E (A, B, C, D, E), with subdivisions of (+) and (-) for ratings below the A category and above the E category (Moody's Investors Service, Inc. 2012).

3.3 The modified Merton model

One of the most famous models for estimating default risk is the Merton (1974) model. The model estimates a firms credit risk by replicating a call option on its equity using the firm's assets as the underlying asset. A European call option is in-the-money when the spot-price exceeds the strike-price at maturity *T*, i.e. the pay-off will be:

$$Max(S_T - K, 0)$$

The Merton model works in a similar way. A firm's asset in time t is given by A, and is financed by equity, E, and a zero-coupon debt D, of the par value K[2] maturing at time T (Wang 2009). The capital structure is given by the following balance sheet:

$$A = E + D$$

The firm's debts are all mapped into a zero-coupon debt, which matures at time T. If $A > K,$ the debt holders will receive the full invested amount and the shareholders value will still be $A - K$. If $K > A$, the firms debt exceeds its assets and the firm will therefore default (Wang 2009). The debt holders will have the first claim on the residual asset A and shareholders will receive a payoff of 0. The equity pay-off can now be shown at maturity T (Wang 2009):

$$E = Max(A - K, 0)$$

As previously mentioned, this pay-off replicates the pay-off of a European call option.

Since Merton's model (1974) is replicating a call option, it's applicable to use the Black-Scholes (1973) pricing formula to calculate the default risk. The Merton model uses the Black-Scholes formula to calculate what is called *distance-to-default* which is a measure of creditworthiness of the equity-issuing firm, using the asset value and asset volatility. For this to be possible, the Merton model will have to follow the same assumptions as the Black-Scholes formula.

The Merton model is constructed in the following way (Hull, Nelken & White 2004) where today's equity price is given by:

$$E_0 = A_0 N(d_1) - Ke^{-rT} N(d_2)$$

Where d_1 and d_2 is given by:

$$d_1 = \frac{\ln(A_0/K) + (r - \frac{1}{2}\sigma_A^2)(T - t)}{\sigma_{A\sqrt{(T-t)}}}$$

$$d_2 = d_1 - \sigma_A \sqrt{(T - t)}$$

Where

[2] The instrumental value of amount of money stated on a bond.

$$E = market\ value\ of\ the\ firms\ equity$$
$$A = Market\ value\ of\ the\ firms\ assets$$
$$K = Total\ amount\ of\ the\ firms\ debt$$
$$T - t = Time\ to\ maturity\ of the\ firms\ debt$$
$$r = risk\ free\ interst\ rate$$
$$N(d1/d2) =\ Cumulative\ normal\ distribution$$

As previously mentioned, the firm's debts are all mapped into one homogenous debt along with the residual equity ($A = E + D$), which is referred to as K. The term A_0/K will be referred to as the leverage ratio (Byström 2006).

Furthermore, the relationship between equity and asset volatility are given by the expression:

$$\sigma_E = \frac{A}{E} N(d_1)\sigma_A$$

The model used in this thesis is based on the original Merton model but modified in a "spread sheet" version (Byström 2006). The model takes three assumptions regarding the original Merton model:

- *The drift term* $(r - \frac{1}{2}\sigma_A^2)(T - t)$ *is assumed to be "small"*
- $N(d_1)$ *is assumed to be "close to one"*
- *The book value of debt is used is used to calculate the leverage ratio.*

The reason for the first assumption is that in most situations, the drift term is found to be small in relativity to the $ln\ (A/K)$ term. It has also been empirically proven that to actually estimate the drift rate of stocks or other assets has been difficult. Therefore, the drift term is often considered to be zero (Byström 2006). The second assumption of $N(d_1)$ being close to one, is based on the observation that only in extreme cases where A is close to K (the option is at-the-money) and the underlying asset volatility is very high, $N(d_1)$ significantly differs from 1 (Byström 2006). The third and final assumption, that the book value is used to calculate leverage ratio and not the market value. In theory, when adding the equity value and debt, the market value should be used, as in the Merton model. The fact that only equity has a quoted market value introduces an error when adding the value of equity to the book value of debt. The method of using book value is also justified by the fact that the book value of debt that has to be paid back in case of a default and not the market value (Byström 2006).

If we elaborate the model and draw back to the first assumption that the drift term is smaller than $ln\ (A/K)$, and making the common assumption that time to maturity $(t \rightarrow T)$ of the debt is one year, the expression of time to default can be reduced to (Byström 2006):

$$DTD^3 = \frac{\ln(A\,/K)}{\sigma_A}$$

If we furthermore consider the relationship between σ_E and σ_A and our second assumption of $N(d_1)$ being close to one, we can replace σ_A with $\frac{\sigma_E\ V_E}{V_A}$. By doing this, we get (Byström 2006):

$$DTD = \frac{\ln(A\,/K)}{\sigma_E\ E/K}$$

Finally, if we define the leverage ratio as $L = \frac{K}{A}$, we can further simplify the expression of *distance-to-default* as:

$$DTD = \frac{\ln(1/L)}{\sigma_E(1-L)} = \frac{\ln(L)}{(L-1)}\frac{1}{\sigma_E}$$

In order to only use observable parameters, we also have to make the assumption that the leverage ratio L, can be calculated as

$$L = \frac{K}{K+E}$$

(Byström 2006).

3.3.1 Argumentation for choosing the modified Merton

The main reason for using the modified Merton model in our report is first and foremost the simplicity of its compounding. By taking the three modified Merton model assumptions into account, we can calculate an accurate *distance-to-default* measure close to the original Merton model.

The original Merton model also imposes problems since the volatility and the amount of debt is assumed to be constant over time. There is no empirical evidence that

[3] Distance to default, DTD.

supports these assumptions, and a dynamic modeling of both debt levels and volatility will probably enhance the performances of the default measure (Byström 2006).

Furthermore, the Merton model tends, along with other implementations of the model, to be analytically complicated and continuously intensive (Wang 2009).

The simplicity of the modified Merton model also makes it more applicable when using dynamic volatility and debt level than the original Merton model since contingent claims analysis is needed to back out A and σ_A (Byström 2006).

The assumptions of the modified Merton model are also backed up by other reports. The level of volatility is noticeable higher for most severely distressed firms than moderately distressed firms (Curry, Elmer & Fissel 2001). The leverage ratio (L) or the amount due to pay creditors relative to the actual value of the firm, along with the equity volatility, is also an important indicator of distress in a firm (Byström 2006 and Curry, Elmer & Fissel 2001).

