UNIVERSITY OF VAASA

FACULTY OF BUSINESS STUDIES

DEPARTMENT OF ACCOUNTING AND FINANCE

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DETERMINANTS OF CREDIT DEFAULT SWAP SPREADS AND CREDIT RISK ASYMMETRY:

Evidence from U.S. non-financial firms in 2007–2012

Master's Thesis in
Accounting and Finance
Finance

VAASA 2014

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Year of Entering the University: 2009
Year of Completing the Thesis: 2014 **Pages:** 97

ABSTRACT

The purpose of this study is to study how accounting-based and market-based credit risk determinants compare in assessing credit risk in different economic regimes by examining a sample of credit default swaps (CDS) on U.S. non-financial firms in 2007–2012. Furthermore, the regime dependency of credit risk determinants is examined during the financial crisis of 2007–2009 and post-crisis. Most importantly, this thesis focuses uniquely on examining the asymmetric, nonlinear effects of credit risk determinants in different levels of credit default swap spread.

In the empirical part, a sample of 207 credit default swap spreads on U.S. non-financial firms is examined together with eight accounting-based variables and six market-based variables, respectively. The data consists of quarterly observations in 2007–2012, covering both the financial crisis period and the post-crisis recovery period. A linear regression is employed to study the relative performance of accounting-based and market-based models. Moreover, a quantile regression method is conducted to provide evidence on asymmetric effects together with symmetric quantiles test.

A majority of the increasing literature on the relationship between credit risk models and credit default swaps find that accounting and market data should be considered as complements rather than substitutes to one another. Similar to previous studies, the results imply that both accounting- and market-based variables contribute to the firm's CDS spread. Moreover, the effects of the most essential accounting-based variables, leverage and return on asset, intensify during the financial crisis period, whereas the most influential market-based variables, volatility and equity return, experience the opposite effect.

Finally, the results suggest that there is an increasing survival effect, which occurs as accelerating nonlinear effects of risk determinants within the higher CDS spread firms. The asymmetric effects are also dependent on the prevailing economic conditions, suggesting higher firm-specific asymmetric effects during the recovery period than the financial crisis.

KEYWORDS: Credit default swap, credit risk, financial crisis, financial distress

1. INTRODUCTION

Credit default swaps (CDS) are one of the most recent innovations in finance and since their invention in 1994, the markets for credit default swaps have exploded. Essentially, credit default swaps are insurance contracts for hedging against an undesirable credit event, that is, the default on the underlying debt. Although, like any other credit derivative, they can be used also for speculation purposes. Recent debate about credit default swaps focuses on their role in the financial crisis of 2007–2009 or in the ongoing Greek debt crisis. Also, the regulation of credit default swap markets has been a very much discussed topic in the aftermath of the financial crisis (e.g. Stulz 2010, Jarrow 2011). According to the Bank for International Settlements (BIS), the total notional amount of the CDS market at the end of 2012 reached over $25 trillion, which is under half of the peak of $62 trillion in the end of 2007. In 2012, non-financial firms accounted for almost $10 trillion of the overall market size (Bank for International Settlements 2013).

The aim of this thesis is to find relevant accounting-based variables to explain firms' credit risk, and additionally, to examine whether market-based variables contribute to the credit risk assessment, as previous studies suggest (e.g. Benkert 2004; Das, Hanouna & Sarin 2009; Ericsson, Jacobs & Oviedo 2009). Different historically relevant measures of financial distress are utilized in the approach of the anatomy of credit risk. Credit default swaps offer a unique platform for measuring the continuous appearance of fundamental credit risk.

Finally, the most unique and important goal of the thesis is to study the asymmetric credit risk dynamics and nonlinear effects in different economic regimes. In respect to previous literature on credit default swaps, the approach employed in the thesis provides an exclusive outlook on dynamics of credit risk assessment.

