Aalto University
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THE RELEVANCE OF ACCOUNTING VERSUS MARKET INFORMATION IN CREDIT RISK MEASUREMENT - EUROPEAN CREDIT DEFAULT SWAP EVIDENCE

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ABSTRACT
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PURPOSE OF THE STUDY
The purpose of this thesis is to address the limited understanding of the relevance of accounting information to the credit markets. Consequently, using credit default swap (CDS) spreads as a proxy for investors’ perceived default risk, the ultimate aim of the thesis is to find out whether accounting information is in fact a relevant source of information to the credit markets and if so, to what extent. More specifically, the thesis provides a detailed comparative analysis on the abilities of accounting and market information to explain the variation in credit default swap spreads. Furthermore, the thesis offers evidence on the industry effects of accounting data relevance as well as on the effects of the global financial crisis of 2008/10.

DATA
The data on European credit default swap spreads for the period reaching from the first quarter of 2005 to the second quarter of 2010 was acquired from Datastream. The necessary accounting and market metrics were obtained from Thomson Worldscope. Data on control variables, namely the risk free interest rate and iTraxx constituent information, was attained from the Bank of Finland’s website and Reuters 3000 Xtra, respectively. The final sample consists of 2 032 firm-quarter observations and it comprises of 155 distinct CDS entities from 10 different sectors and 17 different countries.

RESULTS
The results indicate that accounting information is a relevant source of information to the credit markets. It was, however, found that market information is, in accordance with *a priori* expectations, able to provide more relevant information to the holders of credit derivatives than that which is provided by accounting information. In other words, the market-based regression model is able to explain a larger proportion of the variation in CDS spreads than the accounting-based model. It was furthermore found that accounting information is of incremental relevance which implies that accounting and market information are used in tandem by the CDS markets. Supporting evidence of the existence of industry effects was found while it was similarly witnessed that accounting information relevance decreased in the global financial crisis of 2007-2010.

KEYWORDS
Distance-to-default, structural models, credit risk, credit default swap, value relevance, relevance of accounting information, structural models

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TUTKIELMAN TAVOITTEET
Tutkielman tavoitteena on tuottaa uutta tutkimustietoa tilinpäätösinformaation hyödyllisyydestä velkamarkkinoille. Tutkielmassa käytetään luottojohdannaisia pyrkimyksenä selvittää onko tilinpäätösinformaatio hyödyllistä tietoa velkojille ja velkamarkkinoille ja jos kyllä, niin missä määrin. Tutkielmassa vertaillaan markkina- ja tilinpäätösinformaation kykyä selittää vaihtelua CDS-luottojohdannaisten hintavaihtelussa. Lisäksi tutkitaan poikkeaako tilinpäätösinformaation hyödyllisyys eri toimialoilla ja erilaisissa maailmantaloudellisissa markkinatilanteissa.

LÄHDEAINEISTO
Lähdeaineistona käytetään Datastream-tietokannasta haettuja CDS-luottojohdannaishintoja eurooppalaisille yrityksille vuodesta 2007 vuoden 2010 puoliväliin. Tilinpäätös- ja markkinainformaatio on puolestaan haettu Thomson Worldscope tietokannasta. Kontrollimuuttujana toimiva riskitön korko on peräisin Suomen Pankin Internet-sivuilta ja iTraxx-indeksin koostumustiedot on haettu Reutersista. Aineiston kokonaislukumäärä koostuu yhteensä 2 032 yrityskvartaalista, jotka ovat peräisin 155 eurooppalaisesta yrityksestä 10 eri toimialalta ja 17 eri maasta.

TULOKSET
Tutkimuksen tulokset osoittavat, että markkinainformaatio on tilinpäätösinformaatiota hyödyllisempää velkamarkkinoille. Tilinpäätösinformaatiolle löydetään kuitenkin inkrementaalista hyötyä. Näin ollen todetaan, että tilinpäätösinformaatio tarjoaa hyödyllistä tietoa velkamarkkinoille ja, että tilinpäätös- ja markkinainformaatiota on syytä käyttää rinnakkain yrityksen luottoriskiä arvioitaessa. Lisäksi havaitaan, että tilinpäätösinformaation hyödyllisyys myös vaihtelee toimialoittain. Edelleen havaitaan, että tilinpäätösinformaation hyödyllisyys laskee kun sen hyödyllisyyttä verrataan ennen vuotta 2008 alkanutta talouskriisiä ja toisaalta, sen aikana.

AVAINSANAT
Luottoriski, arvo-relevanssi, tilinpäätösinformaation hyödyllisyys, luottojohdannainen, etäisyys konkurssiin, konkurssiennustemallit

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1 INTRODUCTION

1.1 Background and motivation

A company is in default when it is unable to service its financial liabilities. A considerable amount of research has been conducted toward modeling firms' default probabilities as accurately as possible. Assessing the probability of a company being able to repay its financial obligations is of central importance, not only to providers of capital, but to academics and economists as well. In order to determine the amount of credit risk[1] involved in a certain company, one can rely on different types of credit default models. In all simplicity, there are two types of models available that aim to measure the likelihood of default; market-based models and accounting-based models. Traditional scoring models, for instance Altman's (1968) *Z-score* and Ohlson's (1980) *O-score*, are mostly based on accounting metrics whereas so-called structural models, originally developed by Merton (1974), and reduced form models, extract their data from the market.

There are several concerns involved in using accounting data to model default risk. Firstly, accounting data is based on historic information and is thereby inherently backward-looking and may thus be an inadequate source of information for assessing the future. Secondly, accounting-based models use data derived from a company's financial statements, either from quarterly or annual reports. This means that the models' data inputs are updated somewhat infrequently. Thirdly, accounting conservatism and historical cost accounting means that true asset values may differ substantially from their book values. The latter problem has, however, been alleviated to some extent by the implementation of IFRS and US GAAP. Fourthly, there is the admittedly remote possibility that accounting data has been manipulated by the company's management. Traditional scoring models based on accounting information also usually produce outputs that cannot be easily transformed into actual probabilities of default. Lastly, accounting-based models have been criticized for excluding perhaps the most relevant source of information, namely the

[1] Even though distinct definitions exist, for the purpose of this thesis, credit risk is used more or less interchangeably with bankruptcy risk, default risk and financial distress.

market (e.g., Hillegeist, Keating, Cram and Lundstedt, 2002). These above-mentioned imperfections have brought about a considerable amount of criticism towards accounting-based default models.

Conversely, market-based models use information from the market in order to assess a firm's credit risk. According to the efficient market hypothesis (Fama, 1965), a firm's default probability should be perfectly reflected at all times in the market value of its equity. If the market prices contain all publically available information, accounting-based information should therefore not contain any information that is not reflected in the market price of a company. Structural credit default models' objective is to back out the markets' assessment of a company's credit risk. As a consequence, market-based default metrics have become widely acknowledged by academics and investors in the belief that they offer superior information on default probabilities as compared to accounting-based information.

Whether accounting-based metrics are a relevant source of data to capital providers has been questioned (e.g. Lev and Zarowin, 1999 and Francis and Schipper, 1999). According to the mainstream of these studies, the market responds rather weakly to changes in abnormal earnings, which suggests that the relevance of financial statements is, correspondingly, quite low to providers of equity capital. The relevance of accounting variables to the credit markets has also been studied, but to a much lesser extent (e.g. Das, Hanouna and Sarin, 2009 and Demirovic and Thomas, 2007). In this thesis, I set to find out whether market-based default prediction models, as a proxy for market data in general, indeed offer more relevant information to the credit markets than the traditional models based on accounting information. More precisely, I evaluate and compare how well the two types of default prediction models fare in pricing the risks of default by examining credit default swap (CDS) spreads on a European dataset. Credit default swaps are, in simplest terms, financial securities that provide insurance against a firm's default. Essentially, this thesis studies the relevance of market-based and accounting-based information to the credit markets.

A great majority of the empirical research in academic default literature concentrates on testing the models using samples of actual bankruptcies (e.g. Altman 1968; Ohlson 1980; Hillegeist, Keating, Cram and Lundstedt, 2002). Another common approach is to test how well the models explain corporate bond yields (e.g. Wu and Zhang, 2004; Collin-Dufresne, Goldstein and Martin, 2001; Longstaff and Rajan, 2006 and Huang and Kong, 2005) while Du and Suo (2003) investigate the relationship between credit ratings and default prediction models. However, using CDS spreads to test the relevance of different kinds of default models offers a less studied approach. For instance, Blanco, Brennan and Marsh (2003) note that a change in credit quality of a company is likely to be reflected more quickly in its CDS spread than in its bond yield spread. CDS spreads thus offer an excellent way to study the relevance of the models. Thus, this is the approach this thesis takes.

1.2 Research questions

This thesis studies the information content of accounting-based and market-based data in pricing firms' default risk using a sample of Credit Default Swap (CDS) spreads. More specifically, I compare to what extent accounting-based models and market-based models are able to explain of the variation in CDS spreads. Additionally, I examine whether a superior model can be created that combines both approaches. The most central research question is the following:

i. Is accounting information a relevant source of information to the credit markets, and if so, to what extent?

1.3 Contribution to existing literature

The thesis contributes to prior research in several ways. First of all, the thesis addresses the limited literature on different types of information sources' abilities to explain CDS spreads. It is therefore an additional examination of the relevance of accounting information to debt capital providers which has not nearly been studied to as large an extent as the relevance of accounting metrics to equity investors has been.

Secondly, the brunt of prior research on both credit risk literature and on the relevance of accounting information has concentrated on the U.S. markets whereas my focus is on the European markets. This diminishes the quantity of data available but it simultaneously taps a geographical research area that has been studied to a much lesser degree.

Additionally, even though it is not the main focus, the thesis provides further evidence on the determinants of CDS spreads. However, on the contrary to many prior studies, this thesis does not attempt to map out all relevant factors in the explanation of CDS prices, but rather to compare how large proportions these two kinds of information sources are able explain.

Altogether, the main contributions of this thesis are that it applies an approach that only a handful of studies have used and that it applies it to a geographical area that has been researched relatively little. Furthermore, it simultaneously contributes to several distinct areas of research: the study of the relevance of accounting and market information and on the determinants of CDS spreads and credit risk literature at large.

1.4 Results

This study finds convincing evidence that accounting information is a relevant source of information to the credit markets. More precisely, it is found that the accounting-based model designed to measure the relevance of accounting information in general, is able to explain around 23 percent of the variation in CDS spreads. The market-based model, on the other hand, explains slightly over 48 percent. Thus, in conformity with theory, market information is indeed found to serve as a more relevant source of information to the credit markets than accounting-based metrics.

Then again, when accounting and market-based information was combined into a single hybrid regression model, the explanatory power is found to well surpass the market based model's explanatory power. That is to say, accounting information is found to provide incremental information. The consensus among previous empirical research is that accounting information is able to provide incremental information. However, previous results regarding the comparative relevance between accounting and market information are considerably more widespread. Therefore, the results in this study provide valuable additional evidence on an issue that has thus far yielded contradictory results in prior literature.

Supporting evidence for the hypothesis that there are industry effects in the relevance of accounting data was furthermore found. The explanatory power of the accounting model is witnessed to vary from a low of 14 percent to a maximum of some 63 percent between industries.

In contrast to Demirovic and Thomas (2007) who studies the relevance of accounting information using credit ratings, the market model that includes the distance-to-default metric is found to vary substantially less than the accounting model.

Finally, supportive yet inconclusive evidence of a macroeconomic effect on the relevance of accounting information is found. The sample was divided into a pre-crisis (2005-2007) period and to a crisis period (2007-2010) in order to detect a possible decay in accounting information relevance. A significantly lower reading for the crisis period, in terms of explanatory power, is detected.

1.5 Limitations of the study

The study is subject to certain limitations and constraints of which some are perhaps more conceptual in nature whereas others relate to research design and implementation. First of all, as the market-based model in itself utilizes market data to explain other market data, the model essentially has, due to this endogeneity and at least to a certain extent, an *a priori* support. Secondly, several firms had to be omitted from the sample due to subpar CDS liquidity which effectively means that the final sample could be somewhat distorted in the sense that potentially important information may have been lost. Furthermore, no conclusive evidence of the existence of industry and macroeconomic effects were provided in the thesis.

1.6 Structure of the study

The remainder of this thesis proceeds as follows. The second chapter briefly presents credit default swaps. The relevant credit risk and value relevance literature is introduced in chapter three while chapter four motivates and presents the hypotheses. In chapter five, I discuss the data used whereas chapter six reviews the methodologies applied. Chapter seven outlines the results and chapter eight discusses the robustness of these results. Chapter nine concludes the study whereas references and the appendix are presented in chapters 10 and 11, respectively.

2 CREDIT DEFAULT SWAPS

This chapter provides a concise description of credit default swaps and introduces their importance in modern financial markets.

2.1 Introduction to credit default swaps

Innovation within the financial sector has resulted in the creation of credit derivatives that help to manage credit risk. The vast growth in credit derivatives trade during the last decade can mainly be attributed to the three main participants: commercial banks, insurance companies and global hedge funds (Callen, Livnat, Segal, 2009). For instance, credit derivatives effectively enable banks to transfer credit risk from their loan portfolios while maintaining the loans on their balance sheets. Insurance companies, on the other hand, are usually net sellers of credit derivatives as they seek to enhance investment returns by gaining exposure to risks that are uncorrelated with their existing business risks (Callen, Livnat, Segal, 2009). Hedge funds can, and often do, act both as protection sellers and buyers in the effort to carry out different kinds of arbitrage strategies across varieties of financial markets.

Credit derivatives are financial securities whose payoffs are tied to the issuer's credit quality and they allow the trading of default risk separately from other sources of uncertainty. There are two categories of credit derivatives, single name and multiname derivatives. The most common credit derivative contract is a single name credit default swap which stood for roughly one third of the total trading activity in credit derivatives in 2006 (Ericsson, Jacobs and Oviedo, 2009). Collateralized Debt Obligations (CDOs) are the most popular multiname credit derivatives. In CDOs, a portfolio of debt obligations is created and a structure is created where the cash flows from the portfolio are channeled to various categories of investors (Hull, 2008, pp. 525). A single-name CDS is a form of credit derivative that can be considered as default insurance on a single loan or bond. It is a two-sided over-the-counter contract where the buyer purchases credit protection of a reference company defaulting on its liabilities. It is worth emphasizing that the reference company is not a party to the contract and is therefore neither obligated to pay anything nor is it necessary for the buyer or seller to obtain the reference entity's consent to enter into a CDS contract.

The buyer of a CDS pays a periodic premium, commonly known as CDS spread, to the seller for a predetermined amount of time. Subsequently, if a credit event occurs to the reference entity within the pre-specified time frame, the seller is obliged to compensate the protection buyer. A credit event is usually defined as either bankruptcy or default, depending on the specifics of the contract. A CDS effectively shields the protection buyer from a financial loss in the case of default. If the protection buyer does not hold the reference entity's bonds, then compensation is in the form of a cash payment equal to the difference between the value of the reference entity's bond and its face value. Alternatively, if the protection buyer does hold the bond, then the protection buyer either receives the cash difference or delivers the reference entity's bond to the protection seller for its face value. If no credit event occurs during the maturity of the contract, the protection buyer continues to pay annuity premiums until the end of maturity. CDS maturities usually vary between one and ten years, with five-year maturity being the most common (Callen, Livnat, Segal, 2009).

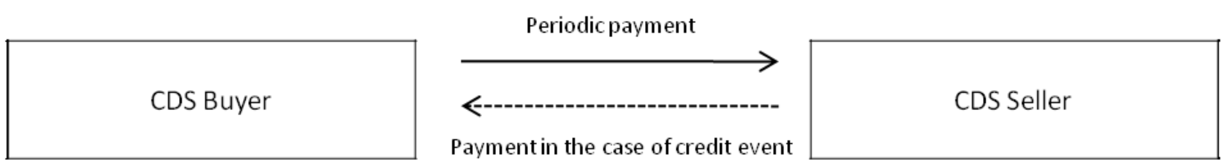

Figure 1: Mechanics of the credit default swap
The figure demonstrates the structure of a basic, one-name CDS contract. The protection buyer, i.e. CDS buyer, carries out periodic payments to the protection seller in return for protection on the reference entity's default. The most common way of dealing with a credit event is that the CDS buyer sells the bonds on the underlying company for their face value to the CDS seller.

(Source based on O'Kane and Turnbull, 2003)

The periodic premium paid by the protection buyer is quoted in basis points (100^{th} of a percent) per annum of the CDS-contract's notional value. As the premiums are usually paid quarterly, a CDS buyer of a 5-year CDS security with a spread of 150 basis points and notional value of € 10 million would make quarterly payments of 0.015 times € 10 million divided by 4, which is equal to € 37 500. The protection buyer keeps compensating the protection seller for carrying the reference entity's default until one of two things happen: the maturity ends or the reference entity defaults. The pricing of CDS contracts is presented in appendix 1.

3 LITERATURE REVIEW

This chapter presents the most relevant literature within this thesis' framework. The first section provides a brief overlook on the relevance of accounting information and the second section presents the most significant accounting-based default literature. The third section discusses the Black-Scholes-Merton (1973) framework, its merits and deficiencies, while the fourth section focuses on highlighting market-based default literature. The fifth section in this chapter briefly introduces the theoretical determinants of credit risk while the last section presents the different approaches for testing credit default models.

3.1 The relevance of accounting data

3.1.1 Relevance to the equity markets

Ball and Brown (1968) were reportedly the first to use an event study in order to examine whether stock prices respond to the information content of financial statements. In essence, they measured how stock prices react to positive and negative earnings announcements using a sample of 261 exchange-listed companies during the years 1957-1965. Their study detected that companies that announced higher earnings than the market had anticipated, posted positive abnormal stock returns in the month of the earnings announcement[2]. Firms that announced lower earnings than the market expected were, on the other hand, strongly associated with negative abnormal stock returns. They did not, however, study the magnitude of the abnormal returns, only the direction. It was, nonetheless, the first study to provide evidence that the markets in fact react to news provided by accounting information and that the information provided by financial statements is useful to investors. This was the starting point of value relevance literature although the concept of value relevance was not launched until Amir, Harris and Venuti (1993). Value relevance is often defined as the measured degree of statistical association between accounting information and equity market values.

Inspired by Ball and Brown (1968), studying the association between capital market values and accounting figures became the most common methodology to test the value relevance of

[2] Ball and Brown (1968) measured abnormal return as the deviation from the Capital Asset Pricing Model (CAPM) predictions at the time. Last year's earnings were used as a proxy for the markets' expectations.

accounting information. This connection is generally statistically measured by the coefficient of determination, R^2, or the Earnings Response Coefficient (ERC). Scott (2009, pp. 154), defines ERC as the measure of extent of a security's abnormal market return in response to the unexpected component of reported earnings of the firm issuing the security. Although Ball and Brown's (1968) study was in essence very simple and did not take the magnitude of the market response into account, it had the important contribution of paving the way for a large body of research that studied the relevance of accounting information further and in greater detail. Their study was reinforced by Beaver, Clarke and Wright (1979), who used a similar approach with the exception of including the magnitude of the abnormal returns in their research. They established results that were in line with the Capital Asset Pricing Model (CAPM): the greater the abnormal return, the greater the stock price reaction. These studies clearly showed that accounting information was, at that time, highly relevant information for investors.

Even though accounting information seems to have been very useful and relevant information for equity markets in the 1960's, Lev and Zarowin (1999), document that the usefulness of accounting values has deteriorated since. According to their study, the accounting information usefulness has weakened steadily for the last 20 years prior to the time of their study due to current reporting systems not being able to adequately reflect firms' operations and economic conditions. They found that both R^2 as well as the ERC gradually declined during the period 1978-1996. Scott (2009, pp. 197) points out that a diminishing ERC is more worrying than a falling R^2, because a falling R^2 might be due to a rising impact of other information sources rather than a decline in the value relevance of accounting figures. A falling ERC, on the other hand, is more direct evidence that accounting measures have lost some of their relevance. Lev and Zarowin (1998) are supported for instance by Collins, Maydew and Weiss (1997) and Brown, Lo and Lys (1999) as they too report a diminishing R^2 in regressions of returns on earnings.