Though the modified Merton model has its advantages, there are some concerns that need to be mentioned. The modified Merton model is, as the name indicates, a modified model, and since three assumptions are made in the model to simplify the model, it does not give an equal measurement of credit risk as the original model. However, in Byströms study (2006) the errors made by the modified model are 30 percent or less (for probability of default < 20 percent), and for most practical situations the errors are much smaller than that. Furthermore, the errors from the modified Merton model are quite small compared to those caused by other deficiencies in the original Merton model, for instance the assumption of constant equity volatility and the use of backward looking balance sheet data (Byström 2006).

Despite the inaccuracies of the modified Merton model, the ranking of firms according to creditworthiness is almost identical. Since our main objective is to analyze the correlation between this model and CDS spreads using the Spearman rank correlation tests (further discussed in chapter 5), it is of importance that the original Merton model matches the modified version.

4. Empirical data used in our thesis

Demarcation

To delineate our thesis we have chosen 60 specific firms to examine, of which 30 are European and 30 are American. 25 firms from each continent are non-financials institutions (non-specific industries), and, consequently, five firms (from each continent) are financial institutions.

We have made this distinction because of the fact that a financial institution, such as a bank, is highly leveraged and not so sensitive to changes in leverage compared to an average firm; this means that the *distance-to-default* does not change much when the leverage changes. The usage of the modified Merton model is therefore better suitable than the original in this case, since it is not crucial to estimate the exact capital structure (Byström 2006). The reason we distinguish European and American markets is because the U.S. has a more widespread financial culture by the use of high-yield securities (Cernicky 2012) and that we can investigate the difference in correlation between the two.

Data Sample

Primarily, to decide which firms that should be included in the survey, we chose firms based on the number of CDS contracts outstanding today (November 2012, beginning with the highest in descending order) from Markit Group's free pricing report (2012). We then made sure that those firms' stock price information, leverage ratio information and CDS spreads also were available in the other sources used (the full list of firms with respective number of outstanding contracts, as well as those firms for which we could not find sufficient information, are listed in Appendix A).

The three main data sources that we are using are the Markit Group's free CDS pricing report (2012), professor Aswath Damodaran's (Stern School of Business at New York University) updated Excel data files, and Thomson Reuters DataStream.

To find CDS spreads and the variables needed to calculate the modified Merton measure, we needed to collect a significant amount of data. CDS spreads for the firms could be found directly from Thomson Reuters DataStream. We gathered time series data of daily CDS spreads for each firm. We only chose 5-year maturity CDS contracts (these are often seen as a standardized contract).

Concerning the modified Merton model, we needed to collect daily stock prices, using Thomson Reuters DataStream, for each firm over our determined period of time in order to calculate the equity volatility. Additionally, we needed to collect the leverage ratio for each firm, and these did we obtain from Professor Aswath Damodaran's detailed Excel data files covering a significant amount of firms in the world. Using the equity volatility together with the leverage ratio, we could define the modified Merton's *distance-to-default* for a firm (Byström 2006).

To obtain credit ratings for each firm we are using rates set by Moody's from the official website. A description of Moody's rating methodology for probability of default was given in chapter 3.

Noticeably, we had to replace some of the firms in retrospect since there were not sufficient information on CDS spreads or leverage ratios for every year. However, concerning Moody's ratings, we could not simply find any information for some years for J.C. Penney Firm, Inc., Peugeot S.A. and Gas Natural SDG S.A.

The time period for the data we use in this thesis is 2007-12-31 to 2011-12-31. The daily observations for the stock prices and the CDS spreads make a total of 250 (number of trading days in a year) observations per year.

While assembling the data we also found that some of the firms had changed names during the limited time period; Fifth & Pacific Firms, Inc. was formerly Liz Claiborne (changed name during 2012), Macy's Inc. was named Federated Department Stores in 2006, British Telecommunications PBL LTD Firm is listed as BT Group PLC and The Jones Group Inc. was formerly Jones Apparel Group, Inc.

All of the assembled data was imported into Excel files and SPSS where we did the necessary calculations needed for our statistical testing.

Criticism of sources

Regarding the validity of the sources used when collecting CDS spreads it is of importance to be aware of possible inadequacies, since the price information is based on the degree of voluntary cooperation on market analyses from financial actors. In Mayordomo et al. (2010) it reads that Bloomberg's CDS data has a better follow up process than for example Thomson Reuters Datastream. Unfortunately, we do not have access to another source.

5. Method

In this part, we explain the methods we are using in order to implement our bachelor thesis calculations. By comparing and examine these specific measures of risk, we have chosen a topic that both take a theoretical and empirical viewpoint into consideration. Moreover, we are using statistical methods to test our data and to come up with the results.

Excel calculations

When having obtained all the necessary data for the CDS spreads, the modified Merton measure and the credit ratings, we imported the data into Excel files where we did the calculations. Firstly, we calculated the modified Merton's "*distance-to-default*" for every firm for each year in the non-financial and the financial sector, respectively. Secondly, we calculated the average spread for each year for every firm. Moody's firm ratings for each year could just be imported from its website into the Excel file.

In addition, we calculated the average modified Merton's *distance-to-default* and the average CDS spread for each firm over the whole time period (four years).

Our main interest is to find the correlation between these credit risk indicators. We started by ranking each firm's modified Merton measure with the CDS spreads for each year, in order to see if the ranking order showed a connection to a certain degree between the two measures. We then did the same for CDS spreads and Moody's credit ratings. The credit ratings were converted from letters into a numerical rating going from 1 to 21, where 21 is the best rating. For banks, which are provided with a different rating methodology, we converted the letters into a numerical rating going from 1 to 12, where 12 is the best rating. Since JPMorgan Chase & CO, MBIA insurance and Morgan Stanley are not rated as banks and receives a rating from 1 to 21, they are divided by 1,75 (21 divided by 12) to give an accurate rating in relation to the bank rating 1 to 12. The full list on rating conversion can be found in Appendix C.

Statistical tests

When ranking statistical material of pairwise observations and rank these two variables against each other (after the *X*- and the *Y*-variable), it´s applicable to use the Spearman rank correlation, or Spearman's "rho". Spearman's rho always takes a value between -1 and 1. Receiving a result of 1 means that there is a perfect correlation and the result of -1 being that it is a perfect negative correlation (Körner & Wahlgren 2010).

Spearman's rho is not sensitive for either outliers or unnatural fluctuations in the data since the method substitutes the initial data values with their specific ranks (De Veaux et al. 2012). Spearman's rho does not urge that there must be a linear trend when measuring consistency between variables. Spearman's rho is called a non-parametic or a distribution-free method, since it is not as distinctive as the Normal model for two variables, Spearman's rho rather measures association, and it also has no parameter that it is linked or tied to (De Veaux et al. 2012).