1.1. Background

There are various ways to measure firm's default risk. The most common approaches are accounting-based and market-based models, of which both include multiple models developed over the years. The modeling of default using accounting numbers has an extended history, such as Altman's Z-score (1968) and Ohlson's O-score (1980), whereas the market-based structural models are newer and more complex. The basis of structural models was developed after the Black-Scholes option pricing model was introduced in 1973, when Merton (1974) used implied volatility from option pricing model to calculate a probability of default. After Merton's model, a number of more sophisticated and developed structural models for predicting financial distress have been introduced, and many of them are currently in commercial use of, for example, credit rating agencies and banks. Market-based default prediction models have gained acceptance by both academics and practitioners, probably because of the theoretical framework behind the models. Accounting-based models are essentially inductive and based on empirical findings, which can make them unattractive in some circumstances. Regardless, both approaches have yielded a number of remarkable results in prediction of financial distress over the time. At the same time, both approaches have also been criticized and some essential flaws have been pointed out.

Since credit default swaps are essentially for hedging the default on underlying debt, they include valuable information of the financial condition of the underlying company and the probability of default. Therefore, the price of CDS should be directly in relation to the probability of going into financial distress. Also, measuring the relationship between the CDS spread over the risk-free rate and the default model can be used as an alternative to using samples of actual bankruptcies. Integrating the default models to actual bankruptcy cases is somewhat difficult, since many of these models require for publicly traded companies. This restriction limits the data available, since there are not many bankruptcies of public companies within recent years, although the occurred ones have been impressively sized. Credit default swaps provide an easy access to measure the default risk with fresh data along with sufficient number of observations. Furthermore, the binary nature of bankruptcy restricts the examination of the escalation of credit risk, whereas the credit default swaps are continuously adjusted for the probability of default. Using CDS spreads instead of bankruptcy cases as a proxy allows for deeper examination of the nature of credit risk.

1.2. Purpose of the thesis

The purpose of this thesis is to study the effects of both accounting- and market-based credit risk determinants on credit default swap spreads of non-financial firms in different economic regimes. The objective is to find accounting-based variables and ratios that are the most influential to explain firm's credit risk, and furthermore, to examine the effects of equity market information to the credit risk assessment. Such variables are determined from extended literature regarding credit risk and financial distress. Credit default swaps on the underlying debt are used as a proxy for firms' credit risk, which allows for continuous analysis of the nature of the risk.

There are many complications when dealing with accounting information, such as valuation and reliability of numbers, but initially they form the base for fundamental analysis and market information. Moreover, credit risk can be approached through equity market information, on which the market models are naturally based on. The further objective of the thesis is to find if including market information to accounting-based models improve the model. The aim is to combine the important common variables from both the accounting-based models and market models to relevant combination.

Moreover, the dynamics of credit risk determinants are examined during the financial crisis of 2007–2009. This approach allows comparing the development of credit risk proxies during the periods of economic recovery as well as high uncertainty. The aim is to study, whether the meaningful credit risk determinants change in respect to corresponding market conditions and if so, how the crisis period is incorporated in these determinants.

Finally, the most unique contribution of the thesis is to examine credit risk asymmetries and deviation of credit risk proxies between high and low CDS spread firms. In contrast to previous studies, where the unbalanced credit risk is studied by controlling for the credit ratings (thus, allegedly for credit risk), the purpose of this thesis is to compare the dynamics of credit risk variables in the tails of CDS spread. This thesis contributes uniquely to the relationship between the asymmetric distribution of credit risk and credit risk determinants, and moreover, presents exclusive remarks on the credit risk asymmetry, dynamic market conditions and various credit risk factors.

1.3. Hypotheses and structure

Next, the research hypotheses are formed in order to approach the research subject empirically. But first, research problems are specified and stated. Questions behind the hypotheses are:

- Do accounting ratios have contribution in explaining firm's credit risk?
- Which ratios are the most important ones?
- Does market information improve the credit risk model?
- Are high and low risk firms affected asymmetrically by credit risk determinants?
- Are the CDS spread determinants affected by different economic regimes?

The price of a CDS contract on a healthy firm with good accounting ratios should reflect those thriving numbers. On the other hand, hedging should be more expensive on the debt of an unhealthy firm with a notable risk of default. Hence, the following hypothesis is formed:

Hypothesis 1
H_0: Accounting-based ratios do not explain CDS spreads.
H_1: Accounting-based ratios explain CDS spread.