However, Collins et al. (1997) reveal that although the value relevance (R^2) of earnings has declined, it has been replaced by the increasing value relevance of book values. That is to say, their study suggests that value relevance lost in earnings has been replaced by the increasing focus on book values. This notion is backed up by Subramanyam and Venkatachalam (1998) who emphasize that book values might correlate with market values because they aggregate both past and current earnings. The afore-mentioned studies implicate that there is no clear consensus of the relevance of accounting information to equity markets.

3.1.2 Relevance to the credit markets

The relevance of accounting data in the measurement of credit risk has been studied to a much lesser extent than the relevance of accounting information to equity investors. Notable exceptions are carried out by Demirovic and Thomas (2007), Hillegeist et al. (2002), Yu (2002) and Das et al. (2009). Even though not all of these papers explicitly study the relevance of accounting information, all of them can, however, be conceptually categorized of as such. The relevance of accounting information can be studied in various ways. Perhaps the most common approach is to use observed bankruptcies and test how well accounting information is able to predict them (e.g. Altman, 1968, Ohlson, 1980, Hillegeist et al., 2002). Another approach is to investigate the relationship between accounting data and credit ratings. Collin-Dufresne et al. (2001) and Longstaff and Rajan (2006) and Huang and Kong (2005) use accounting data, among other data, to infer bond spreads while Das et al. (2009) study the relationship between accounting information and CDS spreads.

Demirovic and Thomas (2007) study the association between credit ratings and various accounting variables as well as Merton's (1973) distance-to-default using data from the period 1990-2002 in the United Kingdom. They find that accounting measures are significant in explaining the variance of credit risk and although collectively offer more explanatory power than Merton's (1974) distance-to-default, distance-to-default is the single most relevant measure of credit risk in their study. Das et al. (2009), on the other hand, discover that accounting-based variables perform comparably, if not better, than market-based models of default. This is in contrast to Hillegeist et al. (2002) who denote that market-based models of default are more accurate distress forecasters than both the Altman Z-score and Ohlson's O-score. Nevertheless, they concur with Demirovic and Thomas (2007) in that accounting-based data still remains incrementally informative.

Yu (2002) studies the connection between perceived accounting transparency and corporate credit spreads[3] and finds that accurate and transparent accounting information yields smaller credit spreads thus effectively lowering the cost of a company's debt. This is supported by Duffie and Lando (2000) who also find evidence that deficiencies in a company's accounting information lead to a higher perceived credit risk by investors. Both Yu's (2002) and Duffie and Lando's (2000) studies thus exhibit the fact that accounting data is, at least to some extent, relevant information for holders debt capital.

3.2 Accounting-based default prediction literature

Accurate default probability forecasts are of great interest to academics, economists, investors and regulators. Consequently, academics and practitioners have been trying to estimate companies' default probabilities for decades, ever since Beaver (1966, 1968) and Altman (1968). Even though default prediction has been around for a lot longer than Beaver and Altman, they constituted the first generation of actual default prediction models.

Finding fundamental information that could reveal the likelihood of potential default is the primary task of accounting-based scoring models. These models advocate the idea that the analysis of certain key financial ratios, in various combinations, could provide a detection mechanism for a company's financial difficulties. Early default prediction literature was mainly based on ratio analysis. Consequently, it relied for the most part on well-known accounting-based metrics, such as profitability, cash flow and leverage ratios as prediction variables. Although univariate models are still used by practitioners, most academicians seem to disapprove of simple ratio analysis as a means of assessing the probability of bankruptcy. The next three sections move on to discuss the most relevant credit scoring models.

3.2.1 Univariate models

Beaver (1966, 1968) was the earliest scholar to apply statistical methods in predicting bankruptcy for a pair-matched sample of firms. He used a univariate approach that evaluated several

[3] Yu (2002) defines credit spread as the difference between the yield to maturity on a corporate bond and the interpolated constant maturity Treasury yields.

accounting ratios, one at a time, and tested how well they predict corporate distress. Beaver found that a number of financial indicators could discriminate between matched samples of failed and non-failed firms for as early as five years before failure. Beaver initially studied 30 different financial ratios that he divided into six different groups: (1) *cash flow ratios*, (2) *net income ratios*, (3) *debt-to-total assets ratios*, (4) *liquid assets-to-total assets ratios*, (5) *turnover ratios* and (6) *liquid assets-to-current debt ratios*. The ratios were selected by popularity and appearance in academic literature. All 30 ratios from the six different groups were subsequently tested for their ability to predict bankruptcy and as a result, the sample was narrowed down to seven accounting measures.[4]

Although Beaver's (1968) study was very straightforward and based on simple univariate analysis, it had the contribution of developing the methodology employing accounting data in order to assess a company's default probability. In a consequent study, Deakin (1972) made use of the same variables as Beaver (1973) and applied them within a series of multivariate discriminant models. Although Deakin attained high classification accuracy three years prior to failure, there was significant deterioration in the model one year prior to failure, thus undermining the model's relevance. Of the early pioneers in credit risk measurement, Altman (1968) has become the most influential. In his seminal work, he developed a scoring model known as the *Z-score*. It is based on five variables that he found had, at the time, the highest predictive power in a multivariate discriminant analysis (MDA). The *Z-score* is still to this day widely used by practitioners and academics. As such, many of its variables provide an excellent basis for analyzing the relevance of accounting information to credit providers.

3.2.2 Multivariate models

As mentioned earlier, prior to Altman (1968), corporate default prediction was mainly univariate in nature (e.g. Beaver, 1966) and no models for default prediction existed. As an example of the shortcomings of the univariate ratio analyses that were used at the time, Altman (1968) cites the following example:

[4] Beaver's (1966) accounting measures: (1) Cash flow/total debt, (2) net income/total assets, (3) total debt/total assets, (4) working capital/total assets, (5) current ratio, (6) no-credit interval and (7) total assets.

"A firm with a poor profitability and/or solvency record may be regarded as a potential bankrupt. However, because of its above average liquidity, the situation may not be considered serious. The potential ambiguity as to the relative performance of several firms is clearly evident."

As a result, Altman (1968) saw fit to build upon traditional univariate ratio analysis by combining several measures into a meaningful predictive model. Altman (1968) employed an MDA approach in his attempt to create his model. MDA is a statistical technique that classifies observations into one of several *a priori* groupings dependent upon the observation's individual characteristics. According to Altman (1968), MDA is primarily used to classify and make predictions in problems where the dependent variable is in qualitative form, in this case bankrupt or non-bankrupt. An MDA then attempts to derive a linear combination of these characteristics which best discriminates between the groups.

Altman (1968) initially started out with 22 potentially useful accounting variables using a sample of 66 companies (33 bankrupt and 33 non-bankrupt firms). Based on these variables, he eventually came up with the famous *Z-score*; a combination of five accounting variables which best discriminated between companies in two mutually exclusive groups: bankrupt and non-bankrupt companies. The final discriminant function, the Altman *Z-score*, is as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (1)$$

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
Z	=	Overall index or score

The Z-score is a survival indicator and it classifies companies based on their solvency. Default risk is diminishing in the Z-score, meaning that a low (high) *Z-score* implies a low (high) default probability. Altman (1986) set critical values between companies based on their survivability indicator and defined companies with a Z-score lower than 1.81 as companies where bankruptcy was likely. Firms with a Z-score over 2.99 were, on the other hand, classified as stable and unlikely to default on their debt payments. A Z-score between 1.81 and 2.99 had no informational value as it meant that bankruptcy could not be easily predicted, one way or the other. Altman (1983) revised his model by updating the coefficients and changing the X_4 variable from market values to book values in order to be able to include private companies[5]. Altman (2000) further revised the original Z-score in order to minimize the potential industry effects by removing X_1 – sales/total assets from the model and once again updated the coefficients[6].

Even though developed as early as in 1968 and using only a small sample of firms from the 1950s and 1960s, Altman's (1968) *Z-score* still remains a widely used tool for evaluating the financial health of companies. In contrast to Altman (1968), Prihti (1975) used a theoretical approach in determining the relevant variables in default prediction. Prihti's (1975) discrimination function is thereby based on three accounting ratios that can be categorized as follows: sufficiency of retained earnings, sufficiency of working capital and indebtedness. In total, Prihti's (1975) sample consisted of 49 bankrupt and 9 624 non-bankrupt Finnish firms.

Some 18 years later after the *Z-score*'s introduction, Zmijewski (1984), Ohlson (1980) and Palepu (1986) demonstrated that Altman's (1968) methodology was in essence somewhat flawed and that the model's predictive abilities were therefore overstated in his study. According to Zmijewski (1984), default prediction literature in general suffered from two sample selection biases. The first bias was a choice-based sample bias that results when the researcher first observes the dependent variable and then selects a sample based on that knowledge. This way the probability of a firm entering the sample depends on the dependent variable's attributes. Zmijewski (1984) lists the second bias as a sample selection bias that results when only observations with complete data are used to estimate the model and incomplete data observations occur in a non-random fashion. In short, the methodological problems with Altman's (1968) research revolved around a choice-based sample data and the fact that possibly useful data were lost when one or more of the estimation parameters were missing.

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[5] The updated version of the Altman Z-score: $Z = 0.717(X_1) + 0.847(X_2) + 3.107(X_3) + 0.420(X_4) + 0.998(X_5)$ where all variables except X_4 remain unchanged. Modified X_4 = Book value of equity / Book value of total debt.

[6] Updated Z-score: $Z'' = 6.56\ (X_1) + 3.26\ (X_2) + 6.72\ (X_3) + 1.05\ (X_4)$ where the sales/total assets variable is removed.

Ohlson (1980) added to the criticism surrounding the so-called first generation default prediction models by noting that they derived their data from a data set called Moody's Manual. The point of concern was that the manual did not indicate at what point in time information about the default was released to the public. If one then employed predictors derived from financial statements that were released after the date of default, it is easier to predict the probability of bankruptcy which, in turn, overstates the models' predictive abilities. Ohlson (1980) further criticized previous bankruptcy literature for the fact that the samples often contained roughly as many bankrupt as non-bankrupt firms, which distorted the models further. Ohlson (1980) used a sample of 105 bankrupt firms and 2 058 non-bankrupt firms while Altman used 33 bankrupt companies and 33 non-bankrupt companies.

The second generation of corporate distress studies employed multinominal choice techniques, including but not limited to maximum likelihood, logit and probit models. Motivated by the discussion of banks' capital regulation, Santomero and Vinso (1977) introduced a stochastic model with respect to bank failure. More particularly, they examined the cross-section riskiness of the US banking sector and its sensitivity to variations in the size of individual banks' capital buffer. Santomero and Vinso (1977) were among the first studies which logically and systematically developed probabilistic estimates of corporate default. This approach was further developed, among many others, by Ohlson (1980) who employed the technique of conditional logit analysis.

Ohlson (1980) found that there are four key factors that affect the probability of corporate failure, which are: the size of the company, financial structure, performance and current liquidity. Ohlson (1980) accordingly picked up different kinds of accounting measures which reflected these afore-mentioned factors. Ohlson's *O-score* can be stated in the following format:

$$O = -1.32 - 0.407(Size) + 6.03(TLTA) - 1.43(WCTA) + 0.08(CLCA) - 2.37(NITA) - 1.83(FUTL) + 0.285(INTWO) - 1.72(OENEG) - 0.53(CHIN) \quad (2)$$

$Size$	=	Log (total assets / GNP price-level index)
$TLTA$	=	Total liabilities / total assets

$WCTA$	=	Working capital / total assets
$CLCA$	=	Current liabilities / current assets
$NITA$	=	Net income / total assets
$FUTL$	=	Funds from operations / total liabilities
OENEG	=	Equal to 1 if the book value of equity was negative for the last two year, zero otherwise
$INTWO$	=	Equal to 1 if net was income negative for the last two years, zero otherwise
$CHIN$	=	$(NI_{t0} - NI_{t-1}) / (\|NI_{t0}\| + \|NI_{t-1}\|)$, where NI is net income

Ohlson's O-score does not represent a certain bankruptcy probability per se, but it can be transformed into such using the logistic transformation formula[7]. Before moving on to market-based default models, the Black-Scholes options pricing model will be briefly presented as it is an important underlying concept in the methodology of this thesis.

3.3 The Black-Scholes option pricing model

The Black and Scholes (1973) option-pricing model was an influential breakthrough in the pricing of derivatives. It allows for a theoretically correct way for valuing options[8]. The model has become widely acknowledged by practitioners and it has influenced the way options are valued. Additionally, it can be considered as being the starting point of the growth and success of financial engineering. The Black-Scholes (BS) formula enables one to calculate the value of an option using the following information: the *time to maturity of the option* (T), the *exercise price* (X) *,* the *current price of the underlying security* (S_0), the *risk-free interest rate* (r) and the *volatility of the underlying security (*σ). Additionally, if the underlying security pays dividends during the option's maturity, then the expected dividend payments affect the value of the option as well.

The Black-Scholes model is a mathematical formula based on the concept that stock prices follow a stochastic process, i.e. future stock prices are independent from their past performance. This is generally known as the random walk of stock prices or geometric Brownian motion. Put mathematically (Hull, 2008, pp 266):

$$\Delta S/S \; = \; \mu \, \Delta t + \sigma \in \sqrt{\Delta t} \qquad (3)$$

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[7] The obtained O-score can be translated into a bankruptcy probability by using the logistic transformation:

$$\frac{e^{O-score}}{1 + e^{O-score}}$$

[8] For criticism on the Black-Scholes option pricing model, see e.g. Haug and Taleb (2009).

Where S is the stock price, ΔS is a small change in the stock price in a small interval of time (Δt) and $\in$ has a standardized normal distribution. The parameter μ is the expected rate of return and σ is the underlying security's volatility. The basic form of the BS model assumes μ and σ as constants. Subsequently, by building on Itô's lemma[9] and BS' underlying assumptions, one can derive the BS option pricing model for a standard European[10] call option (Hull, 2008, pp. 291):

$$c = S_0 N(d_1) - Xe^{-rT} N(d_2)$$

where

$$d_1 = \frac{\ln\left(\frac{S_0}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T} \qquad (4)$$

X is the strike price of the option and N(x) is the cumulative probability distribution function for a standardized normal distribution. That is to say, it is the probability that a variable with a standard normal distribution, Φ(0,1), will be less than x (Hull, 2008, pp. 291). For clarity, the first term of the BS model, $S_0 N(d_1)$, essentially calculates the delta[11] ($N(d_1)$) of the option times the stock price and the second term, $Xe^{-rT} N(d_2)$, calculates the probability adjusted ($S > X$) discounted strike price as $N(d_2)$ is the probability that the option will be eventually exercised.

The model presented above calculates the values for a European call option but is can be easily transformed to calculate the values for European put options as well.

3.4 Market-based default prediction literature

A number of recent academic studies have questioned the quality of accounting-based credit risk models (e.g. Crosbie, 1999 and Hillegeist et al., 2002). Accounting-based models employ

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[9] Itô's lemma essentially formalizes the fact that the randomness in the log changes of stock prices has a variance that is proportional to time.

[10] A European option can be exercised only at maturity whereas American options can be exercised at any time during the options maturity.

[11] The delta of an option is the sensitivity of the option's price relative to small changes in the price of the underlying security.

financial statements data that measure past performance and their implications for estimating future performance is thus often questioned. Additionally, both accounting conservatism and, on the other hand, accounting manipulation can distort the relevance of accounting information. Perhaps the most central deficiency in accounting-based models is, however, the fact that the models usually exclude capital market data and values. Especially the exclusion of asset price volatility is seen as a major deficiency (Caouette, Altman and Narayanan, 1998). Market-based default prediction models seek to remedy the situation by relying on stock market information. Market-based models comprise of two types of models, structural and reduced form models.

The basic reasoning behind structural models (or contingent claims models, e.g. Merton, 1974) is that the equity of a levered firm can be seen as a European call option to acquire the value of the firm's assets by paying off the face value of the debt at the debt's maturity. Thus, default occurs when the value of a firm's assets falls below the value of its liabilities at maturity. In this context, the payment to debt holders at the end of debt maturity is therefore the smaller of the following: the face value of the debt or the market value of the firm's assets (Altman, Resti and Sironi, 2003). Consequently, equity holders have a call option with a strike price equal to the book value of the company's debt and that matures when the debt is due. Reisz and Perlich (2007) accentuate that by using put-call parity shareholders can in effect be seen as holding the firm's underlying assets and a put option with the strike price equal to the face value of the company's debt. Moreover, if the assets of the company are below the value of the debt at maturity, shareholders can simply walk away without having to pay the existing debt obligations. They can do this by exercising the put option which allows them to effectively sell the company to its creditors for the face value of the debt. Consequently, bondholders are at the other end of the deal as they can be seen as holding a portfolio consisting of riskless debt and a short put option on the firm's assets (Reisz and Perlich, 2007).

3.4.1 The Black-Scholes-Merton framework

The basis of the structural credit risk modeling approach goes back to Black and Scholes (1973) and Merton (1974). In Merton's (1974) *distance-to-default*, the equity of a company is viewed as a call option on the firm's assets. This options based analogy is based on Black and Scholes (1973) option pricing theory that was discussed earlier. Black and Scholes (1973) and Merton

(1974) demonstrated that one can see the stock of a company as a European call option on the underlying assets of the company. From one perspective, shareholders have in essence sold the company to their creditors while keeping the option of buying it back by paying the face value of the company's liabilities. A firm is therefore insolvent if the value of the firm's assets falls below what the firm owes its creditors at the time of debt maturity. Thus, asset value falling below the face value of debt triggers default. In the event of default, equity investors would simply hand over the firm's assets to its creditors.

Merton's (1974) approach to calculating default risk measures starts with the assumption that the market value of a firm's total asset value follows a geometric Brownian motion[12] of the form:

$$dV_A \;=\; \mu\, V_A dt + \sigma_A\, V_A dW \qquad (5)$$

where V_A is the firm's asset value, with a drift factor of μ and a volatility of σ_A while W stands for a standard Wiener process[13]. Although the Wiener process, also known as Brownian motion, is an important underlying factor in the Black-Scholes (1983) option-pricing model, its details are outside the limitations of this thesis (see e.g. Hull, 2008) and will hence not be discussed.

If one assumes that there is only one class of debt which pays no coupons and has a maturity time of T and a principal amount of X, then the firm is in default when firm's asset value is less than X at time T. Default risk is therefore characterized by the probability that the firm's asset value falls below the face value of its debt. Consequently, the equity of the firm, V_E, can be regarded as a call option written on the firm's underlying assets. Thus, following it can be expressed through the Black and Scholes (1973) option pricing formula:

$$V_E = \; V_A\, N(d_1) - \; Xe^{-rT} N(d_2) \qquad (6)$$

where

[12] Geometric Brownian motion is a lognormal process that has a variance which grows proportionally to time.

[13] A Wiener process is a continuous time stochastic process that is used widely used in finance and economics to model random stock price behavior.

$$d_1 = \frac{\ln\left(V_{A,t}/X_t\right) + (r + 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}} \quad , \qquad d_2 = d_1 - \sigma_A\sqrt{T} \tag{7}$$

T is the debt's maturity, r is the risk-free interest rate and N is the cumulative probability function of standard normal distribution. The market price of a company's debt can thus be obtained by $V_A - V_E$.