Spearman's rho is calculated in the following way; the lowest value in one category (e.g. *X*) gets replaced by the number 1, the second lowest value gets replaced by number 2, etc., until the highest value is replaced by the number n. The same method in the ranking is used for the other category (e.g. *Y*). The results can later be shown in a scatterplot to analyze the general trend: a linear trend, or a more bent trend, for example. If there is an extreme outlier in the data, the ranking method just sees it as the highest or the lowest value, no matter how extreme it really is (De Veaux et al. 2012).

The Spearman's rho formula is expressed in the following way:

$$r_s = 1 - \frac{6\Sigma {d_i}^2}{n(n^2 - 1)}$$

Where d_i is the differential between the rank numbers in the i^{th} pair (Körner & Wahlgren 2010).

The Spearman rank correlation tests were made with the statistics program SPSS. By inserting our data from every year we chose the correlate function and selected two-tailed Spearman test. The correlation for every year appeared in boxes with respective statistical significance. The boxes in our results are copied directly from SPSS.

When testing whether the correlation between the credit risk indicators were significant or not, we could determine this by a direct affirmation from SPSS certifying that the correlation were significant at the significance level 0,05 or under. If so, the results were statistically significant.

6. Results

6.1 Results for the non-financial firms

We will start by presenting the correlation between the modified Merton model and the CDS spreads for non-financial firms in America and Europe:

The modified Merton model and CDS spreads

America

2008

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.642**
		Sig. (2-tailed)	.	.001
		N	25	25
	CDS	Correlation Coefficient	-.642**	1.000
		Sig. (2-tailed)	.001	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2009

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.818**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.818**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2010

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.740**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.740**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2011

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.637**
		Sig. (2-tailed)	.	.001
		N	25	25
	CDS	Correlation Coefficient	-.637**	1.000
		Sig. (2-tailed)	.001	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

As shown by the four columns, there is a strong relationship between the movement of the modified Merton model and the CDS spreads, the weakest being a correlation of 0.637 and the highest 0.818. All four of the correlations have a 2-tailed significance level of 0.01 or under, which suggest that the results are statistically significant.

We have to acknowledge the fact that the correlation in the boxes is negative. The explanation for this is that the modified Merton model is a measurement of *distance-to-default*, which means that a smaller number has a negative effect on its creditworthiness. The opposite applies for CDS spreads, as a high credit spread means that there is more risk involved with the firm. Therefore, when calculated in SPSS, the correlation will appear to be negative.

If we proceed and look at the results for the non-financial European firms, the correlation average is even higher.

The modified Merton model and CDS spreads

Europe

2008

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.885**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.885**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2009

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.902**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.902**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2010

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.885**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.885**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2011

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.872**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.872**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

As mentioned, the correlation results suggest an even stronger relationship between the modified Merton model and CDS spreads for European non-financial firms compared to American firms in the same category. All four tests show significance at the 0.01 level.

The results for non-financial firms in both America and Europe show a significant correlation between the modified Merton model and CDS spreads. By computing the same test for the credit rating agency Moody's, we can analyze if the CDS spreads are correlated with Moody's credit ratings. The results are as follow for non-financial firms in America and Europe respectively:

Moody's and CDS spreads

America

2008

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.681**
		Sig. (2-tailed)	.	.000
		N	24	24
	CDS	Correlation Coefficient	-.681**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2009

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.823**
		Sig. (2-tailed)	.	.000
		N	24	24
	CDS	Correlation Coefficient	-.823**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2010

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.895**
		Sig. (2-tailed)	.	.000
		N	24	24
	CDS	Correlation Coefficient	-.895**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2011

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.931**
		Sig. (2-tailed)	.	.000
		N	24	24
	CDS	Correlation Coefficient	-.931**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

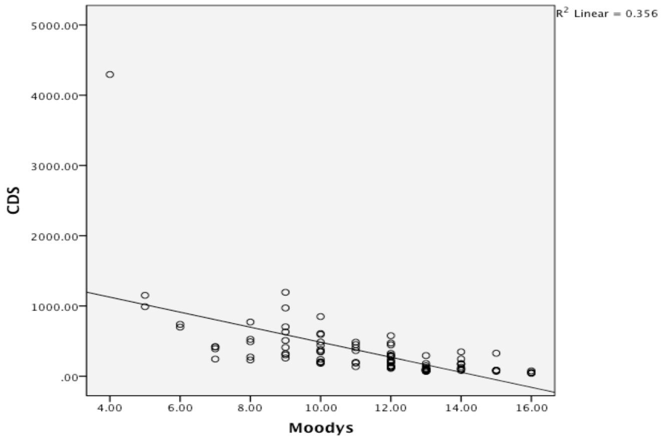
The correlation between CDS spreads and Moody's credit ratings are high, and is on average higher than for the modified Merton model compared to CDS spreads. Again, we have significance at the 0.01 level for every year.

The correlation between CDS spreads and Moody's credit ratings are as for previous tests, negative. Since a low rating grade is compatible with a high CDS spread, the correlation will be negative.

If we combine all the years with CDS spreads on the Y-axis and Moody's credit ratings on the X-axis, we can see the different CDS spreads for each of the given ratings from Moody's. We can see a negative correlation and our R^2 value is 0.356, which means that 35.6 % of the CDS spread is explained by the Moody's credit rating.

Scatterplot between CDS spreads and Moody's

America



The correlation results between Moody's credit ratings and CDS spreads for Europe are presented next:

Moody's and CDS spreads

Europe

2008

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.751**
		Sig. (2-tailed)	.	.000
		N	24	24
	CDS	Correlation Coefficient	-.751**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2009

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.729**
		Sig. (2-tailed)	.	.000
		N	24	24
	CDS	Correlation Coefficient	-.729**	1.000
		Sig. (2-tailed)	.000	.
		N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2010

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.788**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.788**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2011

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.744**
		Sig. (2-tailed)	.	.000
		N	25	25
	CDS	Correlation Coefficient	-.744**	1.000
		Sig. (2-tailed)	.000	.
		N	25	25

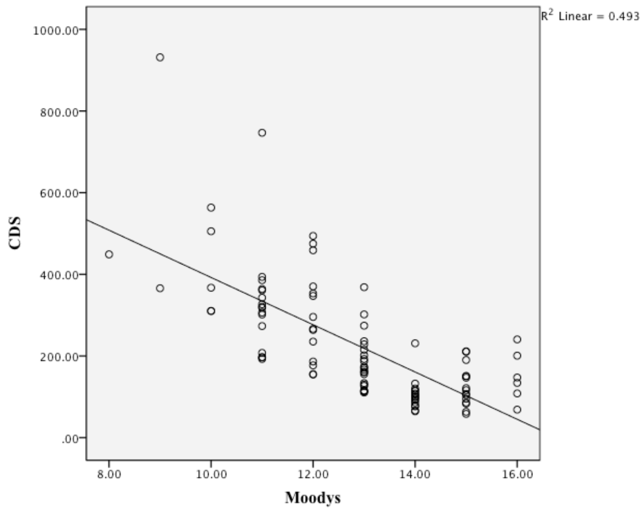
**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

Once again we can see a strong correlation between Moody's credit ratings and CDS spreads. Again, all the tests are significant at the 0.01 level.