To test the first hypothesis, a group of empirically relevant accounting ratios are regressed to explain the CDS premium. The results should reflect the relevance of the different ratios in explaining credit risk. The selected accounting ratios are tested together in order to find their relevance in explaining CDS spread. The main points of interest regarding the first hypothesis are, whether the variables hold their expected signs and whether they are significant in explaining CDS spread. The variables included in the first model are presented in Table 1 together with their expected signs. The variables are chosen in regard to past empirical relevance, as discussed later in the thesis.

Table 1. Predicted signs for accounting-based variables.

ACCOUNTING-BASED VARIABLES	ABBREVIATION	SIGN
Return on assets	ROA	−
Retained earnings / Total assets	RE/TA	−
Interest coverage	COV	−
Current ratio	CR	−
Total debt / Total assets	TL/TA	+
Total debt / Common equity	TL/CE	+
Total assets	TA	−
Working capital / Total assets	WC/TA	−

In addition to first hypothesis, market-based variables are introduced to the model. The market-based variables are chosen based on theoretical framework on firm default presented later in the thesis. Also, stock market performance ratios, earnings per share and dividends per share, are included in the analysis to explore their possible informative power in credit risk assessment. Hence, the second hypothesis is formed:

Hypothesis 2
H_0: *Accounting-based model cannot be improved with equity market information.*
H_1: *Accounting-based model improves with equity market information.*

The second hypothesis introduces equity market information to the first model and, essentially, tests whether the explanatory power of the model increases. Moreover, possible changes in the significance and effectiveness of the initial variables are examined. Predicted signs regarding the market-based variables are presented in Table 2. Based on Merton's (1974) theoretical framework on firm default and structural components, equity return and volatility, market leverage and risk-free rate are selected in the analysis. Additionally, earnings per share and dividends per share ratios are selected to examine the effects of stock market performance ratios on CDS spreads.

Table 2. Predicted signs for equity market variables.

MARKET-BASED VARIABLES	ABBREVIATION	SIGN
Stock return	RET	−
Annualized volatility	VOL	+
Leverage	LEV	+
Earnings per share	EPS	−
Dividends per share	DPS	−
Risk.free rate	RF	−

The third hypothesis tests the impact of the financial crisis of 2007–2009 on the credit risk. At the time, the CDS spreads widened dramatically in all rating classes as a result of economic uncertainty. Especially the CDS spreads of financial institutions climbed to new heights, as they were in the center of the economic crisis. The market conditions have had empirically less impact on the credit spread than the firm characteristics. The third hypothesis tests whether the macroeconomic conditions reflect to accounting-based measures, and hence have an impact on the CDS spread of non-financial firms. The main interest is whether the estimates are associated with high economic uncertainty, and thus change signs or gain (lose) significance. The relationship between accounting-based credit risk and CDS spread in different economic conditions can be summarized as following:

Hypothesis 3

H_0: *Relationship between credit risk determinants and CDS spreads is not dependent on economic regime.*

H_1: *Relationship between credit risk determinants and CDS spreads is dependent on economic regime.*

In addition, possible asymmetric effects between high and low risk firms are examined by quantile regression approach. Such estimation approach allows deeper examination of credit risk dynamics and sensitivity to risk determinants compared to linear estimation. According to previous literature, the firms' exposures to different credit risk variables vary between rating classes, as shown later in the paper. Hence, controlling for different levels of CDS spreads, i.e., credit risk instead of credit ratings, asymmetric responses to credit risk determinants can be observed and examined in a deeper manner. The purpose is to examine, whether the aforementioned credit risk determinants have accelerating survival effects in the high-risk tail. The main attention lies in the convexity or concavity of the variables: Asymmetric, accelerating effects between the high and low credit risk levels would infer increasing survival effects for firms that are closer to default. Thus, the fourth hypothesis is formed as follows:

Hypothesis 4

H_0: *Credit risk determinants do not have asymmetric effects on CDS spreads in higher credit risk levels.*

H_1: *Credit risk determinants have asymmetric effects on CDS spreads in higher credit risk levels.*