The model assumes that the firm's asset value follows the process described in (5), and its debt of amount equal to X matures at time T and the firm defaults when its asset value falls below level X at time T. Thus, following Du and Suo (2003), it can be stated mathematically as:

$$P_{default} = P(V_{A,T} \leq X) \tag{8}$$

Applying the Black-Scholes formula, the company's asset value at time T can then be written as:

$$\ln(V_{A,T}) = \ln(V_{A,0}) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T + \sigma_A z_T \tag{9}$$

A firm's default probability can be calculated as follows:

$$P_{default} = P(\ln\,(V_{A,T} \leq X))$$

$$= P\left(\left(\mu_A - \frac{\mu_A^2}{2}\right)T + \sigma_A z_T \leq \ln\left(\frac{V_A}{X}\right)\right)$$

$$= P\left(z_T \leq -\frac{ln\left(\frac{V_A}{X}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A}\right)$$

$$= N\left(-\frac{\ln\left(\frac{V_A}{X}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A T}\right) \tag{10}$$

With this result, Merton (1974) defines his *distance-to-default* model:

$$Distance\ to\ default = \frac{\ln\left(\frac{V_A}{X}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)T}{\sigma_A T} \qquad (11)$$

A company is in default when the ratio of the value of assets to debt is below one. The model essentially measures how many standard deviations the logarithm of this ratio needs to deviate downwards from its mean before the firm defaults. Once one obtains a firm's distance-to-default, a firm's default probability is simply the likelihood that the final asset value will be below its debt value at debt maturity[14]. To be able to calculate this measure, one needs to estimate the firm's asset growth rate and volatility. However, since only equity (and not the company's assets) is traded, these parameters are not readily observable. There are two ways for obtaining these parameters. The first is to solve a nonlinear system of equations and the other is to adopt an iterative procedure (see Bharath and Shumway, 2005 or Vassalou & Xing, 2004). Figure 2 depicts the main characteristics of the BSM framework and illustrates, among other things, the importance of approximating a firm's asset value and asset value volatility.

[14] The distance-to-default measures can be translated into default probabilities using: $P_{Default} = N(-DD) = N(-\frac{\ln\left(V_{A,t}/X_t\right) + (\mu - 0.5\sigma_A^2)\,T}{\sigma_A\sqrt{T}})$

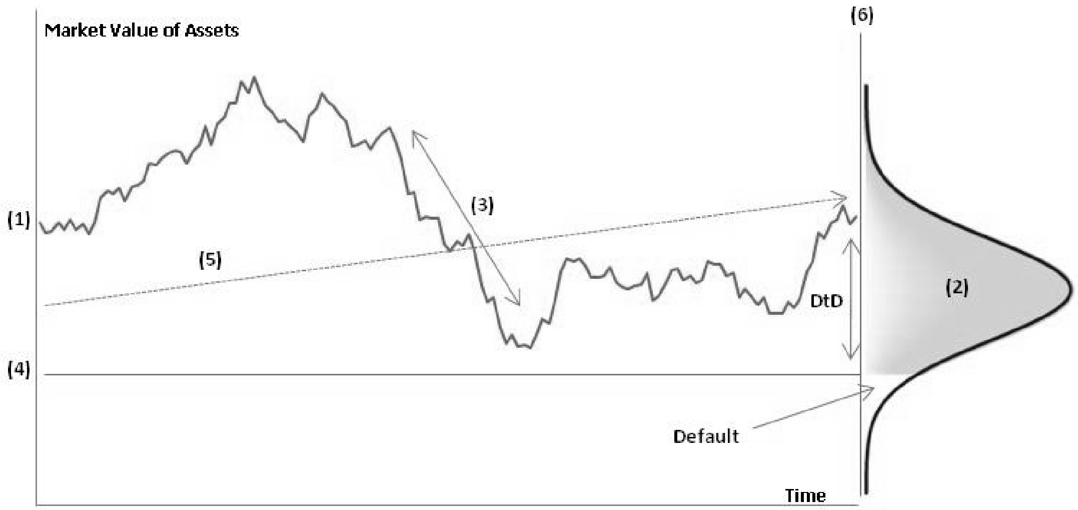


Figure 2: A graphical illustration of Merton's *distance-to-default* model
The figure presents a Monte Carlo simulated Brownian motion asset value path for a fictive company as well as the six key underlying factors in Merton's (1974) *distance-to-default* model. The vertical axis represents the assets' total market value whereas the horizontal axis represents time.

(1) The current asset value
(2) The distribution of the asset value at maturity
(3) The asset value volatility
(4) The book value of total debt, i.e. the point of default
(5) Asset value rate of growth
(6) The length of the horizon, i.e. maturity

The figure essentially shows how the *distance-to-default* increases (decreases) with lower (higher) levels of debt and higher (lower) asset values. Additionally, one can see how the model relies on asset prices being normally distributed.

(Figure reproduced based on Crosbie and Bohn, 2003)

Hillegeist at al. (2002) emphasize that the validity of the BSM option pricing formula relies on the validity of the underlying economic theory. Based on Merton (1974), the most relevant assumptions are:

A.1 *Financial markets are liquid and trading takes place continuously, there are no transaction costs or taxes, there is perfect asset divisibility and that there are no arbitrage opportunities.*
A.2 *Asset values follow geometric Brownian motion.*
A.3 *There is a constant risk-free interest rate that is identical for both borrowers and lenders.*
A.4 *Short selling of all assets, with the full use of proceeds, is allowed.*
A.5 *There are no bankruptcy costs.*
A.6 *The firm issues only zero-coupon bonds.*

The relevance of all of the above-mentioned assumptions will not be discussed in this thesis as that is outside the limitations of this study. However, some of the assumptions will come up in the following paragraphs where I present some of the most relevant merits and the major deficiencies in the BSM framework.

The options analogy is academically appealing as it is based on the efficient market hypothesis (Fama, 1965). Models that are based on the analogy have several advantages as compared to models that back out their information from accounting data. First of all, they are based on equity prices that are traded on a daily basis which results in more reliable up-to-date information (Reisz and Perlich, 2007). Secondly, as it is based on the notion of markets being efficient, the market prices should contain all relevant information, including everything that accounting-data has to offer. Theoretically, accounting-based models should thus not have any role in corporate credit risk assessment as all necessary data can be obtained from the markets. The fact that the BSM framework is supported by the efficient market hypothesis and that it utilizes a modified version of the Black-Scholes (1973) option pricing formula that is widely used by academics and practitioners, makes it an appealing approach towards assessing default probabilities.

Furthermore, the BSM framework, unlike accounting-based models, is not built by comparing the characteristics of defaulted and non-defaulted firms using statistical techniques to derive the variables that best discriminate between the two groups of companies. Moreover, in contrast to BSM, accounting-based models are empirical models that lack an underlying theory. Consequently, Ghargori, Chan and Faff (2006) emphasize that the BSM framework is grounded on economic theory, whereas accounting-based models are based on prior ad hoc specifications of defaulted firms.

Even though the BSM framework is an application of classic finance theory, there are several limitations and deficiencies commonly associated with it. The framework does not distinguish between different types of debt, and assumes that the firm has issued only one single zero-coupon loan (Agarwal and Taffler, 2008). Additionally, Brockman and Turtle (2003) state that standard options are path independent in the sense that their payoff depends on the underlying asset value only at maturity and not the particular path followed up to maturity. This means that a standard option remains alive regardless of the decline in asset value below the strike price. However, in the default prediction framework, a decline in asset value below the strike price (face value of debt) essentially should trigger bankruptcy even if it happens before debt maturity. This has not been taken into account in the BSM framework. Jones, Mason and Rosenfeld (1984) and Franks and Torous (1989) consequently express that this aspect of the model implies credit spreads that are smaller than the actual, empirically witnessed, credit spreads. Brockman and Turtle (2003) thereby argue that down-and-out call options are more appropriate for pricing corporate assets in the default prediction framework. A down-and-out call option is in all aspects similar to a regular call option, except that it is instantly rendered worthless if the underlying asset crosses a pre-specified (in this case the face value of debt) level between the time the option was written and the maturity date.

Furthermore, Reisz and Perlich (2007) underline that equity volatility is usually assumed to be constant over a certain period when applying the option analogy, even though Itô's lemma shows that it is time dependent. Longstaff and Schwartz (1995) put emphasis on the fact that it is difficult to justify that the framework assumes constant interest rates. Yet another shortcoming in the framework is that it assumes that the firm's future asset value follows a paradigm called the random walk of stock prices which is based on the log normality assumption (see figure 2). There is a large body of literature that disapproves with the assumption that stock prices are log normally distributed (e.g. Keim and Stambaugh, 1986, Fama and French, 1988 and Lo and MacKinlay, 1988).

The probability of default is driven by the five primary option pricing parameters: the book value of the company's total liabilities, the current market value of the firm's assets, the standard deviation of the firm's value changes, the average time to the debt's maturity and the spread between the riskless return and firm's dividend payout yield (Charitou and Trigeorgis, 2000). Charitou and Trigeorgis (2000) emphasize that the model essentially relies most on two key factors in predicting corporate failure: the firm's asset value relative to its face value of debt and the volatility of the firm's asset value. This is somewhat problematic as asset values and asset volatilities are directly unobservable in the market place. One has to use approximations that can be obtained by solving two simultaneous nonlinear equations or by iterative calculations. Both of the previously mentioned methods are fairly complicated and as said, provide only approximations of the asset value and asset value volatility of a firm. One might conclude that the BSM framework incorporates several unrealistic assumptions. Many extensions have addressed these deficiencies and the most relevant ones are presented in the next section.

3.4.2 Extensions to the Black-Scholes-Merton framework

The BSM framework laid the foundation for many subsequent structural models that aim to improve on the deficiencies that the framework suffers from. The basic principle in these modified models is precisely the same as they also rely on the option analogy where the firm's liabilities are viewed as contingent claims issued against its assets. Furthermore, they equally back out the necessary data from the stock market in order to infer the probability of corporate default.

Several models have refined the original BSM framework by removing one or several of its assumptions. Black and Cox (1976) relax the assumption that the firm has issued only zero coupon bonds as its source of debt financing by introducing a more complex capital structure that includes subordinated debt in addition to zero coupon bonds. Geske (1977) modifies the framework to be able to include interest-paying debt while Vasicek (1984) revises it so that it is capable of making the distinction between short and long term liabilities. However, even though it is not a particularly realistic assumption that a firm's debt consist only of zero-coupon bonds, Hillegeist et al. (2002) point out that in order to modify the model to include more realistic assumptions, one needs information that is by large unavailable to researchers.

Other well known modifications to the BSM framework are presented by Hull and White (1995) and Longstaff and Schwartz (1995) who added the possibility of default occurring before maturity. Default is therefore triggered whenever the value of the firm's assets falls below an exogenously determined barrier. This is in contrast to the BSM framework where default is only allowed to happen at maturity. However, based on the observation by Huang and Huang (2002) that firms often continue to operate with negative net worth, Leland (2002) specifies a barrier that is a fraction (less than or equal to one) of the face value of the firm's debt. Although the default barrier changes in absolute terms, the ratio is assumed to be stable throughout the prediction horizon. These models essentially presume that bankruptcy is triggered at an exogenously determined asset value, in most cases, the principal amount of debt or some fraction of it.

Black and Cox (1976) and Leland and Toft (1996) use a different approach to determining the eventual default barrier. They assume that the decision to default is made by managers who act in the favor of shareholders by trying to maximize the value of equity in each point of time. The manager thus constantly has to consider whether it is in the best interest of the shareholders to meet the company's debt obligations. Consequently, the manager thereby essentially defines an endogenous default barrier that the assets will have to exceed in order for the company to stay clear of failure. This barrier can be below or above the face value of debt. Endogenous models assume that bankruptcy is declared, not observed. Additionally, in the original BSM framework, it is assumed that the bondholders receive the entire value of the firm when the firm's asset value drops below the face value of debt. Leland and Toft (1996) incorporated this in their model by including bankruptcy costs into the equation.

Even though there is a variety of extensions and improvements that aim to improve the BSM framework, there are still three drawbacks that have remained unaddressed (Altman, Resti and Sironi, 2003). The first is that the framework requires approximations of a firm's value and volatility. Secondly, structural models are unable to include credit rating changes. Altman et al. (2003) point out that most corporate bonds undergo credit downgrades before they default and that any credit default model should take into account the uncertainty associated with credit rating changes. Lastly, structural models assume that the value of a firm is continuous in time and default can therefore be predicted just before it happens. Consequently, Duffie and Lando (2000) emphasize that if the value of a firm is continuous, there are no sudden surprises when a company defaults.

3.4.3 Reduced form models

Reduced form models were created in response to the limitations in structural models. Widely known examples of reduced form models include but are not limited to Jarrow and Turnbull (1995), Litterman and Iben (1991) and Lando (1998). The most significant difference between structural models and reduced form models is that reduced form models do not involve predicting the probability of default from the asset value of the firm. Therefore, parameters related to firm value need not to be estimated. According to the reduced-form approach, default probabilities are estimated using the market prices of corporate bonds. The approach is based on the assumption that corporate bonds can be divided into a risky component and a risk-free component of return. The price of a risk-free bond is the present value of the bond's certain future cash flows while the price of a corporate bond is the present value of its uncertain future cash flows. The uncertain future cash flows of a corporate bond reflect the default probability of the issuer and the expected recovery rate. Subsequently, the reduced form approach derives an implied default probability from the difference between a corporate bond and an equivalent risk-free bond. The most important difference in the logic behind structural and reduced-form models is that reduced-form models assume that a firm can default at any instant of time, independent of the value of assets relative to its debt.

Even though reduced form models do not suffer from the same deficiencies as models based on the BSM framework, empirical results comparing the two sets of models imply that structural models perform slightly better in predicting observed bankruptcies (see e.g. Arora, Bohn and Zhu, 2005). Additionally, since reduced-form models are less used by practitioners than are structural models, they are not included in the methodology of this thesis.

3.5 Theoretical determinants of credit risk

Perhaps due to the various theoretical drawbacks and somewhat subdue performance in certain academic studies, Merton's (1974) distance-to-default has been criticized. Consequently, academic literature has put increasing emphasis on the determinants of credit risk rather than on structural models as such. More specifically, the academic consensus seems to suggest that there are three imperative variables in the evaluation of credit risk. These so-called determinants of credit risk are leverage and asset volatility, the two single most influential variables in distance-to-default, and the risk free interest rate. For instance, Ericsson et al. (2009) report that these theoretical variables explain close to 60 percent of CDS spreads and the authors therefore conclude that the three variables, as suggested by theory, are indeed important determinants of CDS spreads. Zhang et al. (2009), on the other hand, find that once leverage, long-term historical volatility and the risk free rate is supplemented by realized short-term volatility, a range of jump-risk[15] measures and once macroeconomic factors as well as credit ratings and accounting data is controlled for, the variables together account for some 73 percent of the variation in level CDS spreads.

The goal of these studies, however, differs in a crucial manner from the one of this thesis. The studies exploring the determinants of CDS spreads aim to find a model that explains as much as possible of CDS spreads while in this thesis, the goal is merely to compare how well different sources of information fare in the explanation of credit risk.

3.6 Different approaches for testing credit default models

Default prediction models can be analyzed in several different ways. The most common approach to test structural default models is to focus on how well they predict corporate bond yields (e.g. Collin-Dufresne, Goldstein and Martin, 2001 and Wu and Zhang, 2004). This is the natural way of validating structural models since Merton's (1974) original intention was to establish a relationship between the market value of bonds and shares based on the theory of option pricing. However, Elton, Gruber, Agrawal and Mann (2001) illustrate that default risk only explains around 25 percent of bond spreads and as much as 75 percent of the spread can be attributed to other factors. Thus, bond spreads do not seem to offer an adequate proxy for default risk. Thereby, this approach is not exempt of difficulties because in order to reproduce observed credit spreads, one has to take into account all the elements that might influence them, including liquidity risk, the appropriate risk-free rate and a different tax rate that varies from country to country (Peña and Forte, 2006).

Another common approach is to take actual defaults and measure how well the models fare in estimating them (e.g. Bharath and Shumway, 2005 and Hillegeist, Keating, Cram and Lundstedt, 2002, and Vassalou and Xing, 2004). Yet another way of analyzing the functionalities of the models is to study how well the models can predict changes in credit ratings (e.g. Du and Suo, 2003). Dichev (1998), on the other hand, investigates how credit risk models fare in explaining the credit risk in equity prices. Finally, there is the path taken in this thesis, which is to test how much of CDS spreads the models are able to explain. All of the above-mentioned essentially

[15] Jump-risk can be understood as the risk associated with large swings in the price of a certain asset. Zhou (2001) argues that credit spreads increase with jump variance and that a higher jump average is associated with higher equity returns and that it thereby reduces credit spreads.

measure how good the models are, but from slightly differing angles. Table 1 lists the most relevant research in the field of credit risk prediction.

Table 1: Empirical research approaches in credit risk literature – a summary

The table summarizes the relevant default risk literature from different time periods selected by the author of this thesis. Data source indicates the type of data that was used in the study. Sample size is defined as the total of firm-week, firm-quarter or firm-year observations included in the main sample.

Study	Sample size	Sample period	Market	Approach	Data source
Beaver (1966)	158	1954 - 1964	United States	Observed bankruptcies	Accounting
Altman (1968)	66	1946 - 1965	United States	Observed bankruptcies	Accounting
Prihti (1975)	9 673	1964 - 1973	Finland	Observed bankruptcies	Accounting
Ohlson (1980)	2 163	1970 - 1976	United States	Observed bankruptcies	Accounting
Zmijewski (1984)	840	1972 - 1978	United States	Observed bankruptcies	Accounting
Collin-Dufresne, Goldstein and Martin (2001)	688	1988 - 1997	United States	Bond spreads	Market
Hillegeist, Keating, Cram and Lundstedt (2002)	65 960	1979 - 1997	United States	Observed bankruptcies	Accounting & market
Du and Suo (2003)	6 635	1985 - 2002	United States	Credit ratings	Accounting & market
Reisz and Perlich (2004)	5 784	1988 -2002	United States	Observed bankruptcies	Market
Vassalou and Xing (2004)	4 250	1971 - 1999	United States	Equity returns	Market
Bharath and Shumway (2005)	1 016 552	1980 - 2003	United States	Observed bankruptcies	Market
Huang and Kong (2005)	1 554	1997 - 2003	United States	Bond spreads	Macro
Longstaff and Rajan (2006)	435	2003 - 2005	United States	CDO spreads	Market
Das, Hanouna and Sarin (2009)	2 242	2001 - 2005	United States	CDS spreads	Accounting & market
Demirovic and Thomas (2007)	2 431	1990 - 2002	United Kingdom	Credit ratings	Accounting & market
Zhang, Zhou and Zhu (2009)	6 328	2001 - 2003	United States	CDS spreads	Accounting & market
Ho, Hsiao and Lo (2010)	22 048	2001 - 2004	Japan	CDS spreads	Accounting & market

Table 1 shows that the focus has shifted from using only observed bankruptcies to using a wider variety of approaches in order to test the different types of models. Although not reported in table 1, the applied methodology has varied from ordinary least square (OLS) regressions to more sophisticated approaches, such as hazard rate models.[16]

[16] See e.g. Bharath and Shumway (2005).

4 HYPOTHESES

This chapter presents the hypotheses that are tested in the study. The hypotheses are mainly based on existing literature presented in the previous chapter. I will first motivate and present **H_1** which posits that the markets are a more relevant source of information to the credit markets than accounting information. Secondly, I introduce **H_2** which takes one step further by positing that accounting information has no role whatsoever in assessment of credit risk, i.e. it is not of incremental information to credit investors. Lastly, **H_3** and **H_4** concern industry effects in accounting information relevance and the effects of macroeconomic conditions, respectively.