If we make a scatterplot for the results, as made with the American firms, we can see an even higher R^2 value at 0.493 which means that 49.3% of the CDS spreads are explained by the Moody's credit ratings. As we can see from the scatterplot, the higher credit ratings the lower the CDS spreads tend to be.

Scatterplot between CDS spreads and Moody's

Europe



6.2 Results for the financial firms

Observing the results for the financial firms, there is still a correlation, but not as strong as for non-financial firms. The results for financial firms in the America and Europe are as follow:

The modified Merton model and CDS spreads

America

2008

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.400
		Sig. (2-tailed)	.	.505
		N	5	5
	CDS	Correlation Coefficient	-.400	1.000
		Sig. (2-tailed)	.505	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2009

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.500
		Sig. (2-tailed)	.	.391
		N	5	5
	CDS	Correlation Coefficient	-.500	1.000
		Sig. (2-tailed)	.391	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2010

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.900*
		Sig. (2-tailed)	.	.037
		N	5	5
	CDS	Correlation Coefficient	-.900*	1.000
		Sig. (2-tailed)	.037	.
		N	5	5

*. Correlation is significant at the 0.05 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2011

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.600
		Sig. (2-tailed)	.	.285
		N	5	5
	CDS	Correlation Coefficient	-.600	1.000
		Sig. (2-tailed)	.285	.
		N	5	5

Note: The correlation box is copied directly from SPSS

We have discovered a correlation between the modified Merton model and CDS spreads for financial firms in America, but we have only one test that is statistically significant. For 2010 the correlation is 0.9, which indicates a strong correlation, but it is only significant at the 0.05 level. The reason for not having enough statistically significance could be our low N (the number of firms used in the test). This applies for the European financial firms as well. The results are as follow:

The modified Merton model and CDS spreads

Europe

2008

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.700
		Sig. (2-tailed)	.	.188
		N	5	5
	CDS	Correlation Coefficient	-.700	1.000
		Sig. (2-tailed)	.188	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2009

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.700
		Sig. (2-tailed)	.	.188
		N	5	5
	CDS	Correlation Coefficient	-.700	1.000
		Sig. (2-tailed)	.188	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2010

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	-.900*
		Sig. (2-tailed)	.	.037
		N	5	5
	CDS	Correlation Coefficient	-.900*	1.000
		Sig. (2-tailed)	.037	.
		N	5	5

*. Correlation is significant at the 0.05 level (2-tailed).
Note: The correlation box is copied directly from SPSS

2011

Correlations

			ModifiedMerton	CDS
Spearman's rho	ModifiedMerton	Correlation Coefficient	1.000	.000
		Sig. (2-tailed)	.	1.000
		N	5	5
	CDS	Correlation Coefficient	.000	1.000
		Sig. (2-tailed)	1.000	.
		N	5	5

Note: The correlation box is copied directly from SPSS

The correlation between the modified Merton and CDS spreads for financial firms in Europe displays a somewhat strong correlation for 2008 and 2009. For 2009 we have found a strong correlation and it is statistically significant at the 0.05 level. For 2011, we have no correlation at all. By looking at Appendix B, we can find that during the Euro crisis, the average CDS spreads for financial firms in Europe rose, while the modified Merton model had not adapted to the economical environment of that time. We therefore have a low correlation on average.

The correlation between Moody's credit ratings and the CDS spreads for financial firms in America will be presented next.

Moody's and CDS spreads

America

2008

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.600
		Sig. (2-tailed)	.	.285
		N	5	5
	CDS	Correlation Coefficient	-.600	1.000
		Sig. (2-tailed)	.285	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2009

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.300
		Sig. (2-tailed)	.	.624
		N	5	5
	CDS	Correlation Coefficient	-.300	1.000
		Sig. (2-tailed)	.624	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2010

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.700
		Sig. (2-tailed)	.	.188
		N	5	5
	CDS	Correlation Coefficient	-.700	1.000
		Sig. (2-tailed)	.188	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2011

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.700
		Sig. (2-tailed)	.	.188
		N	5	5
	CDS	Correlation Coefficient	-.700	1.000
		Sig. (2-tailed)	.188	.
		N	5	5

Note: The correlation box is copied directly from SPSS

As we can see from the results we cannot find enough correlation to achieve any statistically significance at any level for any year. This is most certainly because of our small N.

Moody’s and CDS spreads

Europe

2008

Correlations

			Moodys	CDS
Spearman’s rho	Moodys	Correlation Coefficient	1.000	.783
		Sig. (2-tailed)	.	.118
		N	5	5
	CDS	Correlation Coefficient	.783	1.000
		Sig. (2-tailed)	.118	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2009

Correlations

			CDS	Moodys
Spearman's rho	CDS	Correlation Coefficient	1,000	-,053
		Sig. (2-tailed)	.	,933
		N	5	5
	Moodys	Correlation Coefficient	-,053	1,000
		Sig. (2-tailed)	,933	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2010

Correlations

			CDS	Moodys
Spearman's rho	CDS	Correlation Coefficient	1,000	,000
		Sig. (2-tailed)	.	1,000
		N	5	5
	Moodys	Correlation Coefficient	,000	1,000
		Sig. (2-tailed)	1,000	.
		N	5	5

Note: The correlation box is copied directly from SPSS

2011

Correlations

			CDS	Moodys
Spearman's rho	CDS	Correlation Coefficient	1,000	,527
		Sig. (2-tailed)	.	,361
		N	5	5
	Moodys	Correlation Coefficient	,527	1,000
		Sig. (2-tailed)	,361	.
		N	5	5

Note: The correlation box is copied directly from SPSS

The results for the European financial firms regarding the correlation between Moody's credit ratings and CDS spreads are not statistically significant. By observing the correlation results we cannot find any correlation to say that the two variables relate to each other. In fact, the result for 2009 is the only one that shows any sign of relation.