In the remainder of the thesis, the theoretical framework behind the hypotheses is introduced. First, features of credit risk are introduced together with different approaches and measures of credit risk, such as ratings and credit models. Second, credit default swaps, CDS markets and the function of CDS contracts are introduced. In the CDS part, the main subject is hedging and the speculation possibilities are not considered widely. After that, accounting-based models credit risk models are presented more closely and their components and the further applications, such as Altman's (1968) Z-score, are examined. In the final part of literature preview, the growing field of studies about the relationship between credit models and credit default swaps are introduced. In this part, different approaches are compared and, based on the empirical findings, the most significant and relevant variables contributing to the relationship are utilized in the empirical part of this thesis.

After the literature preview, the data and the methodologies are presented in section five. Next, the summary statistics and empirical findings are provided and the hypotheses are tested in section six. Finally, in section seven, conclusions are drawn together with the most considerable observations and results.

2. CREDIT RISK

In this chapter, the most important previous studies regarding credit risk, different credit risk models and the relationship between these models and CDS prices are introduced. The goal is to provide the bottom lines from previous literature and associate them to the hypotheses formed earlier. The very basics of firm default risk, and thus the base of credit default swaps, is approached from different angles and a holistic picture of default risk is considered.

2.1. Credit risk

Credit risk means a possibility of a negative outcome that the issuer of debt or bond is unable to meet its obligations. For lender, credit risk is the most significant risk when dealing with corporate debt or bonds and therefore the anatomy of the risk is very well studied. There is a wide range of tools to estimate the counterparty credit risk and the possibility of failure, such as credit ratings by different rating agencies, accounting-based credit scoring systems and structural approach. In this chapter, different approaches and the most common tools to measure the credit risk are introduced.

Credit rating agencies, such as Standard & Poor's, Moody's and Fitch Ratings, provide information on the debtor's abilities to meet its financial obligations and on the possibility of default. Credit rating agencies evaluate the quality of the credit of the underlying firm and summarize it to a single measure, a credit rating. In this thesis, the quoted credit ratings are from Standard & Poor's (S&P) credit rating scale, which runs from AAA (the most creditworthy) to D (default on financial commitments). Note that credit ratings are relative opinions about the credit quality and creditworthiness, not absolute measures of default probability (Standard & Poor's 2012).

Table 3 shows the transitions between different scales of credit rating agencies. Ratings above BBB are called investment grade and, inversely, ratings below the BBB threshold are called non-investment grade or speculative grade. Often, bonds with rating below BBB are called junk bonds. As mentioned, all the ratings quoted in this thesis are from the S&P scale or converted into corresponding S&P form to make them comparable.

Table 3. Credit rating scales for different credit rating agencies.

CREDIT RATINGS

	STANDARD & POOR'S	MOODY'S	FITCH
INVESTMENT GRADE	AAA	Aaa	AAA
	AA	Aa	AA
	A	A	A
	BBB	Baa	BBB
NON-INVESTMENT GRADE	BB	Ba	BB
	B	B	B
	CCC	Caa	CCC
	CC	Ca	CC
	C	C	C
	D	C	D

The default component in corporate bond prices should be equal to corresponding CDS premium as CDS prices should reflect the creditworthiness of the underlying firm. This default component is measured by dividing the corporate yield spread with CDS premium, which is the measure of risk-neutral default component. In 2001–2002, total yield spread explained by default component using Treasury rate as a risk-free proxy was 51 % for AAA/AA-rated bonds, 56 % for A-rated bonds and 71 % for BBB-rated bonds. For speculative, in this case BB-rated, bonds the default component accounted for 83 % of yield spread. These results indicate that default component explains the majority of corporate yield spreads accounting more than 50 % in every investment grade rating class and over 80 % in speculative rating (BB) class. (Longstaff, Mithal & Neis 2005.)