The first hypothesis is a variation of the fairly common hypothesis that structural default models offer superior default information as compared to accounting-based models. Results from academic studies are somewhat mixed in this regard. On one hand, e.g. Hillegeist, Keating, Cram and Lundstedt (2002) and Ghargori, Chan and Faff (2006), claim that structural models provide superior probabilities of default as compared to accounting-based models. Hillegeist et al. (2002) report that probabilities of bankruptcy backed out using the BSM framework are up to 14 times more informative than the ones inferred from accounting-based statistics. On the other hand, Das et al. (2009), find that accounting information is as relevant, if not more relevant, a source of information to credit investors. Then again, Du and Suo (2003) find that Merton's (1974) distance to default is an insufficient statistic for predicting credit ratings and that it performs only comparably to simpler market-based measures. Hence, investigating whether market-based information, proxied by the distance-to-default measure, offers more relevant information than accounting data to the credit markets is a cause worthwhile.

There are several reasons as for why market-based default models should offer more relevant information to the credit markets than accounting-based models. One of the most convincing reasons is related to the efficient market hypothesis originally introduced by Fama (1965). According to the efficient market hypothesis, equity markets always reflect all publically available information about individual stocks and about the stock market at large. Furthermore, the EMH entails that when new market information arises; the news spreads extremely quickly and is immediately incorporated into the prices of securities. Thus, default assessments backed out of the markets should not only contain all relevant information about the default probability of a company but can also be obtained on a much more frequent basis than default probabilities backed out of accounting information.

Additionally, as financial statements are intended to measure past performance, their information content might not be very informative about the future prospects of a firm. Another important problem in using accounting information to assess the probability of corporate default is that financial statements are prepared based on the going-concern principle. That is to say, firms are expected to survive. Furthermore, Hillegeist et al. (2002) point out that accounting conservatism may cause asset values to be understated which, in turn, lead to overstated leverage ratios. Moreover, as opposed to accounting conservatism, accounting manipulation may cause accounting data to be distorted, which adds to the problems in accounting-based measures of default.

Finally, asset value volatility is not included in accounting-based default measures. Hillegeist et al. (2002) remind that asset value volatility is a critical variable in the prediction of default since it captures the likelihood that the value of the firm's assets declines below the value of its debt thus causing the firm to be unable to repay its debt obligations.

Based on the above-mentioned factors, I hypothesize the following:

H_1: *Market-based credit risk models offer more relevant information than accounting-based credit risk models to the credit markets.*

Assuming that markets are entirely efficient, information relevant to the measurement of a firm's credit risk is fully reflected in its equity price. As a consequence, there should be no role for accounting metrics in the prediction of default. However, Bharath and Shumway (2005) underline that if markets are not perfectly efficient, then taking accounting information into account makes sense.

There is a substantial amount of research evidence that shows that accounting information is at least incrementally informative in the prediction of bankruptcy. Demirovic and Thomas (2007) find that several accounting variables and ratios have unexpected negative coefficients in regressions of the accounting variables on credit ratings. However, they further note that accounting-based default measures, as a combination, are more significant than Merton's (1974) distance-to-default in their study. Then again, Demirovic and Thomas (2007) assert that distance-to-default is the single most important variable in the measurement of credit risk. They also point out that accounting information, especially measures of profitability and leverage, are incrementally informative when added to market-based measures of default. That is to say, market-based default prediction models, at least the distance-to-default-measure, does not contain all relevant information and that accounting information does have a role in the assessment of default risk. Demirovic and Thomas (2007) compare the two sources of information by testing how well they are able to explain credit ratings. Furthermore, even though Hillegeist et al. (2002) show that market-based default measures are better predictors of default, accounting information is still found to be incrementally informative.

This contradiction between empirical research and financial theory makes for an interesting hypothesis:

H_2: *Accounting metrics are not incrementally informative in the explanation of credit default swaps.*

In their comparative study between the relevance of accounting and market information, Demirovic and Thomas (2007) hypothesize that the relevance of accounting information (to the credit markets) varies across different industries. Their argument is based on Lev and Zarowin (1999), who call attention to the immediate expensing of intangible assets. They argue that the expensing of intangible assets distorts the principle of matching costs with revenues and that this, consequently, has a negative influence on the information level in financial statements. However, the above-mentioned studies are conducted on U.S. data, meaning that the sample firms operate under U.S. GAAP. According to U.S. GAAP, all research and development costs, for instance, are charged to expense as they occur. According to IFRS standards (IAS 38), however, research costs are to be charged to cost (and thereby cannot be capitalized) whereas development costs are to be capitalized only when the "technical and commercial feasibility of the asset for sale or use have been established". Thus, as IFRS addresses the problems emphasized by Lev and Zarowin (1999), one could assert that as far as research and development costs are concerned, no differences in the relevance of accounting information should exist within European data.

On the other hand, in their study on the strategic choice to declare bankruptcy, Berkovitch and Israel (1998) find that the percentage of companies that enter bankruptcy is higher for companies in mature industries as compared to companies in more growth oriented industries. They reason that underinvestment[17] problems are more important in growth industries. Thus, as underinvestment issues do not directly show up on firms' financial statements, this supports, in contrast to R&D issues, the conjecture that the relevance of accounting information varies from industry to another.

Employing a sample of mobile phone companies, Amir and Lev (1995) report that the value-relevance of accounting information is found to be, as such, value-irrelevant in that particular setting. However, when nonfinancial measures were incorporated into the tests both nonfinancial and financial information turned value-relevant. Consequently, Amir and Lev (1995) posit that nonfinancial information is of increasing relevance, especially so in so called science-based industries and that their findings can be generalized to other similar industries as well. Accordingly, a reasonable inference would be to presume that the relevance of accounting information to the credit markets varies across industries as both the relevance and amount of nonfinancial information is inherently different between industries.

Demirovic and Thomas (2007) find that the incremental significance of accounting variables is in their study caused mainly by fluctuations in the explanatory power of the distance-to-default measure. Accordingly, they conclude that the deviations in the incremental informativeness of accounting information, is most likely not explained by the properties of financial statements. They resolute that the issue demands further research. In the quest to provide additional evidence on both the relevance and on the incremental relevance of accounting information, the following is hypothesized:

H_3: *Accounting information relevance differs across industries.*

Empirical evidence suggests that macroeconomic conditions affect the relevance of accounting information. Demirovic and Thomas (2007) hypothesize that during economic expansions

[17] Underinvestment is an agency problem where the shareholders of a firm reject profitable low-risk investments in the attempt to maximize shareholder value at the expense of debt holders. The underinvestment problem is described in more detail in Myers (1977), for instance.

investors put increasing emphasis on nonfinancial indicators and that consequently a larger portion of firms' values are derived from growth opportunities that are not reflected in financial statements. Turning the logic around, one could argue that during economic downturns, such as the global economic crisis being witnessed at the time of the writing of this thesis, investors would put increased emphasis on financial statements and that their relevance would consequently rise.

In sum, Demirovic and Thomas (2007) construct a seemingly valid hypothesis. However, it is argued in this thesis that the global financial crisis that started more or less in the year 2007 has many extraordinary features. First of all, the crisis originated from the financial sector and essentially culminated in large holdings of certain widely spread toxic assets in the form of CDOs related to the American real-estate sector. Secondly, acknowledging the importance of the financial sector to the functioning of economy at large, markets, both debt and equity, have been highly affected by it. Sorkin (2009, pp 538) mentions that the financial industry had traditionally been seen as an economic backroom which purpose was merely to support the broader economy. However, Sorkin (2009, pp. 538) furthermore asserts that during the years prior to the financial crisis, the finance sector itself became the front room driving the economy. Thus, it seems legitimate to posit that the relevance of accounting information actually decreases when one compares the crisis period to the pre-crisis period. Lastly, the rapidly changing state of affairs in the global economy during the crisis further adds to the conjecture that accounting information is less relevant during economic crises.

Furthermore, anecdotal evidence suggests that during this particular financial crisis investors have seemed to increasingly switch their emphasis to macroeconomic factors at the expense of accounting information. That is, the focus among investors seems to have shifted from so called bottom-up investing, a strategy according to which one mainly focuses on analyzing individual stocks rather than the economy as a whole, to a top-down investing strategy where the main focus is on economic, political and regulatory issues. In other words, increasing attention seems to have been directed towards information that is not always conveyed by firms' financial statements. Although this is an analogy based on equity markets, it is a relatively safe assumption that it applies to the credit markets as well since the role of non-company specific economic information seem to have increased in investors' decision making.

Finally, economic crises are usually associated with high volatility. Thereby, further, although indirect, support for declining relevance of accounting information in financial crises is provided by Francis and Schipper (1999) who report that increased amounts of volatility has a diminishing effect on value relevance. It is expected that this is the case for the relevance of accounting information to providers of credit as well.

All things considered, I posit the following hypothesis:

H$_4$: *Accounting information is less relevant during the financial crisis of 2007-2010 than in the pre-crisis period of 2005-2007.*

5 DATA

This chapter presents the employed sample data, the data collection process and the construction of the regression variables.

5.1 The sample collection process

The data collection process started with the acquiring of a list of all active euro-denominated credit default swaps with a 5-year maturity. This data was obtained from Datastream in the end of October 2010, a list that consisted of 2 193 separate credit default swaps. CDSs with a five-year maturity were chosen due to their higher liquidity as compared to the other maturities. In addition to the maturity restriction, it was further required that all CDSs were senior tier and had a "modified-modified" (MM) restructuring clause. The MM clause was preferred because it is, according to Markit[18], the most popular form of restructuring clause in Europe. Additionally, CDSs with a home market outside Europe were ruled out. These limitations diminished the data down to 342 individual CDSs. Consequently, daily mid-spreads were downloaded for a period 01.01.2005 - 30.06.2010 for these securities. Mid-spreads are averages of bid and quote spreads.

The above data that was acquired from Datastream was then merged with quarterly and semi-annual financial, specified company, and stock market data acquired from Thomson's Worldscope database. Subsequently, as customary, all financial companies were excluded from the sample. Additionally, unlisted companies, governmental and municipal entities were also omitted. This further reduced the amount of data to 189 distinct CDS entities. All variables from Thomson were pulled out on the 1st of November 2010.

The last step in the data collection process was to eliminate all CDS entities that were not liquid enough to allow for any meaningful analysis. It was decided that all CDSs which spread remained unchanged within the sample period for any two consecutive quarters, were removed. In total, 34 companies were removed from the sample due to illiquidity. Thus, the final sample constitutes of 155 entities.

[18] https://www.markit.com/news/Credit%20Indices%20Primer.pdf

5.2 Regression variables

The regressions employed in this thesis consists of the dependent variable, i.e. the credit default swap spreads and the independent variables which are based on both accounting and market information. Furthermore, certain control variables are introduced.

5.2.1 Credit default swap spreads

As the dependent variable, CDS spreads are intended to proxy for the perceived default risk associated in the sample companies. It is, however, evident from the skewed distribution in panel A that the spreads in the sample are not normally distributed. That is why the natural logarithm of the CDS spreads is used. Panel B showcases how the problem is remedied with the use of natural logarithms.

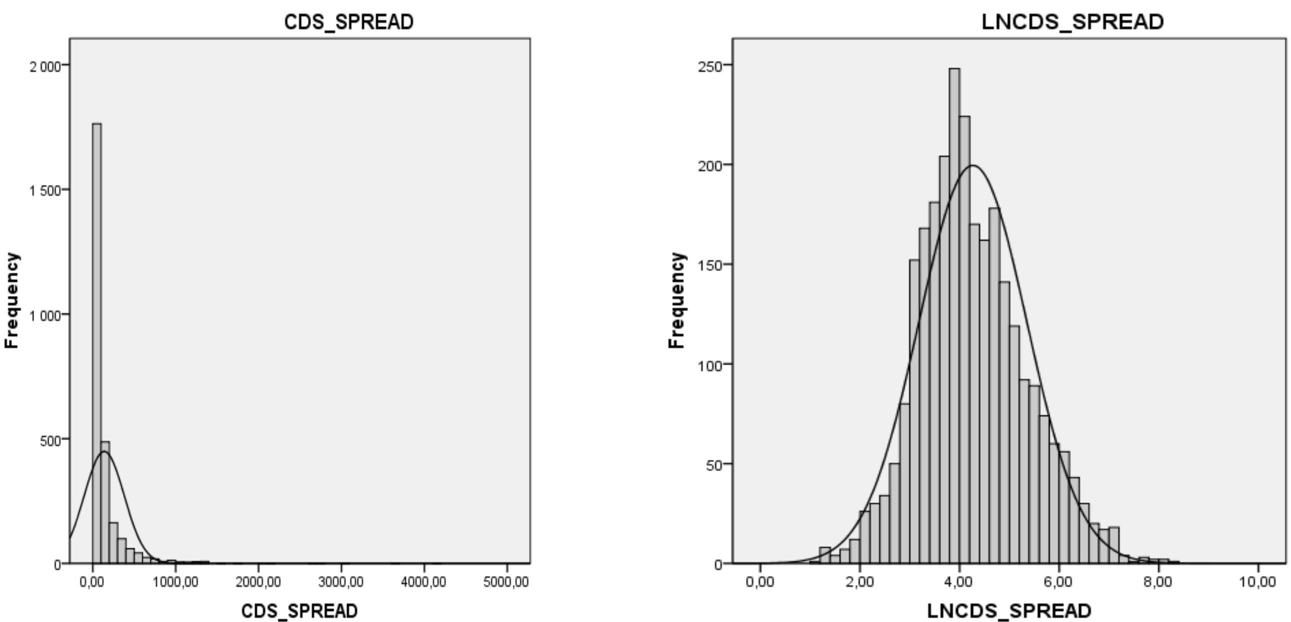


Figure 3: The impact of using log CDS spreads

The figure exhibits the rationale for using natural logs of CDS spreads in favor of regular CDS spreads. The left-hand figure shows the skewed distribution of CDS spreads while the right-hand figure shows how the natural logging of the spreads transforms the distribution in such a way that it is much closer to the normal distribution.

5.2.2 Accounting variables

As a measure for the relevance of accounting data, this thesis uses variables that proxy, among others, for firm size, profitability, leverage and liquidity. Ratios and measures were chosen on the basis of their popularity in assessing credit worthiness in prior literature and on the availability of data. That is, no attempt was made to select the variables on the basis of any particular piece of theory. All financial information was acquired from Thomson Worldscope.

Certain markets, notably the UK and France, do not require their listed issuers to disclose detailed quarterly financial reports. That is, only semi-annual financial information is available for most British and French companies. Sample firms listed in other markets, however, provide financial information on a quarterly basis. Thus, a certain imbalance in the amount of firms included from quarter to quarter is unavoidable. In other words, the sample size varies from quarter to quarter and is always larger in the second and fourth quarter than in the first and third quarters of the year.

Furthermore, whenever Thomson Worldscope reported that firm-quarter variables were missing, these cases were simply excluded from the sample. One solution would have been to replace the missing variables with an average value of the preceding and subsequent observation. However, as the main goal of this thesis is to compare accounting- and market-based models, it would have put accounting information at an unfair disadvantage since market-based variables suffer from missing variables to a much lesser extent.

Firm size is defined as the natural logarithm of the value of total assets (Thomson Worldscope code WS.TotalAssets). Vassalou and Xing (2004), for instance, find that firm size is an important factor in the determination of a company's credit risk. Firms' *leverage* is measured as total liabilities (Worldscope item WS.TotalLiabilities) divided by total assets (Worldscope item WS.TotalAssets). Both prior literature and intuition asserts that a higher level of leverage is associated with an increased level of credit risk. In other words, it is expected that leverage has a negative coefficient in the upcoming OLS regressions.

The cash-to-assets ratio and current ratio (current liabilities divided by current assets) is used to assess the *liquidity* of the sample companies. The respective Thomson Worldscope items are WS.CashAndSTInvestments, WS.TotalAssets, WS.TotalCurrentLiabilities and WS.TotalCurrentAssets. Once again, it is anticipated that increased levels of liquidity will associated negatively with the CDS spreads. Das et al. (2009) find that return on assets (ROA) is a statistically significant factor in the explanation of the variation in CDS spreads. Thus, in addition to EBIT-margin (Earnings before interests and taxes divided by sales), ROA (WS.ReturnOnAssets) is chosen to gauge for *profitability*.

Asset utilization (SalesAssets) is measured as sales (WS.Sales) divided by total assets (WS.TotalAssets). Altman (1968) notes that when combined with other accounting ratios, this particular ratio is a very useful measure in the assessment of bankruptcy probability. Following Ohlson (1980), *consecutive losses* are measured as a dummy variable that receives the value one if net income was negative for the last two quarters and zero otherwise. Finally, *current asset utilization* (SalesCurrent) is measured as sales (WS.Sales) divided by current assets (WS.CurrentAssets).

Table 2: Independent variables and their expected signs

The table summarizes the explanatory variables used in the regressions and displays the expected sign for the coefficients as well the type of data that is used.

Variable	Description	Variable Type	Measure	Predicted sign
ln (Size)	The natural logarithm of total assets	Accounting	Size	-
Lev	Total liabilities / total assets	Accounting	Leverage	+
Cash	Cash and short-term investments / total assets	Accounting	Liquidity	-
Current	Current assets / current liabilities	Accounting	Liquidity	-
ROA	Earnings / total assets	Accounting	Profitability	-
EBIT	Earnings before interests and taxes / sales	Accounting	Profitability	-
SalesAssets	Sales / total assets	Accounting	Asset utilization	-
INTWO	Gets the value 1 if net income is negative for two consecutive quarters and zero otherwise	Accounting	Consecutive losses	+
SalesCurrent	Sales / current assets	Accounting	Current asset utilization	-
EquityVolatility	Annualized equity volatility calculated from prior 100 trading days	Market	Equity volatility	+
Distance-to-Default	Merton's (1974) original distance-to-default measure	Market	Default probability	-
RiskFree	Annualized risk-free rate , euribor 3m	Control	Risk-free rate	+
iTraxx	Assumes the value 1 if the CDS entity was, at the time of the observation, a constituent of the iTRAXX Europe Main or iTRAXX Europe Crossover CDS index and zero otherwise	Control	CDS liquidity	-

5.2.3 Market variables

As mentioned earlier in this thesis, the approach for measuring the market's assessment of the probability of default, Merton's (1974) distance-to-default is used. In order to calculate a firm's distance-to-default, one needs to obtain the following inputs:

(i) Value of assets (V_A)
(ii) Volatility of assets (σ_A)
(iii) The amount of debt (K)
(iv) Expected return on assets (μ)
(v) The maturity of debt (T)
(vi) Risk-free interest rate (r)

The problem with the acquiring of these variables is that neither the volatility of assets nor the value of assets is directly observable. The solution is to solve two non-linear simultaneous equations. The first is one is equation (6) that was presented earlier in this thesis. The second equation states that the volatility of a firm's asset value is related to the volatility of its equity in the following manner:

$$\sigma_E E_0 = N(d1)\sigma_V V_0 \tag{12}$$

where $\sigma_E$is equity volatility and E_0 is the value of a company's equity at time 0, $d1$ is defined as in equation (7), σ_V stands for equity volatility and $V_0$for the value of assets at time 0. Equations (6) and (12) are needed to solve the asset value and the volatility of assets:

$$\begin{cases} F\ (\sigma_V, V_0): V_E = \ V_A\, N(d_1) - \ Ke^{-rT}N(d_2) & (6) \\ G\ (\sigma_V, V_0):\ \ \sigma_E E_0 = N(d1)\sigma_V V_0 & (12) \end{cases}$$

In order to find appropriate values for V_E and σ_V, the starting point is to back out estimations of equity volatility from historical stock returns. In this case, equity volatility was annualized using the preceding daily stock returns from 100 trading days. Next, as has been the norm in prior studies, T is set to one. That is, the model assumes a one-year forecasting horizon, i.e. it calculates the distance-to-default in one year from now. Following Vassalou and Xing (2004) and Das Hanouna and Sarin (2009), the face value of debt (K) is calculated as current liabilities (Worldscope item WS.TotalCurrentLiabilities) plus 0.5 times long-term debt (Worldscope item

WS.TotalLTDebt). Vassalou and Xing (2004) remind that even though the portion of long-term debt included in the calculations is somewhat arbitrary, it nevertheless adequately captures the financing constraints of a firm.