6.3 Data put together 2008-2011

The modified Merton model and CDS spreads

America, financials

Correlations

			MertonModel	CDS
Spearman's rho	MertonModel	Correlation Coefficient	1,000	-,397
		Sig. (2-tailed)	.	,083
		N	20	20
	CDS	Correlation Coefficient	-,397	1,000
		Sig. (2-tailed)	,083	.
		N	20	20

Note: The correlation box is copied directly from SPSS

Europe, financials

Correlations

			MertonModel	CDS
Spearman's rho	MertonModel	Correlation Coefficient	1,000	-,012
		Sig. (2-tailed)	.	,960
		N	20	20
	CDS	Correlation Coefficient	-,012	1,000
		Sig. (2-tailed)	,960	.
		N	20	20

Note: The correlation box is copied directly from SPSS

America, non-financials

Correlations

			MertonModel	CDS
Spearman's rho	MertonModel	Correlation Coefficient	1,000	-,840**
		Sig. (2-tailed)	.	,000
		N	100	100
	CDS	Correlation Coefficient	-,840**	1,000
		Sig. (2-tailed)	,000	.
		N	100	100

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

Europe, non-financials

Correlations

			MertonModel	CDS
Spearman's rho	MertonModel	Correlation Coefficient	1,000	-,606**
		Sig. (2-tailed)	.	,000
		N	100	100
	CDS	Correlation Coefficient	-,606**	1,000
		Sig. (2-tailed)	,000	.
		N	100	100

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

If we observe the tables above, we can see a significant correlation between non-financial firms in America and Europe. However, by putting together all the observations from every year for financial firms, and by that raising our N, we still cannot find any significant correlation for either American or European firms.

Moody's and CDS spreads

America, financials

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.580**
		Sig. (2-tailed)	.	.007
		N	20	20
	CDS	Correlation Coefficient	-.580**	1.000
		Sig. (2-tailed)	.007	.
		N	20	20

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

Europe, financials

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.298
		Sig. (2-tailed)	.	.201
		N	20	20
	CDS	Correlation Coefficient	-.298	1.000
		Sig. (2-tailed)	.201	.
		N	20	20

Note: The correlation box is copied directly from SPSS

America, non-financials

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.787**
		Sig. (2-tailed)	.	.000
		N	96	96
	CDS	Correlation Coefficient	-.787**	1.000
		Sig. (2-tailed)	.000	.
		N	96	96

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

Europe, non-financials

Correlations

			Moodys	CDS
Spearman's rho	Moodys	Correlation Coefficient	1.000	-.748**
		Sig. (2-tailed)	.	.000
		N	97	97
	CDS	Correlation Coefficient	-.748**	1.000
		Sig. (2-tailed)	.000	.
		N	97	97

**. Correlation is significant at the 0.01 level (2-tailed).
Note: The correlation box is copied directly from SPSS

By doing the same test as we did for CDS spreads and the modified Merton model, we can further observe that there is still a strong significant correlation for the non-financial firms regarding CDS spreads and Moody's credit ratings. For the financial firms we have not discovered a significant correlation for the European firms. However, the American financial firms do display a significant correlation between CDS spreads and Moody´s credit ratings.

7. Analysis

The results we have reached from our Spearman rank correlation tests show that there is a significant correlation overall between the modified Merton model and the CDS spreads, as well as between Moody's credit ratings and the CDS spreads. We therefore believe that CDS spreads statistically qualify as a well accepted credit risk measurement. This against the background that credit ratings by a public rating institute such as Moody's are widely trusted by market actors and are used as guidelines when investments are made by observing the investment grade ratings (Daniels & Jensen 2005). The original Merton model, likewise, is a familiar and a good default risk measure based on market information and Byström (2006) shows that the modified Merton model matches the original Merton model well.

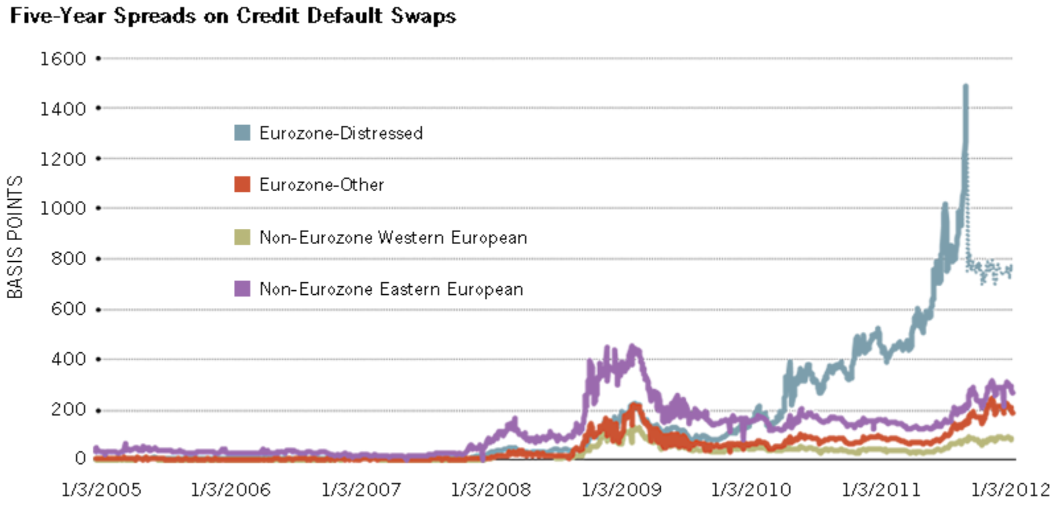
The statistical test for financial firms in Europe is the only test that shows no or negative correlation. As CDS spreads differ from day to day as a consequence of both systematic and unsystematic risk, it takes much information into consideration in a short period of time (Jacobs et al. 2010 and Zhang, Zhou & Zhu 2005). Our test includes the firms with the most outstanding CDS contracts, which includes two Spanish banks. The poor correlation for financial firms in Europe could therefore be explained by the ongoing debt crisis in Europe. Since 2009, when the Euro crisis began to emerge, the Spanish banks were facing severe solvency problems (Harrington 2011).

As an effect of the crisis, CDS spreads rose with several bps. Unlike CDS spreads, updates of Moody's credit ratings are an ongoing process between the issuer and Moody's analysts where the issuer is encouraged to deliver essential materials and raise concerns about the firm if necessary (Moody's 2012b). Moody's is also taking current economic environment into consideration. Moody's credit ratings are therefore not updated as often as CDS spreads which in time of crisis has an obvious effect on the rank correlation. The modified Merton model uses the volatility of the stock price along with the leverage ratio as parameters. The volatility is calculated with data from a whole year (250 trading days) and the leverage ratio is a percentage from the same year. This has a similar effect on the rank correlation and the results, as they do not adapt as quickly as CDS spreads.

By observing the correlation between our traditional credit risk measurements and the CDS spreads for the financial firms in America, the correlation is stronger for 2010 and 2011 than for 2008 and 2009. The financial crisis in America at the time made the spreads rise due to high level of risk and uncertainty in the economic environment (Hull, Predescu & White 2004).