Credit risk can be observed by examining the yield spread between corporate bonds and Treasury bonds of comparable maturities. Huang and Huang (2002) find that for investment-grade bonds (credit rating equal or higher than BBB), credit risk accounts for less than 20 % of the credit spread between corporate bond and Treasury bond of corresponding maturity, except for BBB-rated bonds with maturity of 10 years (29,1 %). For the speculative grade bonds, credit risk accounts for a much larger proportion of the credit spread: For BB-rated bonds with maturities of 4 and 10 years, the credit risk accounts for 53,9 % and 60,1 % of spread, whereas for B-rated bonds with corresponding maturities, credit risk accounts for 94,8 % and 82,5 %, respectively. Interestingly, the fraction of the credit risk decreases heavily for the B-rated bonds when moving from medium-term to longer-term maturity, while investment grade bonds capture the opposite effect with equivalent maturities. For example, the fractions of spread due to default for AAA-rated bonds with maturities of 4 years and 10 years are 2,1 % and 15,8 %, respectively. This is explained by mean reversion of credit quality over the time, which expects higher credit risk for investment rate bonds as the maturity increases.

Mean reversion and its effects on bond yield spreads for different rating classes are presented in Figure 1. As discussed earlier, empirical results suggest that the yield spreads tend to converge with time to maturity: on one hand, yield spread for higher grade bonds have a tendency to increase with the maturity, whereas on the other hand, the yield spreads of lower rated bonds tend to be narrower at the long end, as visualized in Figure 1. (Crouhy, Galai & Mark 2000.)

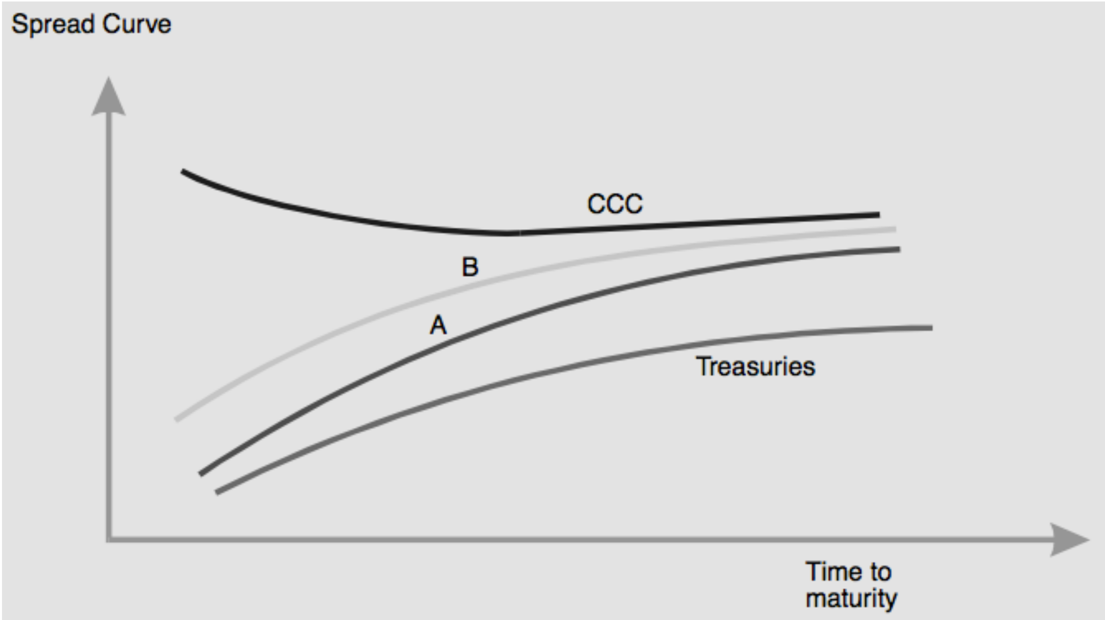

Figure 1. Spread curves for different credit qualities. (Crouhy et al. 2000.)

Both Longstaff et al. (2005) and Huang and Huang (2002) conclude that the remaining fraction of the credit spread not explained by credit risk is mostly caused by liquidity and tax treatment regarding corporate bonds. In addition, when liquidity of corporate bonds decreases, the fraction of nondefault component increases, that is, bonds with higher illiquidity usually have a larger liquidity component included in their yield spreads.