Daily market values of equity were acquired from Thomson Datastream (item DS.MarketValue). The expected return on assets is not readily available from the market place. Thus, it was decided that the expected return on assets is equal to the annualized risk-free rate. Conceptually, the expected return on assets cannot be below the risk-free rate and as KMV (1998) empirically shows, the expected growth rate in asset value has little discriminating power in the Merton model. Thus, the risk-free rate is an adequate choice for the expected growth rate for assets.

As a result of collecting the above-mentioned variables, all variables in equation (6) and (12) were thus at hand, except for the asset value and asset value volatility. Following Sundaresan (2009, pp. 214), the below function is minimized in order to solve for the missing values:

$$F\ (\sigma_V, V_0)^2 +\ G\ (\sigma_V, V_0)^2 \tag{13}$$

The equation is solved with Microsoft Excel's Solver tool by setting the actual values of both (6) and (12) as restrictions[19]. As it is a tedious, lengthy and error prone process to execute manually, an Excel macro was specially designed to calculate the missing variables for all cases. As a final step, these obtained variables were used to calculate the distance-to-default measure as in formula (11).

5.2.4 Control variables

Two control variables are introduced into the models in the attempt to hold constant other than accounting- or market-based factors affecting CDS spreads. As an interesting addition to the variables employed in prior literature, a dummy variable that assumes the value one if the CDS entity was, at the time of observation, a constituent of either the iTraxx Europe Main or iTraxx Europe Crossover CDS index. The main index includes 125 most liquid European investment grade CDS entities and it is rolled over every six months. The crossover index is composed of 50 most liquid CDS names that are, for the most part, rated below investment grade. The variable is

[19] A convergence level of 1E-04 was deemed appropriate

included in order to control for the impact of CDS liquidity as only the most liquid CDSs are included in the indices. Information on iTraxx constituents was obtained from Reuters 3000 Xtra.

Following Das et al. (2009), the risk-free rate is included in the models to proxy for macroeconomic conditions as well as to act as a control for the time clustering in the data. The risk-free rate that is used through-out the sample is the 3-month Euribor rate. Daily observations were collected from the Bank of Finland's website[20] and these observations were subsequently transformed to an annualized form.

5.3 Sample characteristics

The employed sample consists of 155 separate corporate entities from various industries and countries within Europe. Figure 4 showcases the average CDS spread and the number of CDS entities in each quarter. Panel A in figure 5 depicts the industry classifications in the sample while panel B portrays the classification by country.

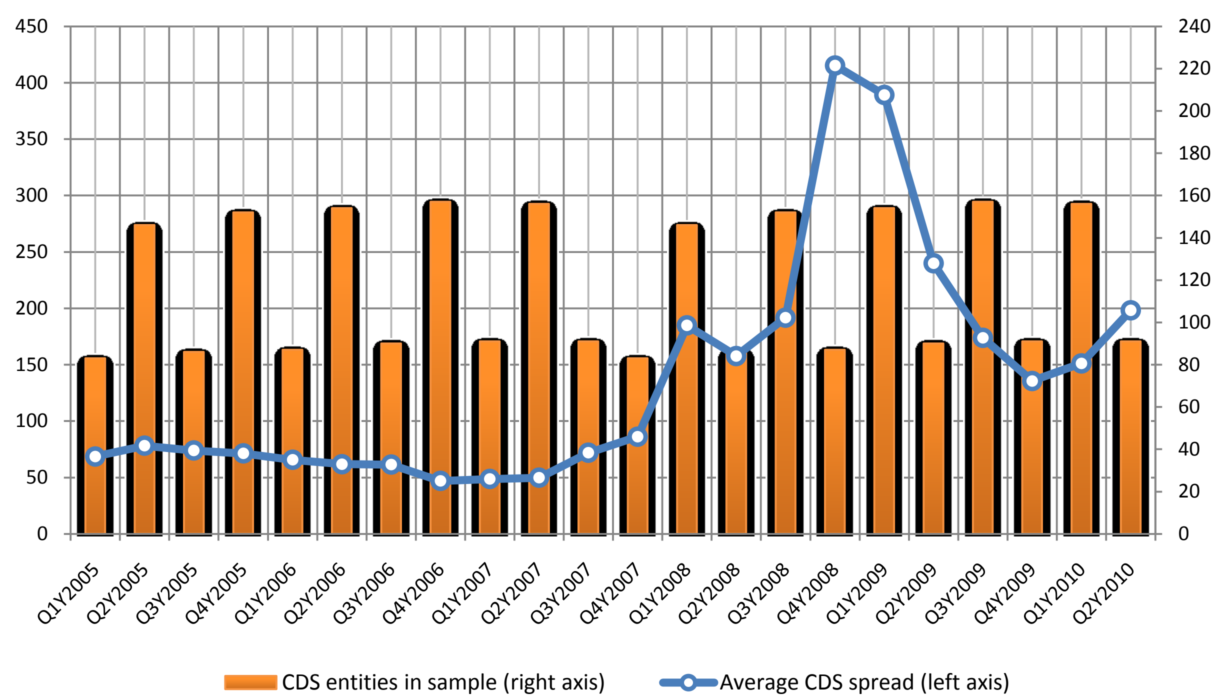


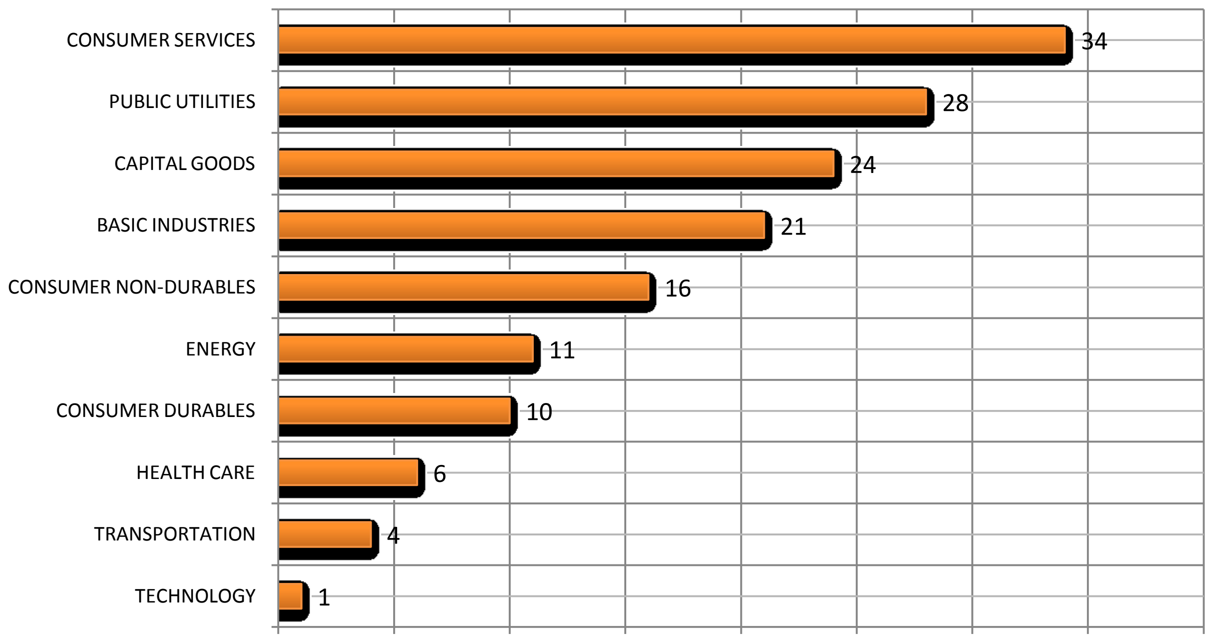
Figure 4: Development of the average CDS spread and entity sample size

The figure displays the development of the average credit default swap spread. The impact of the financial crisis is noticeable as a sharp rise in the average spread in the fourth quarter of 2007. The figure also shows the quarterly

[20] www.bof.fi

changes in the amount of entities in the sample due to the unavailability of quarterly financials on most French and British companies included in the sample.

Panel A. Entities included in the sample classified by industry



Panel B. Entities included in the sample classified by country

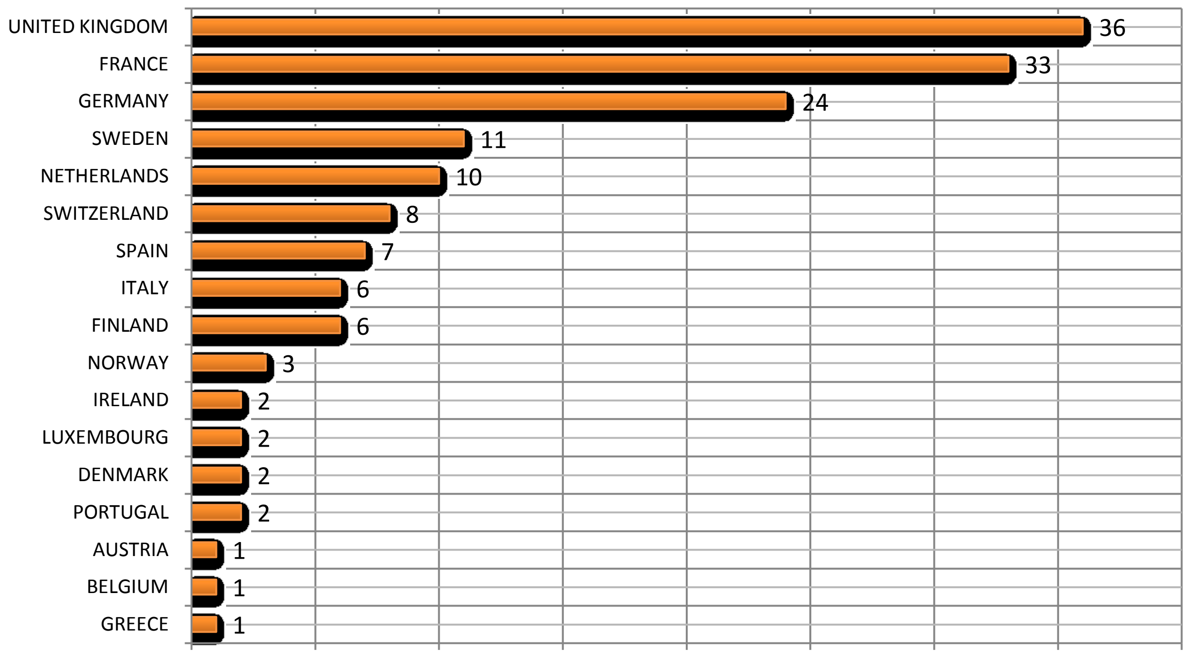


Figure 5: Sample characteristics by domicile and industry

Panel A displays how the sample entities are divided by industry. The industry classification is according to I/B/E/S and the data is downloaded from Thomson using data item IBH.SectorName. Panel B shows the division of the sample entities in terms of domicile. The domicile data is from Thomson Financial (item TF.CountryCode).

Table 3 presents the relevant descriptive statistics for the independent variables used in the OLS-regressions. Skewness and Kurtosis are important concepts in finance and economics. Skewness measures how asymmetrical a variable's distribution is compared to the normal distribution. Kurtosis, on the other hand, measures the extent of how flat or peaked variables' distributions are, again compared to the normal distribution. The normal distribution has a 0 value for both Skewness and Kurtosis. That is, the closer a Kurtosis and Skeweness values are to 0, the more the distributions resemble the normal distribution.

Table 3: Descriptive statistics

The table presents relevant descriptive statistics for all variables included in the regressions. Skewness measures measures how flat or peaked the variable distribution is. High absolute values of kurtosis indicate that a high proportion of the variable's variance stems from extreme observations. As for the dummy variables, *INTWO* and *iTraxx* assumed the value one 74 and 1 365 times, respectively.

Variable	Mean	Median	Minimum	Maximum	Std. Deviation	Variance	Skewness	Kurtosis	N
ln (CDS Spread)	4.2789	4.1620	2.0149	7.0557	0.9607	0.9229	0.3679	-0.1840	2032
Distance-to-Default	9.5852	9.1632	0.8247	26.4808	4.8117	23.1521	0.5206	-0.1026	2032
ln (Size)	10.1399	10.1191	5.3129	13.3216	1.1960	1.4304	-0.0731	-0.0919	2032
Lev	0.6674	0.6693	0.3297	1.0852	0.1252	0.0157	0.1184	0.1658	2032
Cash	0.0919	0.0759	0.0065	0.3173	0.0624	0.0039	1.1983	1.2683	2032
Current	1.1798	1.1185	0.4364	3.0958	0.4104	0.1685	0.9681	1.1901	2032
ROA	0.0610	0.0577	-0.0898	0.2303	0.0440	0.0019	0.3099	0.9657	2032
EBIT	0.1210	0.1056	-0.2143	0.4825	0.1002	0.0100	0.5786	0.8926	2032
SalesAssets	0.2528	0.2164	0.0505	0.8568	0.1436	0.0206	1.3902	1.8826	2032
INTWO	0.0364	0.0000	0.0000	1.0000	0.1874	0.0351	4.9531	22.5557	2032
SalesCurrent	0.7496	0.6460	0.2305	3.1405	0.3884	0.1509	1.8396	4.9970	2032
EquityVolatility	0.1981	0.1679	0.0772	0.6259	0.0973	0.0095	1.4979	2.2018	2032
RiskFree	0.1187	0.1208	0.0256	0.2284	0.0667	0.0044	0.0424	-1.3402	2032
iTraxx	0.6718	1.0000	0.0000	1.0000	0.4697	0.2206	-0.7321	-1.4655	2032

Although some of the variables indicate moderate skewness and kurtosis, no alarming detections are made. The descriptive statistics table further shows that there is somewhat significant cross-sectional variance in the data. For example, the distance-to-default measure varies from a minimum of 0.82 to a maximum of 26 standard deviations to default while ROA varies from minus 9 percent to plus 23 percent. Less variance is understandably witnessed in the risk free rate of interest.

6 METHODOLOGY

This study employs ordinary least squares (OLS) regression in order to test the relevance of three distinct models. The first model is based entirely on accounting variables and its purpose is to measure how much of the variation in CDS spreads the model is able to account for. The second model, on the other hand, is a model based on market variables, namely Merton's (1974) distance-to-default and equity volatility. The first hypothesis can be answered by analyzing the results from these models and by comparing their explanatory powers. The third model constitutes of a hybrid model that combines all variables of regression models *(i)* and *(ii)*. Its function is to measure whether accounting information is of incremental information to the market-based model and it is designed to answer the second hypothesis of this thesis. In order to answer the third hypothesis of the thesis, the sample is divided into 9 distinct sub-samples according to their sector classification. Finally, investigating the fulfillment of the fourth hypothesis, the pooled sample is divided into crisis and pre-crisis subsamples. These procedures are clarified in sections 6.5 and 6.6. The fulfillment, or lack thereof, of the OLS assumptions are discussed after the test methodology is presented.

6.1 OLS regression

Ordinary least squares regression is the prevailing methodology used to test the hypotheses in this thesis. The OLS regressions are defined as follows: Ŷ

$$Y = \beta_1 + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + u_i \qquad (16)$$

where X_2, X_3 and X_n are independent variables on which variable Y is dependent upon and u is the error term. The OLS regression is used to fit Y, X_2, X_3, …, X_k, in a sample of n observations, the equation:

$$\hat{Y} = \beta_1 + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} \qquad (17)$$

where the values of β_1, β_2, …, β_k are fitted into the model so that the sum of the residuals' squares is minimized. Thereby, the OLS regression provides a linear model to estimate the dependent variable Y.

6.2 The accounting model

The following OLS regression for the accounting model is estimated for each firm-quarter observation:

$$\ln(CDS\ Spread_{it}) = \beta_0 + \beta_{1i}\ln(Size)_{it} + \beta_{2i}Lev_{it} + \beta_{3i}Cash_{it} + \beta_{4i}Current_{it} + \beta_{5i}ROA_{it} + \beta_{6i}EBIT_{it} + \beta_{7i}SalesAssets_{it} + \beta_{8i}INTWO_{it} + \beta_{9i}SalesCurrent_{it} + \beta_{10i}iTRAXX_{it} + \beta_{11i}RiskFree_{it} + \varepsilon_{it} \qquad (i)$$

Where $\ln(Size)$ is the natural logarithm of total assets and Lev is total liabilities divided by total assets. $Cash$ and $Current$ are measures of operational liquidity and defined as cash and short-term investment divided by the total amount of assets and current assets divided by current liabilities, respectively. As for the profitability ratios, ROA (return on assets) is calculated as earnings divided by assets and $EBIT$ is calculated as quarterly sales divided by quarterly earnings before interest and taxes. $SalesAssets$ proxies for asset utilization and is defined as quarterly sales divided by total assets. $INTWO$ is a dummy variable that measures consecutive losses. It receives the value one if a firm reported negative net income figures for two consecutive quarters and zero otherwise. The metric for current asset utilization, $SalesCurrent$, is calculated as sales divided by the amount of current assets. $iTraxx$ is a dummy variable for the crude measurement of CDS liquidity. It receives the value one if the CDS entity has at any point of time been a constituent of either iTraxx Europe main or iTraxx Crossover index and zero otherwise. $RiskFree$ is the annualized 3 month euribor rate and $\ln(CDS\ Spread)$ is the natural logarithm of CDS spreads.

6.3 The market model

The following OLS regression for the market model is estimated for each firm-quarter observation:

$$\ln(CDS\ Spread_{it}) = \beta_0 + \beta_{1i}DistancetoDefault_{it} + \beta_{2i}EquityVolatility_{it} + \beta_{3i}iTraxx_{it} + \beta_{4i}RiskFree_{it} + \varepsilon_{it} \qquad (ii)$$

Where $DistancetoDefault$ is Merton's (1974) distance-to-default measure as defined in equation 9. $EquityVolatility$ is the annualized volatility of equity calculated from historical prior 100 days of trading. $iTraxx$ is a dummy variable for the crude measurement of CDS liquidity. It receives the value one if the CDS entity has at any point of time, been a constituent of iTraxx Europe Main or iTraxx Europe Crossover and zero otherwise while $RiskFree$ is the annualized 3 month euribor rate and ln $(CDS\ Spread)$ is the natural logarithm of CDS spreads.

6.4 Hybrid model

Based on the accounting and market models, the following OLS regression for the hybrid model is estimated for each firm-quarter observation:

$$\ln (CDS\ Spread_{it}) = \beta_0 + \beta_{1i} DistancetoDefault_{it} + \beta_{2i} EquityVolatility_{it} + \beta_3 \ln (Size)_{it} + \beta_{4i} Lev_{it} + \beta_{5i} Cash_{it} + \beta_{6i} Current_{it} + \beta_{7i} ROA_{it} + \beta_{8i} EBIT_{it} + \beta_{9i} SalesAssets_{it} + \beta_{10i} INTWO_{it} + \beta_{11i} SalesCurrent_{it} + \beta_{12i} iTraxx_{it} + \beta_{13i} RiskFree_{it} + \varepsilon_{it} \qquad (iii)$$

Where all variables are specified as in regressions *i* and *ii*.

6.5 Accounting information relevance – industry effects and financial crisis

In order to test for differences in the relevance of accounting information, the data is split into 10 subsamples based on their industry. The division of the sample is done according to the I/B/E/S (item name IBH.SectorName) sector classification displayed in figure 5, panel A. As there is only one technology company in the main sample, the technology sector is omitted from the analysis. Consequently, 9 subsamples are formed out of the pooled sample.