The peculiar events in the financial sector, both in America and in Europe, have undoubtedly affected the tests for our financial firms. A recent report from the World Bank states that countries with a more liberalized banking system and weak supervision have higher co-dependence in their banking sector, especially for European and American banks (Anginer & Demirguc-Kunt 2011).

Diagram 7.1



Source: Noeth & Sengupta (2012)

By studying the Bloomberg graph above, we can see that the volatility of CDS spreads for the "distressed Eurozone" (where Spain is included) countries began to rise when the Euro crisis took off. In Appendix B we present diagrams for the financial and the non-financial sector on how the average value of CDS spreads have been fluctuating during 2008 to 2011. These diagrams clarifies that the spreads react distinctively on macroeconomic events. As previously mentioned, the modified Merton model can differ with relatively small numbers while CDS spreads can differ in high number in a short period of time, which will effect the rank correlation.

We must also acknowledge the fact that our N (number of observations) for financial firms are small compared to the non-financial. This is also an important factor to why we cannot find any significant correlation between the different methods of measuring default risk. If we look at the last results, we have combined all the results for every year in one correlation. For financial firms in America, there is a significant correlation between Moody's credit ratings and CDS spreads. Though there is a correlation between Moody's credit ratings and CDS spreads for financial firms in Europe, it is not strong enough to show any statistical significance.

The non-financial firms for both territories show a strong and significant correlation, despite the financial crisis in our timespan. As previously mentioned, there are several reports indicating that financial institutions are more volatile in financial crisis and we therefore have a hard time finding any significant correlation for these. Anginer & Demirguc-Kunt (2011) wrote that the increased interdependence globally in the banking industry (with similar risk and market exposure) makes it more volatile in times of "economic, liquidity and information shocks". Banks in developed countries especially (e.g. America and countries in the EU), have experienced a higher co-dependence (Anginer & Demirguc-Kunt 2011).

Consequently, regarding the CDS market, the spreads for banks have increased when there has been a shock in the credit market resulting in higher spreads for globally interconnected banks due to systematic risk (Miquel, Lukac & Gonzalez-Urteaga 2012). The financial situation in the market is therefore important to bear in mind when analyzing why our correlation is not statistically significant.

8. Conclusion

This report on the relationship between CDS spreads, the modified Merton model and Moody's credit ratings aims to give a contribution to an increased discussion on credit risk measures. By comparing these different credit risk indicators we would like to point out how they behave in relation to some common parameters in the credit risk environment.

By testing the CDS spreads against the modified Merton's *distance-to-default* measure and the credit ratings from Moody's, we are able to show that CDS spreads are plausible indicators of default risk. We are able to make this assumption since credit ratings from Moody's are well accepted by the market as a measure of default risk (Daniels & Jensen 2005) and the modified Merton model is based on a well-used traditional estimator of default risk (Byström 2006).

Essentially, we find our correlation results for non-financial firms to be statistically significant for both the American and the European market, as we in this case found strong correlations both between CDS spreads and the modified Merton measure, as well as between CDS spreads and Moody's ratings. However, we cannot show the same for the financials firms.

It is of importance to bear in mind the financial situation in the market when drawing conclusions of the correlations. In times of financial distress there are some measures that react faster than others. In the case of the European financial firms, where we could not find any correlation between either CDS spreads and the modified Merton model or CDS spreads and Moody´s credit ratings, the CDS spreads fluctuated substantially. We draw the conclusion that CDS spreads react more distinctively to shocks in the market than credit ratings and the modified Merton's *distance-to-default* measure. Previous reports do indeed support the fact that CDS spreads faster adapt to anomalies in the market, which have had an obvious effect on the rankings and therefore the correlation of the financial firms.

When to assess which of the measures that is the most reliable when it comes to credit risk, it is impossible to say, this because none of the firms in the report has yet to default. In conclusion, we would like to stress the fact that the measures used in this thesis are not a guarantee of default; they should rather be seen as indicators of probability of default.

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Appendices

Appendix A

Europe: (Financial)	CDS contracts:	America: (Financial)	Cds contracts:
Banco Santander, S.A	8,031	Bank of America	8,331
Deutsche Bank Aktiengesellschaft	7,131	MBIA insurance	8,029
Commerzbank Aktiengesellschaft	6,648	Morgan Stanley	7,468
The Royal Bank of Scotland Public	6,428	Goldman Sachs	7,320
Intesa SauPaulo SPA	6,177	JPMorgan Chase & Co.	7,291