Huang and Huang (2002) argue that speculative grade bonds may be even more liquid than investment grade bonds because of higher trading volumes. The level of illiquidity does not fluctuate as severely as the level of credit risk around the investment grade threshold. Longstaff et al. (2005) find that for AAA/AA-rated bonds, the nondefault component is about -13 basis points lower than average, which suggests that there is a small flight-to-quality premium in the prices of the highest-rated bonds.

Credit risk is likely to be positively correlated with levels of liquidity spreads, that is, the higher the credit risk, the higher the liquidity spread of the bond. The liquidity spreads should have a negative relationship with time to maturity, whereas the credit risk is an increasing function of time to maturity. In addition, yield spreads are driven positively by stock market volatility, which increases the likelihood of default, except for AAA-rated bonds, whose yield spreads are more likely to be affected by liquidity than credit risk. The volatility effect is stronger when moving from higher rating bonds to junk bonds, which confirms the relationship between credit risk and yield spread. (Ericsson & Renault 2006.)

In contrary to results presented above, Elton, Gruber, Agrawal and Mann (2001) argue that most of the corporate yield spread over the government bonds is not explained by expected default loss, but tax premium and systematic risk premium. In fact, their evidence suggests that no more than 25 % of the corporate spot yield spreads is explained by default risk. The corporate spot rates are derived based on a risk neutrality assumption, so that the modeled spot rates incorporate only the risk due to expected default losses. Corporate spot yield curve shows that the bonds are priced as if the ratings captured the real information regarding default risk, and that there is a positive relationship between the corporate spot yield spreads and the maturity of the spot. Hence, default risk leads to higher spot rates for corporate bonds.

As mentioned earlier, the relationship of credit risk to the maturity of the bond is nonlinear over time because of the mean reversion. This arises because bonds drift between rating classes over time and, thus, the probability of default increases for the high-rated bonds and, contrariwise, decreases for the lower-rated bonds. Within one year period, an AAA-rated bond has zero probability of defaulting, whereas the probability for CCC-rated bond equals to 22,05 %. Moreover, if the CCC-rated bond survives 19 years without defaulting, the probability of default deteriorates to 2,93 %, while the probability for the AAA-rated bond increases to 0,33 %. This credit rating transition does not hold equally for all rating classes and, for example, CCC-rated bonds have lower conditional probability of default than B-rated bonds after 12 years of existence due to this credit migration. (Elton et al. 2001.)

Assessing credit risk solely through credit ratings is potentially hazardous and fallacious, since the industry confronts an impending conflict of interest in their operations. Rating the products of the firms that form the primary source of income and at the same time dealing with a vast group of investors in the financial markets and producing widely followed information, or more accurately opinions, about credit risk makes credit rating business a looming source of conflicts. Moreover, the fallacious nature of credit rating industry is supported by inefficient duopoly between S&P and Moody’s, which causes the issuer to have more possibilities to shop for desired rating or for the best rating available. Including Fitch and so on extending the duopoly to three big rating agencies makes no difference, while in fact, it increases the effect. This phenomenon is rather deeply rooted, since the credit rating industry has very high, absolute barrier to entry. (Bolton, Freixas & Shapiro 2012.)

Furthermore, the quality of the ratings depends on the market conditions, the market participants and the reputation of the rating agency, that is, the timeliness and accuracy of assessments of credit risk. In good, booming market conditions, when the number of trusting investors that take ratings at face value, such as pension fund managers or other institutional investors, the credit rating agencies' ratings seem to inflate, causing an upward bias in ratings. (Bolton et al. 2012.)

Moreover, He, Qian and Strahan (2011) find that both the size of the issuer and the market conditions are related to the rating of its products. The inflated ratings received by large issuers causes the issued products to underperform compared to small issuers. The fraction of the underperformance of the highest rated mortgage-backed securities (MBS) is related to the size of the issuer and the effect is particularly strong during the market boom, supporting the findings of Bolton et al. (2012). These findings indicate that the credit rating agency is more prone to rate the issuer of the underlying rather than the actual product, especially when dealing with more complex financial products. Together with the fact that credit rating agencies can make adjustments to their model outputs before final rating, these findings are robust evidence of the introverted and conflicting nature of rating industry and, furthermore, the use of credit ratings as (absolute) proxy for credit risk is somewhat delusive.