Once the data has been partitioned, regression model (*i*) is estimated for all subsamples in the intention of finding out whether the relevance of accounting data varies between industries. More specifically, for each sector, the relevance of accounting data is measured using the model's explanatory power as a proxy for relevance. Consequently, the adjusted coefficients of determination are then compared across subsamples.

In order to study the effects of the financial crisis, the pooled sample was divided into two distinct non-overlapping subsamples based on whether the observation is in the pre-crisis or crisis period which are defined as [Q1 2005 – Q1 2008) and [Q1 2008 – Q2 2010), respectively. The financial crisis is often considered to have started in late summer of 2007 in the U.S. and in the beginning of 2008 in Europe. The pre-crisis sample consists of 930 firm-quarter observations while the crisis period consists of 1102 observations. Once again, the adjusted R^2s of the model estimated for the two subsamples are used for comparison of the relevance of accounting data.

Before moving on to test the hypotheses described in chapter four, it is crucial to consider some of the potential problems associated with OLS regressions in this particular data-setting. These issues are discussed and, if needed and possible, remedied in the following sub-sections.

6.6 Elimination of outliers

According to Maddala (2001, pp. 88), outliers are observations that are far removed from the rest of the observations and are often created by unusual factors. There are several potential causes of outliers in this study. For instance, as most of the accounting variables are based on ratios, certain observations offer no relevant information due to either the numerator or denominator being very small or close to zero. Furthermore, as the equity volatility used to approximate asset value volatilities that are in turn used to calculate the distance-to-default measures, is calculated based on 100 day historical returns, there are certain cases where volatility amounts to unreasonable levels. An example of such a situation is Volkswagen's short squeeze in the end of October 2008 when the company's market value soared over 120 percent and over 82 percent on two consecutive trading days, only to decline 44 percent a day later. These kinds of rare situations cause outliers in the market-based variables. As the existence of these outliers can cause substantial changes in OLS regressions (Maddala, pp. 88), it is warranted that 2 percent of all variables are trimmed out from the sample.

6.7 Multicollinearity

Hair et al. (1998, pp. 2) defines multicollinearity as the extent to which a variable can be explained by the other variables in included in the analysis. Thus, multicollinearity is a problem of too high a correlation between variables. As a consequence, the interpretation and analysis of the effects of any single variable gets more complicated. One approach, and often the first step in detecting multicollinearity, is to examine the determinants of the correlation matrix for high correlations between variables. Correlations over 0.7 are often considered as a warning sign of the presence of multicollinearity. Klein (1962, pp. 101), however, argue that intercorrelation of variables is only a problem when it is high relative to the overall degree of multiple correlation. Thus, Klein (1962) suggests that multicollinearity should be regarded as a problem only when the inter-variable correlation is higher than the overall degree of multiple correlation. In addition to examining the correlation determinants, variance inflation factors (VIF) are also considered. According to Hair et al (1998, pp 148), high VIF values indicate a high degree of multicollinearity.

6.8 Heteroskedasticity

One of the main assumptions in OLS regression is that the error terms in equation (17) have a common variance. This is called homoskedasticity (Maddala, 2001, pp. 199). Heteroskedasticity, on the other hand, refers to a situation where the error terms do not have a common variance. Maddala (2001, pp. 212) suggests two possible solutions for solving heteroskedastic problems. The first remedy is to transform the data to logarithms and the other involves deflating the variables by some selected measure of size. Perhaps the most effective, and certainly the most simple, way of detecting the presence of heteroskedasticity is to visually examine the error terms' distribution.

6.9 Autocorrelation

Autocorrelation is a common concern in time-series data. Gujarati and Porter (2009, pp. 313) define it as the correlation between members of observations ordered in time or space. That is, the error terms in the regression are in some way related to each other and are therefore not independent. This notion can be stated as follows:

$$E(u_i u_j) \neq 0 \qquad i \neq j \tag{15}$$

In this thesis, two approaches are taken in order to detect potential autocorrelation. Firstly, the Durbin-Watson d statistics are investigated. The Durbin-Watson test is, according to Gujarati and Porter (2009, pp. 320), the most widespread test for detecting autocorrelation:

$$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \tag{16}$$

where d values lie between 0 and 4. Generally put, d values close to 2 indicate that autocorrelation is not a concern whereas d values close to 0 imply positive autocorrelation and d values close to 4 imply negative autocorrelation (Gujarati and Porter, 2009, pp. 322).

Once again, another simple way of looking out for autocorrelation is to visually examine the residuals in a time-sequence plot where the residuals are on the vertical axis and time is on the horizontal axis.

7 RESULTS

This chapter presents the results of the empirical tests that were conducted in order to test the hypotheses presented in chapter four and thereby answer the research question introduced in the first chapter of this thesis. The first section of this chapter presents and discusses the correlations between the variables. The second section addresses the findings on the accounting-based model and the third section covers the results for the market-based model. The fourth section presents the results for the hybrid model. The fifth and sixth presents and discusses the results regarding the industry effects and effects of the financial crisis, respectively. Lastly, the chapter ends with a discussion on the obtained results.

7.1 Correlation analysis

The main goals of this correlation analysis are to investigate the presence of multicollinearity as well as to lay the foundation for the upcoming regressions. The correlation matrix that contains both Pearson and Spearman correlations for all variables is presented in the appendix, shows that the independent variables are, for the most part, moderately correlated. The exception lies within the correlation between equity volatility and distance-to-default as both Spearman and Pearson correlation are high for this pair, -0.92 and -0.80 respectively. Even though the correlation is strong, the fact remains that even high correlations between explanatory variables can only indicate multicollinearity. It is therefore not a decisive measure of it. A high correlation between two dependent variables does, however, serve as a warning signal that additional tests are in order. As, however, neither standard error nor the VIF-statistic support the existence of multicollinearity, the variable is kept in the model. After all, equity volatility is a crucial market-variable that has empirically been demonstrated to have a strong relationship with the probability of default (see e.g. Ericsson et al., 2009). Nevertheless, in order to ensure robustness, both the market and hybrid models are also tested without equity volatility present.

As measured by Pearson correlation, 9 out of the 13 independent variables have a statistically significant correlation with the dependent variable while 11 of the independent variables' Spearman correlations are statistically significant. The only explanatory variables that show statistical insignificance in both Spearman and Pearson correlations are *Current* (current ratio) and *SalesCurrent* (sales to current ratio). As one would expect, the natural logarithm of CDS spreads has a strong statistically significant negative correlation with distance-to-default. It follows that the dependent variable also correlates strongly with equity volatility.

7.2 Accounting model

The results in table 4 show that the accounting model is able to provide statistically significant ($F_{11,2020} = 54.70$, $p < 0.001$) information on CDS spreads. The model's adjusted coefficient of determination (adjusted R^2) denotes that the accounting information included in the model accounts for 23 percent of the variance in CDS spreads. Furthermore, 9 out of the model's 11 explanatory variables are statistically significant at the 1 percent level. More specifically, the *cash* variable is the only independent variable that is not significant at any conventional level of statistical significance while *iTraxx* is significant only at the 5 percent level. Furthermore, a large part of the variables' predicted signs are in line with the variables' actual signs in the coefficients. The fact that, the cash to assets ratio does not show statistical significance is further evidence on the variable's inability to explain CDS spreads (see Das et al., 2009).

In line with intuition, firms' *size*, as measured by the natural logarithm of the value of total assets, is negatively associated with CDS spreads. The size-variable has a large absolute t-value and a low p-value which indicates that its impact on CDS spreads is noteworthy. As both the size and CDS variables are log transformed, the interpretation of the coefficient is that a one percent increase in size should, according to the model, decrease the average CDS spread by around 0.14 percent, other things held equal. That is, the credit markets view larger firms as less likely to default. It is supported by the empirical findings in prior literature (see e.g. Ohlson (1980), Queen and Roll, 1987, Hillegeist, Keating, Cram and Lundstedt, 2002 and Vassalou and Xing, 2004). A univariate regression of the natural logarithm of CDS spreads on the natural logarithm of size shows that *size* is able to explain around 4 percent of the variance in CDS spreads.

On a similar note, leverage (*lev*) is statistically significant, carries a large absolute t-value and conforms to its predicted sign. As the independent variable is log transformed, a coefficient of approximately 0.01 indicates that a one percentage point increase in leverage should result in an estimated 1 percent[21] increase in CDS spreads. Therefore, in addition to statistical significance,

[21] Wooldridge (2009, pp. 190) shows that whenever the dependent variable is natural log transformed, the estimation of a one point increase in a non-log independent variable can be calculated as follows:

this result has some economical significance as well and as expected, increased amounts of leverage is perceived as increased risk of default by the credit markets. Ericsson, Jacobs and Oviedo (2009) suggest that leverage is perhaps the most relevant element in the probability of default. A univariate regression of log CDS spreads on leverage confirms that leverage is indeed a relevant factor but as its R^2 is only around 2 percent, this study does not reinforce the notion that leverage, as such, is the key variable in default assessment.

Interestingly, *current ratio*, one of the two liquidity measures included in the accounting-based model, seems to carry a positive coefficient. At first notice, this seems counterintuitive as current ratio measures the liquidity buffer a firm has. On the other hand, an excessively high current ratio can be a signal of potential problems in the sense of a firm's management not being able to invest its surplus cash efficiently. Additionally, as Das, Hanouna and Sarin (2009) point out, firms struggling with credit issues may find it difficult to finance its operations with current liabilities, leading to a decrease in the current ratio and to an increase in the firms CDS spread. The variable's economical significance is, however, rather insignificant.

Table 4: Results (accounting model)
The table presents the results from the OLS regression for the accounting-based model.

Variable	Predicted sign	Unstandardized coefficient	Standardized coefficient	Standard error	T statistic	P-value
Intercept		5.3086		0.2761	19.2236	0.0000
ln (Size)	-	-0.1388	-0.1728	0.0168	-8.2795	0.0000
Lev	+	0.0104	0.1355	0.0017	6.1479	0.0000
Cash	-	0.0091	0.0593	0.0036	2.5536	0.0107
Current	-	0.0021	0.0881	0.0006	3.4526	0.0006
ROA	-	-0.0530	-0.2426	0.0056	-9.4469	0.0000
EBIT	-	-0.0117	-0.1219	0.0026	-4.4595	0.0000
SalesAssets	-	-0.0176	-0.2633	0.0025	-7.0829	0.0000
INTWO	+	0.5840	0.1139	0.1070	5.4575	0.0000
SalesCurrent	-	0.0045	0.1835	0.0009	4.9665	0.0000
RiskFree	-	-0.0110	-0.0761	0.0030	-3.6991	0.0002

$\%\Delta\hat{y} = 100 * [Exp(\hat{\beta}) - 1]$

iTraxx	-	0.0526	0.0257	0.0413	1.2725	0.2033
Adjusted R2:	**0.2253**					
N:	**2032**					

The model includes two measures of profitability, *EBIT* and *ROA*. A strong negative relationship between return on assets and credit default swap spreads is discovered. This is what one would expect a priori, as increasing profitability is an encouraging sign of the company's business operations. ROA's large coefficient indicates that the variable has high economical significance. A slope coefficient of -0.05 connotes that a one percentage point increase in a firm's return on assets decreased CDS spreads, on average, around 5.2 percent. ROA also has a sizeable standardized coefficient which is evidence further evidence on its importance. Additionally, the univariate regressions show that ROA has the highest explanatory power (R^2: 0.137) of all accounting variables. Altogether, the evidence implies that the return on a firm's assets is of importance in default assessment. EBIT, the other profitability variable, is also statistically significant at the one percent level but its economical significance is insignificant.

The sales-to-assets variable (SalesAssets) is statistically significant and as expected, its coefficient carries a negative sign. The sales-to-assets ratio is a ratio that measures how well the firm is using its assets in order to create sales revenue. It can thereby serve as a sign of managerial effectiveness and is naturally bound to have a negative relationship with default. Even though the explanatory power of sales to assets is low in the univariate regression, the standardized coefficient of the variable is, in fact, the highest one in the accounting-based model. That is, a one standard deviation increase in SalesAssets resulted in a 0.26 standard deviation decrease the sample log CDS spreads. These results suggest that liquidity is a significant variable in determining default probabilities when it is combined with other meaningful accounting measures.

On the surprising side, sales-to-current (SalesCurrent), which measures the current assets utilization rate, has a positive coefficient. A decreasing sales-to-current assets ratio is commonly seen as a negative sign as it indicates that the firm's current assets are unable to generate adequate sales. There seems to be no rational economic explanation for this result. However, accounting ratios showing surprising signs in the prediction of default is not uncommon as several empirical studies have come across similar results (see e.g. Hillegeist, Keating, Cram and Lundstedt, 2002 and Demirovic and Thomas, 2007). This is especially true for measures of liquidity. Demirovic and Thomas (2007) argue that it may be due to the liquidity measures not being able to proxy for day-to-day liquidity needs as a lower working capital, for instance, might indicate bargaining power rather than liquidity problems.

Consecutive losses were measured with the dummy variable *INTWO*. As anticipated, firms that reported negative income in two consecutive quarters demonstrated a positive relationship with CDS spreads. The interpretation of the coefficient (0.58) is interesting as firms with consecutive losses were associated, ceteris paribus, with 79 percent higher CDS spreads than firms without consecutive negative net income quarters. The direction of these results conforms to empirical findings and particularly to Ohlson (1980) and Hillegeist et al. (2002). The extent of the result is, of course, rather surprising. The economical interpretation is, however, not straightforward as the above-mentioned relation implied by the large coefficient would only hold true if a company reported negative earnings on two consecutive quarters while all other things were being held equal. That is impossible since ROA, for instance, is, by definition, affected by changes in earnings. Unreported statistics show that observations with consecutive losses (INTWO = 1) had an average CDS spread of around 230 basis points whereas other observations' (INTWO = 0) average was around 70 basis points. All in all, the results seem to suggest that consecutive losses demonstrate statistical significance but their economical significance remains ambiguous.

Finally, as economic downturns are commonly associated with low interest rates, it is unsurprising that the results show that there is a negative relationship between the risk-free rate and the dependent variable. This contradicts with CDS pricing theory as an increase in the risk-free rate should, ceteris paribus, result in a higher CDS spread. The negative relation is, however, in line with empirical findings and it seems that CDS spreads are particularly sensitive to macroeconomic conditions. That is to say, the macroeconomic sensitivity seems to subdue the somewhat marginal impact of the risk free rate in the pricing of CDSs.

The regression results are analyzed for multicollinearity, autocorrelation and heteroskedasticity. In regard to the accounting-based model, there are no signs of multicollinearity evident in the correlation matrix presented in table 10 in the appendix. The VIF statistics for all the variables are well below their threshold values and multicollinearity is thus not identified as a major problem and no alarming signs of heteroskedasticity are found while autocorrelation, as measured by the Durbin-Watson d-statistic, is in the zone of indecision.

7.3 Market model

Table 5 shows the summarized results for the market-based model. The model's adjusted coefficient of determination is of central interest. The adjusted R^2 entails that the model is able explain 48 percent of the variation in CDS spreads. This exceeds the accounting model's explanatory power by around 8 percentage units. Furthermore, as the model is also statistically significant ($F_{4,2027} = 471.93$, $p < 0.001$), it suggests that the market-based variables included in the model are able to offer relevant information to the credit markets.

All of the four explanatory variables are statistically significant and have low standard errors. As estimated a priori, distance-to-default is negatively associated and equity volatility is positively associated with CDS spreads. More specifically, as distance-to-default measures how many standard deviations a firm's asset value is from default, it follows that that a firms with larger distance-to-default values are less likely to default. This result conforms to both prior literature and the theory presented in chapter three.

Table 5: Results (market model)
The table presents the results from the OLS regression for the market-based model.

	Predicted sign	Unstandardized coefficient	Standardized coefficient	Standard error	T statistic	P-value
Intercept		4.3096		0.1118	38.5511	0.0000
Distance-to-default	-	-0.0718	-0.3596	0.0053	-13.4601	0.0000
EquityVolatility	+	3.4608	0.3505	0.0456	13.1291	0.0000
iTraxx	-	0.2173	0.0764	0.2636	4.7611	0.0000
RiskFree	-	-1.8262	-0.1267	0.2311	-7.9012	0.0000
Adjusted R2:	**0.4815**					
N:	**2032**					

Of the variables included in the market model, distance-to-default has a high absolute standardized coefficient (-0.36) which implies that a one standard deviation change in distance-to-default should, according to the model and other things held equal, result in a 0.36 standard deviation decline in log CDS spreads. Furthermore, the univariate regression shows that distance-to-default is able to explain slightly over 42 percent of the variation in log CDS spreads. Thus, as distance-to-default has a high absolute standardized coefficient low standard error and it generates the highest explanatory power in its univariate regression, one can conclude that of the variables included in the models, it is the single most important one in the explanation of the variance in CDS spreads. Demirovic and Thomas (2007) find similar results in their study using credit ratings as a proxy for credit risk.

Not surprisingly, the coefficient of equity volatility is positive which suggests that an increase in equity volatility is in relation with larger CDS spreads. The goodness of fit of the univariate regression of log CDS spreads on equity volatility shows that the volatility of equity explains slightly less than 41 percent out of the log CDS spreads in the sample. In the multivariate regression (the market model), equity volatility also has an unstandardized coefficient which is at comparable levels with distance-to-default's corresponding measure. It is somewhat surprising that equity volatility seems to be, in this data setting, almost as important a variable in the assessment of credit risk as Merton's (1974) distance-to-default.

Interestingly, in contrast to the accounting model, the *iTraxx* variable is statistically significant at the 1 percent level in the market-based model. CDS liquidity seems therefore to offer information that is not captured by market information. The estimated coefficient on the variable is, however, opposite to what was anticipated. The result implies that firms included in either iTraxx Europe Main or iTraxx Europe Crossover indices have, on average, higher CDS spreads than firms not included in the index. These are CDS names that have high liquidity and the result is therefore surprising. The reasoning behind the reverse relationship was based on empirical evidence from equity markets according to which investors demand higher premiums for low liquidity stocks. Furthermore, Berndt, Douglas, Duffie, Ferguson, and Schranz (2005) and Blanco, Brennan, and Marshall (2005) suggest that liquidity may be an important factor in the determining of CDS spreads while Tang and Yan (2007) find strong evidence of the existence of an illiquidity premium in the CDS markets. Thus, the sign of the coefficient is surprising and seems to lack empirical justification. It is worth emphasizing that the positive relationship found is more likely to be a result of a misspecification in the models rather than of a true economical relationship. As was the case in the accounting model, the risk-free rate variable is statistically significant at the 1 percent level and carries a negative coefficient.

The regression results are analyzed for multicollinearity, autocorrelation and heteroskedasticity. There are some alarming signs of multicollinearity evident in the correlation matrix presented in table 10 in the appendix. However, as unreported VIF statistics for all the variables are well below their threshold values, multicollinearity is not identified as a major problem. The issue is, however, addressed further in the robustness analysis chapter of this thesis. No alarming signs of heteroskedasticity are found while autocorrelation, as measured by the Durbin-Watson d-statistic, is in the zone of indecision.

7.4 Hybrid model

The hybrid model contains all variables from both the accounting and the market model and its results are displayed in table 6. The explanatory power of the hybrid model well exceeds the explanatory powers of both the accounting-based and the market-based model. The model is statistically significant ($F_{13,2020} = 204.01$, $p < 0.001$) and its explanatory power mounts up to 57 percent (adjusted R^2).

Table 6: Results (hybrid model)
The table presents the results from the OLS regression for the hybrid model (regression model *(iii)*).