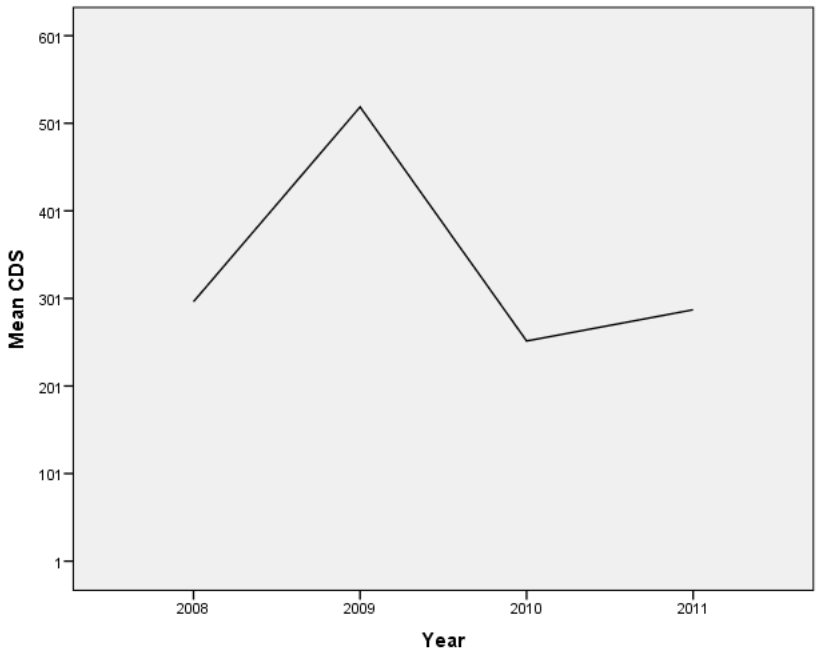
Europe:	CDS contracts:	Sector:	America:	CDS contracts:	Sector:
Continental Aktiengesellschaft	5,788	Consumer Goods	Lennar Corporation	5,095	Consumer Goods
Telecom Italia SPA	5,767	Telecommunications Services	Sprint Nextel Corporation	4,855	Telecommunication Services
Daimler AG	5,694	Consumer Goods	Fifth & Pacific Companies, INC	4,529	Consumer Services
Deutsche Telekom AG	5,274	Telecommunications Services	Limited Brands. INC	4,472	Consumer Services
Telefonica, S.A.	5,239	Telecommunications Services	Gannett CO., INC.	4,456	Consumer Services
Peugeot SA	5,004	Consumer Goods	Supervalu INC.	4,219	Consumer Services
France Telecom	4,891	Telecommunications Services	R.R. Donnelley & Sons Company	4,176	Industrials
Wolkswagen Aktiengesellschaft	4,888	Consumer Goods	The Jones Group INC.	4,164	Consumer Goods
Portugal TelecomInternational Finance l	4,742	Telecommunications Services	J.C. Penney Company, INC.	4,157	Consumer Services
Brittish Telecommunications PBL LTD	4,600	Telecommunications Services	Whirpool Corporation	4,067	Consumer Goods
Lafarge	4,578	Industrials	Alcoa INC.	3,945	Basic Materials
Renault	4,475	Telecommunications Services	Safeway INC.	3,871	Consumer Services
Enel S.P.A.	4,311	Consumer Goods	Louisiana-Pacific Corporation	3,856	Consumer Goods
Vodafone Group Public Limited Compa	4,091	Utilities	Verizon Communcations INC.	3,847	Telecommunication Services
Valeo	4,073	Consumer Goods	Macy´s, INC.	3,807	Consumer Services
Edp - Engergias de Portugal, S.A.	4,050	Telecommunications Services	Southwest Airlines CO.	3,746	Industrials
Deutsche Lufthansa Aktiegesellschaft	3,946	Consumer Goods	CBS Corporation	3,739	Consumer Services
Vivendi	3,908	Basic Materials	Universal Health Services, INC	3,645	Healthcare
Stora Enso OYJ	3,894	Industrials	The McClatchy Company	3,506	Consumer Services
Gas Natural SDG SA	3,864	Telecommunications Services	Hewlett-Packard	3,488	Technology
FIAT S.P.A	3,817	Consumer Goods	The Kroger Co.	3,428	Consumer Services
Aktiebolaget Volvo	3,816	Consumer Goods	Autozone INC.	3,416	Consumer Services
UPM-KYMMENE OYJ	3,569	Basic Materials	Nordstrom INC.	3,373	Consumer Services
Marks and Spencer PLC	3,559	Consumer Services	The New York Times Company	3,366	Consumer Services
Wolters Kluwer N.V	3,419	Consumer Services	Altria Group INC.	3,366	Consumer Goods

Insufficient:

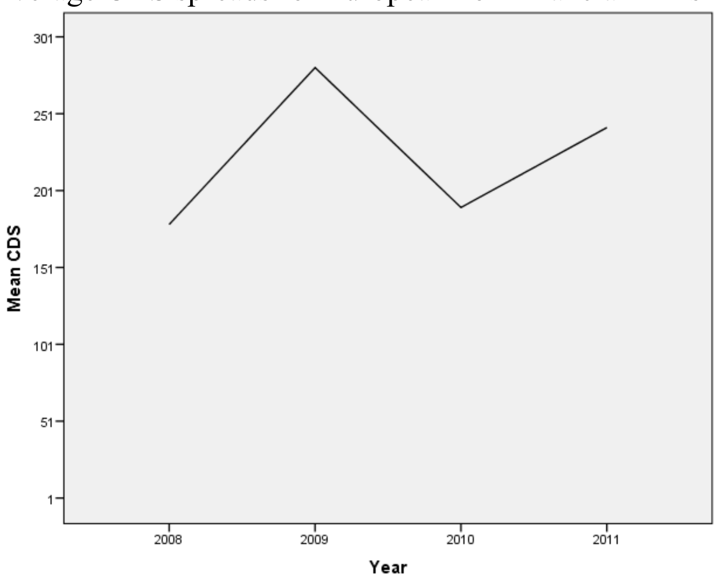
Europe:	America:
Barclays	Clear Channels Communications
Banco Bilbao	Caesars Entertainment operating company
Koninklijke	Centex Corp.
BMW	Centurylink, INC.
Glencore	The Hillshire Brands
Dixons Retail PLC	International Paper Company
Hellenic Telecommunications	Computer Sciences Corporation
Arcelormittal	Pultegroup INC.

Appendix B

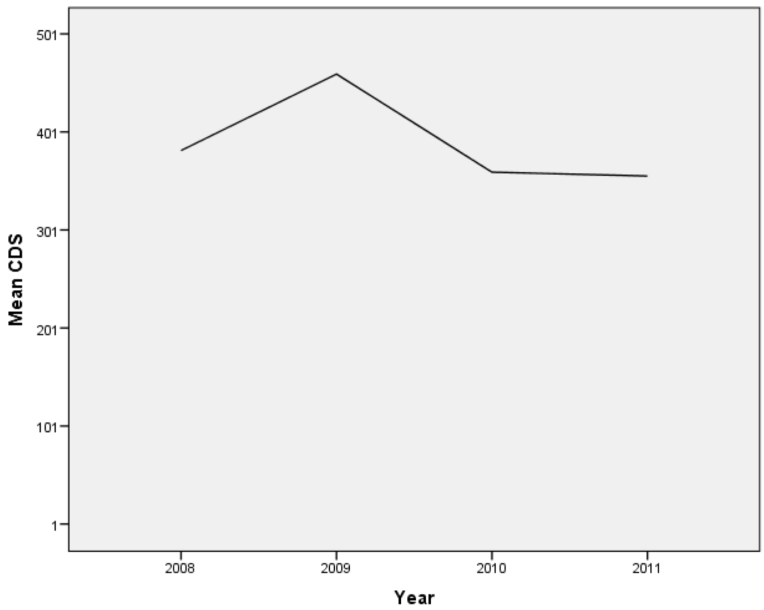
Average CDS spreads for American non-financial firms