All in all, the ratings by credit rating agencies are widely used and applied, even required in some instances in practice but, as shown, they involve a lot of fallacious information and biasedness. The usefulness and feasibility of ratings as a credit risk proxy is summarized by anonymous analyst at on of the major credit rating agencies as follows (Securities and Exchange Commission 2008):

"The deal ... could be structured by cows and we would rate it."

In the following section, more fundamental and transparent credit risk models are presented. Credit risk is assessed first by inductive accounting-based models, which are based heavily on empirical findings of default determinants. Additionally, market-based structural models are covered to provide a theoretically more attractive, deductive approach to credit risk.

2.2. Credit risk models

As mentioned, there are several ways to estimate credit risk. First, probability of default can be estimated from accounting variables and financial ratios. Accounting-based credit-score systems, such as the linear probability model, the logit model, the probit model and the discriminant analysis model, use a combination of accounting variables to calculate a single measure for probability of default. Second, increasingly popular and useful credit risk models are "risk of ruin" models that utilize option pricing model in the estimation of the probability of distress. Option pricing based credit risk models calculate the probability of the market value of firm's assets to fall below its (short term) outside debt based on the implicit volatilities from Black-Scholes-Merton model. The models provide "distance-to-default" value, which measures how many standard deviations the equity values are above short-term debt. The probability of going into distress is based on the distance of how far the firm is from the default situation, and what percentage of firms actually defaulted from that distance. These structural models are originally based on Merton's (1974) asset value model, and there are several applications developed on the basis of this model, such as Moody's KMV. Third, the term-structure of corporate yield spread can be used to calculate the implied probabilities of default. Implied forward rates are derived from the yield curve to measure the risk premium of default over the risk-free bond. Finally, probabilities of default can be derived from past data on bond defaults by credit rating grade and maturity. These models are based on the mortality rates of bonds with certain attributes and utilize historical data together with credit ratings by rating agencies. (Altman & Saunders 1998.)

In the remainder of this chapter, the development of credit risk measuring and different prediction models, that are meaningful for the remainder of this thesis, are introduced. First, credit risk assessment is covered with accounting-based models and important financial statement ratios to measure credit risk are provided and examined. Furthermore, theoretical framework behind the structural risk of ruin models is presented. Also the defects regarding both approaches are discussed shortly.

2.2.1. Accounting-based models

Credit risk models and bankruptcy prediction based on accounting ratios have a rich empirical history starting from Beaver (1966) and followed by Altman (1968) and Ohlson (1980). Over time, as more complex and theoretically more accepted models have been introduced, these accounting-based credit risk models have drawn more debate about their acceptability and qualities to predict possible financial failures. Accounting-based models are essentially built by searching through a large number of financial ratios with the ratio loadings estimated on a sample of failed and non-failed firms. One reason for the criticism is their bottom-up nature as they rise strongly from empirical findings, whereas the structural models are built deductively top-down, starting from the theory. However, regardless their inductive nature, the accounting-based credit risk models prove themselves as useful tools to measure the fundamental risk of failure and more effortlessly provide essential information about the financial health of a company.

The most known accounting-based default model is the Altman's (1968) Z-score, which is a discriminant analysis method that is based on five most influential empirically found financial ratios. The original model concentrated on finding the significant differences between the common features of the distressed firms and the common features of healthy firms. In Equation 1, the original combination resulting from the analysis is presented:

(1) $$Z = 1{,}2X_1 + 1{,}4X_2 + 3{,}3X_3 + 0{,}6X_4 + 0{,}999X_5$$

where X_1 = Working Capital / Total Assets (WC/TA)
X_2 = Retained Earnings / Total Assets (RE/TA)
X_3 = Earnings Before Interest and Taxes / Total Assets (EBIT/TA)
X_4 = Market Value of Equity / Book Value of Total Liabilities (MVE/TL)
X_5 = Sales/ Total Assets (S/TA)

Firms with Z-score above 2,99 are in the safe zone and concluded as "non-bankrupt", while firms with Z-score less than 1,81 are all bankrupt. The zone between 1,81–2,99 is denoted as the "gray area" because of the error classifications of the model. (Altman 1968.)