	Predicted sign	Unstandardized coefficient	Standardized coefficient	Standard error	T statistic	P-value
Intercept		5.7880		0.2375	24.3668	0.0000
Distance-to-default	-	-0.0656	-0.3284	0.0054	-12.0367	0.0000
ln (Size)	-	-0.1657	-0.2063	0.0127	-13.0543	0.0000
Lev	+	0.0037	0.0486	0.0013	2.8893	0.0039
Cash	-	0.0054	0.0354	0.0027	2.0319	0.0423
Current	-	0.0009	0.0390	0.0005	2.0232	0.0432
ROA	-	-0.0223	-0.1021	0.0044	-5.0911	0.0000
EBIT	-	-0.0017	-0.0178	0.0020	-0.8618	0.3889
SalesAssets	-	-0.0136	-0.2026	0.0019	-7.2539	0.0000
INTWO	+	0.5321	0.1038	0.0802	6.6313	0.0000
SalesCurrent	-	0.0041	0.1676	0.0007	6.0437	0.0000
EquityVolatility	+	0.0328	0.3323	0.0025	13.0295	0.0000
RiskFree	-	-0.0131	-0.0912	0.0022	-5.9175	0.0000
iTraxx	-	0.1030	0.0504	0.0311	3.3161	0.0009
Adjusted R2:	**0.5651**					
N:	**2032**					

As for the statistical significance of the independent variables, 11 out of the model's 13 variables are statistically significant at the one percent level. All statistically significant variables retain signs consistent with the accounting and market models. Similarly to the accounting model, size is statistically significant and its estimated sign is negative. Both its standardized and unstandardized coefficients as well as its t-statistic have, in absolute terms, increased as compared to the accounting model. Once again, as both the dependent variable and the independent variables are natural log transformed, the variables coefficient (-0.17) can be construed so that a 1 percent increase in leverage should decrease the average CDS spread by around 0.17 percent, other things equal.

Leverage is statistically significant at the 0.01 level. Its economical significance has, however, significantly decreased as all its relevant statistics have diminished. One possible explanation for this is that the distance-to-default measure already captures the leverage aspect and that this consequently decreases the leverage variable's significance. The same reasoning can be applied to *EBIT* as it is no longer statistically significant in the hybrid model. *ROA*, on the other hand, is again both statistically (at the 1 percent level) and economically significant although its economical significance has slightly declined from the accounting model.

The results further show that SalesAssets, the measure of asset utilization, is statistically significant ($p < 0.01$) and that its t-statistic has increased from the accounting-based model. The variable's standardized coefficient is high, second only to distance-to-default and equity volatility. The *INTWO* variable is also statistically significant at the one percent level and has, again, a seemingly economically significant coefficient. However, as discussed in the previous section, the economical interpretation of the coefficient is unclear at best.

As expected, also the results from the hybrid model continue to support the statistically significant ($p < 0.01$) negative relationship between distance-to-default and CDS spreads. The variable has a high t-statistic and its standardized coefficient has increased slightly from the market model.

As for the fulfillment regarding the OLS assumptions, no evident signs of autocorrelation or heteroskedasticity are detected. However, as is the case for the market-based model, the hybrid model also includes the equity volatility and distance-to-default variables which demonstrate high correlation between each other. Therefore, additional attention is paid in identifying potential multicollinearity. As however, the highest VIF value is found to be 3.6, it is concluded that multicollinearity, at least the kind that is captured by the VIF, does not bias the results. Moreover, autocorrelation, as measured by the Durbin-Watson d-statistic, is again in the zone of indecision.

7.5 Industry effects

The results of the industry effects regressions are displayed in table 7. All accounting models are significant at the 0.01 level except for the model estimated for the health care section which is only significant at the 0.05 level. The average adjusted R^2 of the accounting model is approximately 33 percent. In line with hypothesis three, the explanatory power of the estimated accounting model varies from 14 percent (public utilities) to 63 percent (transportation) across the subsamples. This indicates the existence of industry effects in the relevance of accounting information. A closer look at the data reveals that a large part of the public utilities sector is contained of telecommunication firms which are typically associated with considerable amounts of intangible assets. As previously discussed, the amount of intangible assets is a possible cause for the discrepancy in the relevance of accounting information across industries.

Although not of direct interest to the hypothesis, it is nonetheless interesting to also note that the incremental relevance, i.e. the difference between the explanatory powers of the market and hybrid models, also fluctuates across the different sectors. The smallest incremental relevance is witnessed in the consumer durables (0.03) sector while the largest incremental relevance is found to be within the consumer services (0.19) sector. Interestingly, even though transportation has the highest explanatory power by a relatively large margin in the accounting model, its incremental relevance is still found below average (0.09 < 0.10). The small incremental relevance of accounting data in the consumer durables is unsurprising since the consumer durables sector is mainly made of firms operating in the automotive industry. The European automotive industry is a fairly mature one and it does not, for instance, suffer from the underinvestment problem to the same extent as growth-oriented sectors. This is, of course, only one possible factor causing deviations in the explanatory powers of the models and the evidence is not strong enough for definite conclusions.

Demirovic and Thomas (2007) attribute the industry variation to the varying significance of the distance-to-default variable. In this study, however, the relevance of accounting information varies more than the relevance of the market-based model. This is what one would expect a priori as there is no particular reason why the market-based model would not work equally well across industries. Although, it is worth emphasizing that the market model is found not to be completely free of industry effects. The market model estimated for public utilities, for instance, only explains around 36 percent of the variability in the subsample data while it is over 60 percent for both transportation and basic industries.

In conclusion, the results suggest that there are, in fact, differences in the relevance of accounting information across industries as industry specific estimation for regression model (*i*) provided explanatory powers of varying levels. A detailed presentation of the industry effect results can be found in table 7.

Table 7: Results (industry effects)

The table displays the results for regressions *(i)*, *(ii)* and *(iii)* estimated for the 9 different subsamples. The subsample division is according to I/B/E/S industry classification standards (data item IBH.SectorName). The technology sector was discarded from the estimates due to the lack of observations within that sector. Incremental relevance is calculated as the difference between the adjusted R^2s of the market model and the hybrid model.

	Basic industries	Capital goods	Consumer durables	Consumer non-durables	Consumer services	Energy	Health care	Public utilities	Transportation
(*i*) Accounting model (Adj. R2)	**0.4195**	**0.1894**	**0.3838**	**0.2550**	**0.4484**	**0.2287**	**0.2308**	**0.1405**	**0.6313**
F-statistic	21.1716	8.0321	9.1588	7.2547	27.1559	5.9802	2.3367	7.2279	11.2735
Significance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0260	0.0000	0.0000
(*ii*) Market model (Adj. R2)	**0.6061**	**0.5448**	**0.5147**	**0.4945**	**0.4874**	**0.5111**	**0.4840**	**0.3598**	**0.6894**
F-statistic	158.4940	133.0468	47.3112	66.5473	113.1822	59.5319	16.3232	79.5059	45.3821
Significance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
(*iii*) Hybrid model (Adj. R2)	**0.7381**	**0.6207**	**0.5431**	**0.6264**	**0.6749**	**0.6012**	**0.5602**	**0.4523**	**0.7771**
F-statistic	67.5616	42.6725	13.9787	26.9243	57.5319	22.1018	16.3232	27.6184	18.4314
Significance	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Incremental relevance	**0.13**	**0.08**	**0.03**	**0.13**	**0.19**	**0.09**	**0.08**	**0.09**	**0.09**
N	307	332	132	202	355	169	50	420	61

7.6 Effects of the financial crisis

The pooled sample was divided into two subgroups based on whether the observation is in the pre-crisis or crisis period which are defined as [Q1 2005 – Q4 2007] and [Q1 2008 – Q2 2010], respectively. Based on several conjectures, it was hypothesized that the relevance of accounting data suffers as we move from the pre-crisis period to the crisis period. The results of the accounting model estimated for the two subsamples are displayed in table 8. The results indicate that there is a noteworthy difference in the explanatory powers between the two time periods. The relevance of accounting information during the pre-crisis period is witnessed to be around 35 percent while it is only around 27 percent for the crisis period equaling an 8 percentage point decrease in the relevance of accounting data.

Table 8: Results (Macroeconomic effects)

Regressions (regression model (*i*)) for the pre-crisis (Q1 2005 – Q4 2007) and the crisis period (Q1 2008 – Q2 2010) are shown below. T-statistics are in parentheses below the variables' coefficients. * indicates statistical significance at the 10 percent level. ** indicates statistical significance at the 5 percent level and *** indicates statistical significance at the 1 percent level.

Variable	Pre-crisis period	Crisis period
Intercept	6.22***	5.94***
	(20.31)	(19.04)
ln (Size)	-0.25***	-0.14***
	(-12.61)	(-7.79)
Lev	0.01*	0.01***
	(2.78)	(5.59)
Cash	0.02***	-0.00
	(4.0167)	(-0.65)
Current	0.00	0.00***
	(0.17)	(3.23)
ROA	-0.04***	-0.06***
	(-5.62)	(-9.48)
EBIT	-0.01***	-0.01***
	(-4.71)	(-3.40)
SalesAssets	-0.01***	-0.01***
	(-5.05)	(-5.46)
INTWO	0.91***	0.30***
	(6.45)	(2.82)
SalesCurrent	0.00***	0.00**
	(4.14)	(2.19)
RiskFree	-0.0149	0.01**
	(-2.61)	(2.59)
iTraxx	0.17***	-0.10**
	(3.89)	(-2.10)
Adjusted R2:	**0.3555**	**0.2683**
N:	**930**	**1102**

In conclusion, it was hypothesized that the relevance of accounting data varies between different macroeconomic conditions. Francis and Schipper (1998) find that the value-relevance, i.e. the relevance of accounting information to equity markets, deteriorates in times of high volatility. Davis-Friday and Gordon (2002), on the other hand, find that the impact of the 1995 Mexican financial crisis on value-relevance was quite small. Even though these studies have concentrated on the relevance to equity markets, this study relates to these papers in a larger conceptual framework of the relevance of accounting information in general. Overall, the results seem to support the notion that the relevance of accounting data to the credit markets varies between different macroeconomic conditions.

7.7 Discussion on the results

The first hypothesis of this thesis posited that market-based information is able to provide more information to the credit markets than accounting-based information. As a proxy for the usefulness (or relevance) of each information source, the adjusted coefficients of determinations were compared between the models. Thus $\mathbf{H_1}$ essentially posits the following: $Adjusted\ R^2_{Accounting} < Adjusted\ R^2_{Market}$. As the adjusted R^2 of the accounting model is slightly below 23 percent while the market model's adjusted R^2 is over 48 percent, these results leads one to accept the hypothesis. That is to say, market information seems to provide more relevant information to the credit markets than accounting-based information. This is an interesting result as there is mixed evidence regarding the comparative relevance of accounting and market based information. In order to test for statistical differences in the explanatory powers between the accounting and market models and F-test on residual variances was conducted. The results of the F-test indicate that there is strong evidence of a statistically significant difference in the two models' explanatory powers[22].

In contrast to the results discovered in this thesis, Das et al. (2009) find that accounting-based metrics perform slightly better than market-based information in the explanation of CDS spreads. To the best of my knowledge, Das et al. (2009) is the only study where CDS spreads are used as a proxy for the relevance of different information sources. This relative superiority of accounting information is corroborated by Demirovic and Thomas (2007) who show that even though

[22] F observed $\approx$ 1.49, critical F (2020, 2027) $\approx$ 1.1 ($\alpha = 0.01$)

distance-to-default is the single most important variable in their study, accounting information seem to predict credit ratings more effectively. Hillegeist, Cram, Keating and Lundstedt (2002) who study the ability of different information sources to predict actual bankruptcies, on the other hand, ascertain that market-based information is more useful than accounting information. This study provides additional evidence that equity markets are a more relevant source of information to credit markets than accounting information.

The main purpose of the hybrid model was to find out whether accounting information is of incremental information over market information to the credit markets. This is measured by the goodness of fit of the models. It was earlier hypothesized (**$\mathbf{H_2}$**) that according to the strongest form of the efficient market hypothesis, accounting information should not be able to add any information to market information. Mathematically stated, **$\mathbf{H_2}$** is true only if $adjusted\ R^2_{Market} \geq adjusted\ R^2_{Hybrid}$. The results displayed in tables 4 and 6 show that the hybrid model's explanatory power of 56 percent is significantly higher than the market model's corresponding figure of 48 percent. The incremental relevance of accounting information is thereby slightly over 8 percentage points.

Interestingly, in their study on U.S. data, Das, Hanouna and Sarin (2009) also discover an 8 percentage point difference between the explanatory powers of their market-based model and their comprehensive model. Furthermore, Demirovic and Thomas (2007), who study the relevance of accounting and market information using credit ratings as a proxy, find a 5-6 percentage point deviation in the explanatory powers of their models. Hillegeist et al. (2002) also find that accounting information is able to provide incremental information to market-based information. Although the applied methodology and approach differ significantly among the studies mentioned, they all conclude that accounting metrics do, in fact, offer significant incremental information. Moreover, an F-test on residual variances provides evidence that the models' goodness-of-fits differ from one another in a statistically significant manner[23]. The second hypothesis is thereby rejected.

As for **$\mathbf{H_3}$**, the results are supportive in the sense that the relevance of accounting information seems to vary across industries. Once the accounting model was estimated for the nine industry-

[23] F observed ≈ 1.19, critical F (2027, 2018) ≈ 1.1 ($\alpha = 0.01$)

based subsamples, it was found that the explanatory power varies from a low 14 percent to a maximum of 63 percent across the industry samples. The average adjusted R^2 was 33 percent which is considerably higher than the adjusted R^2 of the accounting model for the pooled sample. There are various reasons that support the hypothesis of industry effects in accounting relevance but the main arguments provided in this thesis are related to the treatment of intangible assets, the relevance and amount of nonfinancial information and the underinvestment problem.

These stylized facts indicate that macroeconomic conditions appear to affect the relevance of accounting information as the relevance of accounting information is significantly higher for the pre-crisis period than for the crisis period of 2008 to 2010. Even though it was hypothesized that the relevance of accounting information to credit investors varies in distinct macroeconomic conditions due to the similar effects witnessed in value-relevance literature and due to the anecdotal evidence, there are virtually countless possible reasons why this could be the case. For instance, Volvo AB, a Swedish auto manufacturer included in the sample, was producing stable truck sales during the year 2008 up until December when suddenly its net sales turned negative as its order cancellations outstripped its sales by over 1 800 cancellations. Thus, it is worth emphasizing that these kinds of surprises that are common during widespread economic crises surely affect the relevance of financial statements as measured in this thesis since investors receive information from more timely sources. The rapidly changing state of affairs only exacerbates this phenomenon. In this manner, supportive evidence for $\mathbf{H_4}$ is found in this thesis.

8 ROBUSTNESS

In order to assure the robustness of the achieved results, several robustness tests were conducted. Firstly, as companies from the UK and France form a large part of the sample and furthermore considering that most of these companies only disclose financial information on a semi-annual basis (as opposed to quarterly information disclosed by most other companies), the models are re-estimated without these firms. Secondly, equity volatility was evidenced to be highly correlated with the distance-to-default measure and the models are, thus, re-estimated without *EquityVolatility* in regression models (*ii*) and (*iii*). Thirdly, it can be argued that the use of OLS regression might not be econometrically appropriate and that, consequently, a panel data regression approach with either fixed or random effects should alternatively be favored. Finally, following common practice, the original pooled sample is divided into

Excluding French and British firms from the pooled sample drops the amount of firm-quarter observations to 1 354 from the original 2 032. Unsurprisingly, the relevance of accounting data seems to be higher for the group that excluded firms from UK and France (Adj R^2: 0.291). The results concerning $\mathbf{H_1}$ and $\mathbf{H_2}$ do not, however, qualitatively change as the explanatory powers for the market-based and the hybrid model are around 0.462 and 0.638, respectively. Many of the subsamples divided according to industry are already borderline cases for conducting any meaningful analysis. Therefore, as the subsamples would be further substantially diminished, this particular robustness test is not conducted for the tests for $\mathbf{H_3}$. As for $\mathbf{H_4}$, the results remain virtually unchanged once British and French firms are removed from the sample. After the afore-mentioned adjustments, the accounting model estimated for the pre-crisis sample demonstrates a significantly higher explanatory power as compared to the model estimated for the crisis period (adjusted R^2s of 0.362 and 0.285 respectively).

The omission of the equity volatility variable yields an adjusted R^2 of around 44 percent for the market-based model which is some 4 percentage points less than the explanatory power of the original market-model that includes the equity volatility parameter. The Durbin-Watson statistic is slightly above 1.7 and the VIF statistics for all three independent variables are close to 1. Accordingly, these improved statistics indicate a higher probability for autocorrelation in the original models. As, however, the results for all the hypotheses remain virtually unchanged with the exclusion of equity volatility, it is concluded that autocorrelation is not a primary concern.

Furthermore, the regressions were re-estimated using the panel data technique. Specifically, a random effects model is estimated using the same variables as in regressions *(i), (ii)* and *(iii)*. Panel data in general allows for taking advantage of the fact that the data features properties from both time-series and cross-sectional data. Stock and Watson (2007, pp. 278) point out that fixed effects regressions are able to control for omitted variables in panel data. Accordingly, Das, Hanouna and Sarin (2009), emphasize that fixed effects regressions have the advantage of eliminating unobserved effects that could be correlated with the independent variables. In particular, fixed effects regressions can be merited for being able to detect potential firm-specific effects that were omitted from the OLS-regressions. In this case, examples of such are corporate governance and the skills of the management team. As for the results of the fixed effects model, they remain virtually unchanged as the overall adjusted R^2s are slightly lower for all three models, 21, 48 and 56 percent for the accounting, market and hybrid models respectively. Furthermore, all variables retain their original coefficient signs from the original regressions. In the effort to maintain certain brevity in this thesis, the quantitative results of the fixed effects regressions are not presented. As a conclusion, it can be stated that the results are robust to these particular tests.

9 CONCLUSION

This thesis studied the relevance of accounting information to the credit markets and, on the other hand, how accounting data compares to market based information in terms of their relevance. Thus, the thesis essentially combines several related yet distinctive areas of research: the value-relevance of accounting information, credit risk literature and the study on the determinants of CDS spreads.

Value-relevance (i.e. the relevance of accounting information to the equity markets) has been studied intensely by academics in the past few decades, ever since Ball and Brown (1968). Lev and Zarowin (1999) argue that the value-relevance has deteriorated during the last decades due to financial statements not being able to adequately capture firms' financial and economic conditions. The main reason for this, as mentioned by Lev and Zarowin (1999), is the treatment of intangible assets, and more specifically their immediate expensing as is the case under US GAAP.

Nevertheless, the relevance of accounting data in the measurement of credit risk has been studied to a noticeably lesser extent. Demirovic and Thomas (2007), Hillegeist et al. (2002), Yu (2002) and Das, Hanouna and Sarin (2009) were mentioned as notable exceptions earlier in this thesis. The relevance of accounting data can be investigated in several ways. Testing how well accounting data performs in predicting actual bankruptcies is the most common approach while the prediction and explanation of credit spreads and credit ratings are alternative approaches that have gained popularity during the last decades. However, credit default swap spreads offer an additional, novel approach, to assessing the usefulness of accounting data to the credit markets.

Credit default swaps are financial securities that can be considered as default insurance on a specific loan or bond. In effect, CDSs are two-sided over-the-counter contracts where the buyer purchases credit protection on a reference company. In other words, CDSs offer financial protection against a firms default on its liabilities. As CDSs allow for investors to trade default risk separately from other risks associated with the company, it constitutes a very good proxy for the credit market's assessment of the underlying entities' default risk.

The fact that accounting measures, and the information it provides, are inherently backward-looking is one of the main points of concern in using accounting data in the measurement of credit risk. Additionally, the book values of assets might not necessarily adequately reflect their true assets values due to, for instance, accounting conservatism and historical cost accounting which adds to the concerns of accounting relevance. Also, accounting information is disclosed somewhat infrequently, on a quarterly basis at best, which might further decay its relevance to investors.