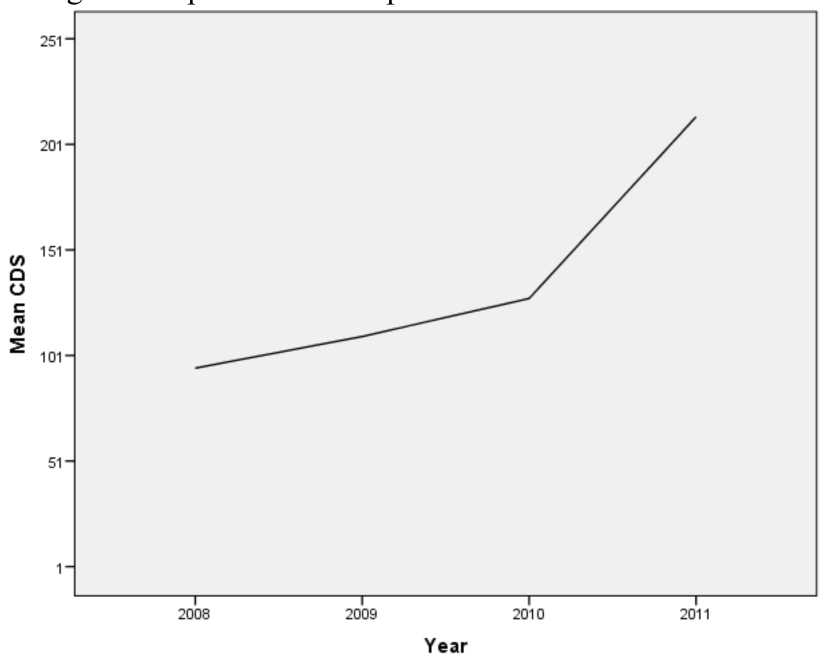
Average CDS spreads for European non-financial firms



Average CDS spreads for American financial firms



Average CDS spreads for European financial firms



Appendix C

	2008		2009		2010		2011	
America								
Lennar Corporation	Ba3	9	B2	7	B2	7	B2	7
Sprint Nextel Corporation	Baa3	12	Ba2	10	Ba3	9	B1	8
Fifth & Pacific Companies, INC	Ba1	11	Ba3	9	B3	6	B3	6
Limited Brands. INC	Ba1	11	Ba2	10	Ba2	10	Ba1	11
Gannett CO, INC.	A3	15	Ba2	10	Ba2	10	Ba2	10
Supervalu INC.	Ba3	9	Ba3	9	Ba3	9	B1	8
R.R. Donnelley & Sons Company	Baa2	13	Baa3	12	Baa3	12	Ba1	11
The Jones Group INC.	Ba1	11	Ba2	10	Ba2	10	Ba2	10
J.C. Penney Company, INC.	*	*	*	*	*	*	*	*
Whirlpool Corporation	Baa2	13	Baa3	12	Baa3	12	Baa3	12
Alcoa INC.	Baa1	14	Baa3	12	Baa3	12	Baa3	12
Safeway INC.	Baa2	13	Baa2	13	Baa2	13	Baa2	13
Louisiana-Pacific Corporation	Ba2	10	Ba3	9	B2	7	Ba3	9
Verizon Communications INC.	A3	15	A3	15	A3	15	A3	15
Macy's INC.	Baa3	12	Ba2	10	Ba1	11	Ba1	11
Southwest Airlines CO.	Baa1	14	Baa1	14	Baa3	12	Baa3	12
CBS Corporation	Baa3	12	Baa3	12	Baa3	12	Baa2	13
Universal Health Services, INC.	Baa3	12	Baa3	12	Ba2	10	Ba2	10
The McClatchy Company	Ba3	9	Caa2	4	Caa1	5	Caa1	5
Hewlett-Packard	A2	16	A2	16	A2	16	A2	16
The Kroger Company	Baa2	13	Baa2	13	Baa2	13	Baa2	13
Autozone, INC.	Baa2	13	Baa2	13	Baa2	13	Baa2	13
Nordstrom, INC.	Baa1	14	Baa2	13	Baa2	13	Baa1	14
Altria Group, INC.	Baa1	14	Baa1	14	Baa1	14	Baa1	14
The New York Times Company	Baa3	14	B1	8	B1	8	B1	8
Europe								
Continental Aktiengesellschaft	Ba1	11	Ba3	9	B1	8	Ba3	9
Telecom Italia SPA	Baa2	13	Baa2	13	Baa2	13	Baa2	13
Daimler AG	A3	15	A3	15	A3	15	A3	15
Deutsche Telekom AG	Baa1	14	Baa1	14	Baa1	14	Baa1	14
Telefonica, S.A.	Baa1	14	Baa1	14	Baa1	14	Baa1	14
Peugeot SA	*	*	Baa3	12	Baa3	12	Baa3	12
France Telecom	A3	15	A3	15	A3	15	A3	15
Wolkswagen Aktiengesellschaft	A3	15	A3	15	A3	15	A3	15
Portugal TelecomInternational Finance B.V	Baa2	13	Baa2	13	Baa2	13	Baa3	12
Brittish Telecommunications PBL LTD company	Baa1	14	Baa2	13	Baa2	13	Baa2	13
Lafarge	Baa2	13	Baa3	12	Baa3	12	Ba1	11
Renault	Baa2	13	Ba1	11	Ba1	11	Ba1	11
Enel S.P.A.	A2	16	A2	16	A2	16	A3	15
Vodafone Group Public Limited Company	Baa1	14	Baa1	14	Baa1	14	A3	15
Valeo	Baa3	12	Ba2	10	Ba1	11	Baa3	12
Edp - Engergias de Portugal, S.A.	A2	16	A3	16	A3	16	Baa3	12
Deutsche Lufthansa Aktiegesellschaft	Baa3	12	Ba1	11	Ba1	11	Ba1	11
Vivendi	Baa2	13	Baa2	13	Baa2	13	Baa2	13
Stora Enso OYJ	Ba1	11	Ba2	10	Ba2	10	Ba2	10
Gas Natural SDG SA	*	*	*	*	Baa2	13	Baa2	13
FIAT S.P.A	Ba1	11	Ba1	11	Ba1	11	Ba2	10
Aktiebolaget Volvo	A3	15	Baa2	13	Baa2	13	Baa2	13
Marks & Spencer	Baa2	13	Baa3	12	Baa3	12	Baa3	12
Wolters Kluwer N.V.	Baa1	14	Baa1	14	Baa1	14	Baa1	14
UPM-Kymmene OYJ	Baa3	12	Ba1	11	Ba1	11	Ba1	11
America								
Bank of America	A-	11	D	3	C-	5	C-	5
MBIA insurance	A2	16	B3	6	B3	6	B3	6
Morgan Stanley	A1	17	A2	16	A2	16	A2	16
Goldman Sachs	B	9	B-	8	B-	8	B-	8
JPMorgan Chase & Co.	Aa2	19	Aa3	18	Aa3	18	Aa3	18
Europe								
Banco Santander, S.A	B	9	B-	8	B-	8	B-	8
Deutsche Bank Aktiengesellschaft	B	9	B	9	C+	7	C+	7
Commerzbank Aktiengesellschaft	C	6	C-	5	C-	5	C-	5
The Royal Bank of Scotland Public	B	9	C-	5	C-	5	C-	5
Intesa SauPaulo SPA	B-	8	B-	8	B-	8	C+	7