In contrast, market information, and more specifically the structural models based on it, rely on rigorous financial theory and should accordingly offer more relevant information to providers of debt capital. The empirical findings are, however, relatively mixed in terms of performance as it has been found, for instance, to substantially under-predict credit spreads on bonds (see e.g. Ogden, 1987 and Lyden and Saraniti, 2001).

The existence of these imperfections in both accounting and market information thus provided the basis for testing which source of information, in fact, is of more relevance to the credit markets. This was the underlying logic behind $\mathbf{H_1}$ which posited in accordance with the efficient market hypothesis that market-based information is more relevant to the credit markets than accounting information. Regular OLS regressions were estimated and the hypothesis was tested using a European sample of CDS spreads consisting of 2 032 firm-quarter observations. It was found that the accounting-based model had an adjusted R^2 of 23 percent while the market-based model's explanatory power mounted up to 48 percent. As an F-test on the two models' regression errors suggests that there is statistical difference (at the 1 percent level) in the explanatory powers of the models, $\mathbf{H_1}$ is accepted.

It was furthermore hypothesized in the form of $\mathbf{H_2}$ that the market-based model is efficient enough for accounting information not to be able to provide incremental relevance. Specifically, the hypothesis posited that the explanatory power of the hybrid model which combines both the accounting and the market model into one comprehensive model is equal or smaller than the explanatory power of the market model. No evidence for this hypothesis was found as the market model's adjusted R^2 (48 percent) was found to be clearly below the adjusted R^2 of the hybrid model (57 percent). Moreover, an F-test carried out on the mean square error terms indicated that there is a statistically significant difference in the explanatory powers between the models. In light of these findings, $\mathbf{H_2}$ was rejected and it was concluded that accounting information does, in fact, offer incremental information for the credit markets.

The third hypothesis asserted that there is an industry effect in the relevance of accounting data. This was tested by dividing the original sample into 9 distinct subsamples according to specific industries. Subsequently, the accounting model was estimated separately for each subsample. It was found that there are significant differences in the explanatory powers between the explanatory powers across industries. For instance, the accounting model estimated for the public utilities sector was found to only explain around 14 percent of the variance in (natural logged) CDS spreads. Conversely, the same model estimated for the transportation sector was found to have an explanatory power of 63 percent. Additionally, it was found that the incremental relevance of accounting information varies from 3 percentage points up to 19 percentage points. In line with one would expect *a priori* and in contrast to Demirovic and Thomas (2007), the cause of this cross-sectional deviation was not found to be caused by the deviations in the explanatory power of Merton's (1974) distance-to-default model as much as by the deviations in the explanatory power of the accounting model.

The fourth hypothesis suggested that accounting information relevance suffers as we move from the pre-crisis period of 01.01.2005 – 31.12.2007 to the crisis period of 01.01.2008 -30.06.2010. The reasoning behind the hypothesis is based on empirical and anecdotal evidence. It was stated, for example, that during the crisis period accounting data relevance declines due to investors' increasing focus on macroeconomic factors and due to the amplified influence of the financial sector. Moreover, the empirical findings of Francis and Schipper (1999) show that periods of high volatility are associated with low accounting information relevance. Supporting evidence of a considerable decay in the relevance of accounting information to credit investors was found. The accounting-based model estimated for the pre-crisis period was found to be some 35 percent while a significantly lower explanatory power of 27 percent was witnessed for the crisis period.

The established results can be considered robust. Firstly, it was found that when firms with only semi-annual financial information available were excluded (i.e. companies from the U.K. and France), the results remain qualitatively unchanged. Secondly, when equity volatility which displayed a high correlation with the distance-to-default variable was excluded, results were virtually unchanged. Moreover, further confirmation of the results' robustness is provided by a fixed effects regression which shows no signs of qualitative changes in the results.

This thesis was mainly motivated by the need to address the relatively scarce empirical research in the field accounting information relevance to the credit markets. In sum, partly these results provide additional evidence on the relevance of accounting information to the credit markets in a general sense and are, on the other hand, partly novel as there seem to exist virtually no studies on the industry and macroeconomic effects of accounting information relevance from the credit markets' perspective. Furthermore, in contrast to the research on U.S. data, this was the first study to investigate accounting information relevance using European CDS data, to the best of my knowledge.

Suggestions for further research include the examination of the relevance of market data using a more sophisticated version of Merton's (1974) distance-to-default model which suffers to various limitations to a lesser extent. For instance, examples of such include Hull and White's (1995) or Longstaff and Schwartz's (1995) models which allow for the possibility of default occurring before maturity. Additionally, as cash flow measures as well as data on intangible assets were omitted from this study due to their scarce quarterly availability, one could pursue a more comprehensive accounting model by attempting to include these figures by collecting them manually. What is more, a more rigorous approach to control for CDS liquidity could be attempted, for instance, by including the spread between bid and ask prices of the CDS spread quotes. Finally, an interesting addition to the study of accounting information relevance, specifically from the credit markets' perspective, would be to study the differences between geographical areas with dissimilar accounting policies and regulations.

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11 APPENDIX

Table 9: Sample companies

The table displays all firms included in the sample. Also, the specific sector and country of domicile are presented. In total, the final sample consists of 155 distinct CDS entities.

CDS entity	Sector	Domicile
ABB LIMITED	CAPITAL GOODS	SWITZERLAND
Accor	CONSUMER SERVICES	FRANCE
Adecco SA	CONSUMER SERVICES	SWITZERLAND
Air France-KLM	TRANSPORTATION	FRANCE
Air Liquide	BASIC INDUSTRIES	FRANCE
Akzo Nobel NV	BASIC INDUSTRIES	NETHERLANDS
Alcatel-Lucent	CAPITAL GOODS	FRANCE
Alstom SA	CAPITAL GOODS	FRANCE
Anglo American PLC	BASIC INDUSTRIES	UNITED KINGDOM
Arcelormittal	BASIC INDUSTRIES	LUXEMBOURG
Assa Abloy AB	CAPITAL GOODS	SWEDEN
ASTRAZENECA PLC	HEALTH CARE	UNITED KINGDOM
Atlas Copco AB	CAPITAL GOODS	SWEDEN
Autostrade Meridionali	PUBLIC UTILITIES	ITALY
BAE Systems PLC	CAPITAL GOODS	UNITED KINGDOM
BASF SE	BASIC INDUSTRIES	GERMANY
Bayer AG	BASIC INDUSTRIES	GERMANY
BMW AG	CONSUMER DURABLES	GERMANY
Bouygues SA	CAPITAL GOODS	FRANCE
BP PLC	ENERGY	UNITED KINGDOM
British Airways PLC	TRANSPORTATION	UNITED KINGDOM
British American Tobacco PLC	CONSUMER NON-DURABLES	UNITED KINGDOM
British Sky Broadcasting Group PLC	CONSUMER SERVICES	UNITED KINGDOM
BT GROUP PLC	PUBLIC UTILITIES	UNITED KINGDOM
Cable & Wireless Communications PLC	PUBLIC UTILITIES	UNITED KINGDOM
CADBURY PLC	CONSUMER NON-DURABLES	UNITED KINGDOM
Cap Gemini SA	CONSUMER SERVICES	FRANCE
Carlsberg AS	CONSUMER NON-DURABLES	DENMARK
Carrefour SA	CONSUMER SERVICES	FRANCE
Casino Guichard-P	CONSUMER SERVICES	FRANCE
Centrica PLC	ENERGY	UNITED KINGDOM
Clariant AG	BASIC INDUSTRIES	SWITZERLAND
Codere SA	CONSUMER SERVICES	SPAIN
Colt Group SA	PUBLIC UTILITIES	LUXEMBOURG
Compass Group PLC	CONSUMER NON-DURABLES	UNITED KINGDOM
Continental AG	CAPITAL GOODS	GERMANY
Daimler AG	CONSUMER DURABLES	GERMANY

CDS entity	Sector	Domicile
Danone	CONSUMER NON-DURABLES	FRANCE
Deutsche Lufthansa AG	TRANSPORTATION	GERMANY
Deutsche Post AG	CONSUMER SERVICES	GERMANY
Deutsche Telekom AG	PUBLIC UTILITIES	GERMANY
Diageo PLC	CONSUMER NON-DURABLES	UNITED KINGDOM
E On AG	PUBLIC UTILITIES	GERMANY
Edison	ENERGY	ITALY
EDP Energias De Portugal SA	PUBLIC UTILITIES	PORTUGAL
Electricite De France	PUBLIC UTILITIES	FRANCE
Electrolux AB	CONSUMER DURABLES	SWEDEN
Enbw Energie Baden-Wurttemberg AG	PUBLIC UTILITIES	GERMANY
Endesa SA	PUBLIC UTILITIES	SPAIN
Enel Spa	ENERGY	ITALY
ENI	ENERGY	ITALY
Ericsson Telephone AB	CAPITAL GOODS	SWEDEN
Experian PLC	CONSUMER SERVICES	IRELAND
Finmeccanica Spa	CAPITAL GOODS	ITALY
Fortum OYJ	ENERGY	FINLAND
France Telecom	PUBLIC UTILITIES	FRANCE
FRESENIUS MEDICAL CARE AG	HEALTH CARE	GERMANY
Gas Natural SDG SA	PUBLIC UTILITIES	SPAIN
GDF Suez	PUBLIC UTILITIES	FRANCE
GKN PLC	CAPITAL GOODS	UNITED KINGDOM
Havas SA	CONSUMER SERVICES	FRANCE
Heidelbergcement AG	CAPITAL GOODS	GERMANY
Heineken NV	CONSUMER NON-DURABLES	NETHERLANDS
Hellenic Telecommunications Organisation	PUBLIC UTILITIES	GREECE
Henkel AG & Company Kgaa	CONSUMER NON-DURABLES	GERMANY
Iberdrola SA	PUBLIC UTILITIES	SPAIN
Imperial Tobacco Group PLC	CONSUMER NON-DURABLES	UNITED KINGDOM
International Power PLC	PUBLIC UTILITIES	UNITED KINGDOM
Invensys PLC	CAPITAL GOODS	UNITED KINGDOM
ITV PLC	CONSUMER SERVICES	UNITED KINGDOM
Kingfisher PLC	CONSUMER SERVICES	UNITED KINGDOM
Koninklijke Ahold NV	CONSUMER SERVICES	NETHERLANDS
Koninklijke DSM	BASIC INDUSTRIES	NETHERLANDS
Koninklijke KPN NV	PUBLIC UTILITIES	NETHERLANDS

CDS entity	Sector	Country	CDS entity	Sector	Country
Koninklijke Philips Electronics Na	CONSUMER DURABLES	NETHERLANDS	Smurfit Kappa Group PLC	CONSUMER SERVICES	IRELAND
Lafarge SA	CAPITAL GOODS	FRANCE	Sodexo	CONSUMER SERVICES	FRANCE
Lanxess AG	BASIC INDUSTRIES	GERMANY	Sol Melia SA	CONSUMER SERVICES	SPAIN
Linde AG	CAPITAL GOODS	GERMANY	Solvay SA	BASIC INDUSTRIES	BELGIUM
LVMH	CONSUMER NON-DURABLES	FRANCE	Statoil ASA	ENERGY	NORWAY
Marks & Spencer Group PLC	CONSUMER SERVICES	UNITED KINGDOM	Stmicroelectronics NV	TECHNOLOGY	SWITZERLAND
Merck Kgaa	HEALTH CARE	GERMANY	Stora Enso OYJ	BASIC INDUSTRIES	FINLAND
Metro AG	CONSUMER SERVICES	GERMANY	Suedzucker AG	CONSUMER NON-DURABLES	GERMANY
Metso OYJ	CAPITAL GOODS	FINLAND	Swedish Match AB	CONSUMER NON-DURABLES	SWEDEN
Michelin	CONSUMER DURABLES	FRANCE	Syngenta AG	BASIC INDUSTRIES	SWITZERLAND
M-Real OYJ	BASIC INDUSTRIES	FINLAND	Tate & Lyle PLC	CONSUMER NON-DURABLES	UNITED KINGDOM
Nestle SA	CONSUMER NON-DURABLES	SWITZERLAND	TDC A/S	PUBLIC UTILITIES	DENMARK
Nokia Corporation	CAPITAL GOODS	FINLAND	Technip	ENERGY	FRANCE
Norske Skogindustrier ASA	BASIC INDUSTRIES	NORWAY	Telecom Italia	PUBLIC UTILITIES	ITALY
Novartis AG	HEALTH CARE	SWITZERLAND	TELEFONICA SA	PUBLIC UTILITIES	SPAIN
Pearson PLC	CONSUMER SERVICES	UNITED KINGDOM	Telekom Austria AG	PUBLIC UTILITIES	AUSTRIA
Pernod-Ricard	CONSUMER NON-DURABLES	FRANCE	Telenor ASA	PUBLIC UTILITIES	NORWAY
Peugeot SA	CONSUMER DURABLES	FRANCE	Teliasonera AB	PUBLIC UTILITIES	SWEDEN
Portugal Telecom Sgps SA	PUBLIC UTILITIES	PORTUGAL	Tesco PLC	CONSUMER SERVICES	UNITED KINGDOM
PPR SA	CONSUMER SERVICES	FRANCE	Thyssenkrupp AG	BASIC INDUSTRIES	GERMANY
Prosieben SAT 1 Media AG	CONSUMER SERVICES	GERMANY	TNT NV	CONSUMER SERVICES	NETHERLANDS
Rallye	CONSUMER SERVICES	FRANCE	Tomkins PLC	CONSUMER DURABLES	UNITED KINGDOM
Rank Group PLC	CONSUMER SERVICES	UNITED KINGDOM	Total SA	ENERGY	FRANCE
Renault SA	CONSUMER DURABLES	FRANCE	TUI AG	CONSUMER SERVICES	GERMANY
Rentokil Initial PLC	CONSUMER SERVICES	UNITED KINGDOM	Unilever NV	CONSUMER NON-DURABLES	NETHERLANDS
REPSOL-YPF SA	ENERGY	SPAIN	United Business Media Limited	CONSUMER SERVICES	UNITED KINGDOM
Rhodia	BASIC INDUSTRIES	FRANCE	United Utilities Group PLC	PUBLIC UTILITIES	UNITED KINGDOM
RIO TINTO PLC	BASIC INDUSTRIES	UNITED KINGDOM	UPM-Kymmene OYJ	BASIC INDUSTRIES	FINLAND
Roche Holding AG	HEALTH CARE	SWITZERLAND	Valeo	CAPITAL GOODS	FRANCE
Rolls-Royce Group PLC	CAPITAL GOODS	UNITED KINGDOM	Vedanta Resources PLC	BASIC INDUSTRIES	UNITED KINGDOM
Royal Dutch Shell	ENERGY	NETHERLANDS	Veolia Environnement	PUBLIC UTILITIES	FRANCE
RWE AG	PUBLIC UTILITIES	GERMANY	Vinci SA	CAPITAL GOODS	FRANCE
Sainsbury (J) PLC	CONSUMER SERVICES	UNITED KINGDOM	Virgin Media Inc	CONSUMER SERVICES	UNITED KINGDOM
Saint Gobain	CAPITAL GOODS	FRANCE	Vivendi	CONSUMER SERVICES	FRANCE
Sanofi-Aventis	HEALTH CARE	FRANCE	Vodafone Group PLC	PUBLIC UTILITIES	UNITED KINGDOM
SAS AB	TRANSPORTATION	SWEDEN	Volkswagen AG	CONSUMER DURABLES	GERMANY
SCA AB	BASIC INDUSTRIES	SWEDEN	Wolters Kluwer NV	CONSUMER SERVICES	NETHERLANDS
Scania AB	CAPITAL GOODS	SWEDEN	Volvo AB	CONSUMER DURABLES	SWEDEN
Schneider Electric SA	CAPITAL GOODS	FRANCE	WPP PLC	CONSUMER SERVICES	UNITED KINGDOM
Securitas AB	CONSUMER SERVICES	SWEDEN	Xstrata PLC	BASIC INDUSTRIES	UNITED KINGDOM
Siemens AG	CAPITAL GOODS	GERMANY			

Table 10: Correlation matrix

The table presents the correlations for all variables included in regression models *(i), (ii)* and *(iii)*. Pearson correlations are displayed in the lower triangle below the diagonal. Spearman correlations are presented in the upper triangle above the diagonal. * indicates statistical significance at the 10 percent level. ** indicates statistical significance at the 5 percent level and *** indicates statistical significance at the 1 percent level.

	ln (CDS Spread)	Distance-to-Default	ln (Size)	Lev	Cash	Current	ROA	EBIT	SalesAssets	INTWO	iTraxx	SalesCurrent	EquityVolatility	RiskFree
ln (CDS Spread)	**1**	-0,6805**	-0,1595**	0,1292**	0,0687**	-0.0106	-0,3428**	-0,2742**	-0,0521*	0,1990**	0,0484*	-0.0077	0,6513**	-0,1576**
Distance-to-Default	-0,6488**	**1**	-0,0474*	-0,1905**	-0,1061**	0.0149	0,3727**	0,3208**	0.0065	-0,1264**	0.0033	0,1191**	**-0,9184****	0,0480*
ln (Size)	-0,1997**	-0,0448*	**1**	-0,0516*	-0,0926**	-0,1410**	0,0608**	0,1639**	-0,2413**	-0,0539*	-0,0543*	-0,1421**	-0.0415	-0.0377
Lev	0,1418**	-0,1840**	-0,1007**	**1**	0,2362**	-0,2965**	-0,1471**	-0,0797**	0,0456*	0,0488*	0,1399**	-0,0917**	0,0464*	-0.0215
Cash	0.0401	-0,0695**	-0,1065**	0,1496**	**1**	0,2699**	-0.0362	-0,1162**	0,2397**	-0,0458*	0,0597**	-0,3046**	0,0969**	-0,1289**
Current	0.0170	0.0192	-0,1396**	-0,2788**	0,2797**	**1**	0.0271	-0,0691**	0,1348**	-0.0326	0,0643**	-0,3864**	0,0882**	-0,0575**
ROA	-0,3700**	0,3792**	0,0563*	-0,0701**	0.0187	0.0373	**1**	0,5986**	0.0427	-0,2357**	-0,1833**	0,0832**	-0,2129**	0,2489**
EBIT	-0,2653**	0,3041**	0,1241**	-0,0537*	-0,0831**	-0,0639**	0,5620**	**1**	-0,3711**	-0,2791**	-0,1290**	-0,0993**	-0,2159**	0,0799**
SalesAssets	-0.0369	0.0081	-0,2594**	0,0901**	0,1841**	0.0393	0.0035	-0,3389**	**1**	-0,0703**	-0,0670**	0,5411**	0.0182	0,0531*
INTWO	0,2332**	-0,1164**	-0,0480*	0.0403	-0,0451*	-0.0147	-0,2345**	-0,2694**	-0,0654**	**1**	0.0212	0.0235	0,1105**	-0,0571**
iTRAXX	0,0570*	-0.0029	-0.0404	0,1272**	0.0404	0.0368	-0,1940**	-0,1367**	-0.0173	0.0212	**1**	-0,0879**	-0,0591**	0.0183
SalesCurrent	-0.0071	0,0794**	-0,1749**	-0.0161	-0,2166**	-0,3401**	0.0334	-0,1090**	0,6873**	-0.0068	-0,0753**	**1**	-0,0873**	0,0466*
EquityVolatility	0,6385**	**-0,7989****	-0.0269	0,0638**	0,0483*	0,0857**	-0,2118**	-0,2126**	-0.0164	0,1082**	-0,0512*	-0,0702**	**1**	0.0382
RiskFree	-0,1634**	0,0707**	-0.0345	-0.0202	-0,1044**	-0,0606**	0,2343**	0,0708**	0.0336	-0,0474*	0.0194	0.0076	-0.0364	**1**