The original Z-score is primarily designed to test the financial distress among manufacturing firms. For non-financial firms and emerging markets, the initial model was revised to new Z''-score. Equation 2 shows the new model for non-financial firms:

(2) $Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$

where the variables are the same as in the original Z-score presented in Equation 1. Only Sales/Total Assets measure is left out to minimize the potential industry effect. The classification zones for Z''-score are exactly the same as in the original model. (Altman, Hartzell & Peck 1995.)

Furthermore, a seven variable model called ZETA model is developed from the basis of the original model. The ZETA model is a commercial model that includes the most reliable variables; it accounts for return on assets (ROA), stability of earnings, debt service (interest coverage ratio), cumulative profitability (retained earnings to total assets), liquidity (current ratio), capitalization (common equity to total capital) and size (total assets). The model itself is not available because of its commercial nature. Compared to the original Z-score, the ZETA model succeeds to identify distressed firms more accurately two to five years prior to bankruptcy event. The Z-score has a classification accuracy of 93,9 % one year prior to bankruptcy, while ZETA model estimates 96,2 % correctly. In the case of non-bankrupt firms, the respective accuracy is 97,0 % (89,7 %) for Z-score (ZETA score). (Altman, Haldeman & Narayanan 1977.)

Ohlson (1980) points out several problems associated with models using multivariate discriminant analysis, such as Z-score, which can be avoided with the use of conditional logit analysis method. Unlike multivariate discriminant analysis models, which result a score with very little intuitive interpretation, the conditional logit analysis estimates directly the probability of failure within a prespecified period of time. Moreover, no assumptions regarding the prior probabilities or the distributions of the predicting variables are necessary, which is a significant advantage.

In the empirical part of forming the probabilistic model of bankruptcy, a set of nine different independent variables is tested to construct a valid model to estimate the probability of failure. The main criterion for deciding among different variables is simplicity of the predictors and, ultimately, the model included such variables as logarithm of total assets (SIZE), total liabilities to total assets (TLTA), working capital to total assets (WCTA), current liabilities to current assets (CLCA), net income to total assets (NITA), funds provided by the operations to total liabilities (FUTL), change in net income (CHIN), and two dummy variables regarding negative net income (INTWO) and negative equity (OENEG). The coefficients of the financial statement variables, that is, variables 1–4, and the coefficients of the performance variables (variables 5–9) are uncorrelated, and thus both sets of predicting variables seem to have some independent predicting power. The logit model based on these variables shows serious predictive power with 96,12 % of correctly predicted bankruptcies one year before failure. This suggests that accounting measures include information about company's health and that they can be used to estimate the credit risk of the underlying company. Lastly, the differences in results provided by different models based on financial ratios can be mostly explained by the selection of predictors and the lack of nonaccounting-based data, such as market-based data, and the choice of estimation procedures. (Ohlson 1980.)

A comparative analysis between different estimation procedures and predictors included in these models shows that the choice of methodology affects the variable specification. The use of discriminant analysis, logit analysis and neural networks all lead to different model specifications and also the number of variables included in the models varies. From the 31 most empirically influential financial ratios divided into three typical dimensions, liquidity, profitability and solidity, the discriminant analysis selects two liquidity measures (cash flow to total debt and quick assets to total assets), one profitability measure (net sales to total assets) and one solidity measure (total debt/equity) one year before failure. Moreover, the logit model leaves out the profitability dimension one year prior to failure, including the same liquidity measures as discriminant analysis model together with total debt to total assets ratio as a measure of solidity. However, based on variables two years prior to failure, both models incorporate completely different predictors as well as larger number of predicting variables. In addition, liquidity seems to be generally the most attributable aspect to the firm's default risk. Overall, a comparative analysis shows that the logit analysis uses a fewer number of variables than discriminant analysis to combine information regarding financial failure and still manages to outperform it on year prior to failure. This evidence clearly supports Ohlson's conclusion about the possible effects the choice of the estimation procedure. (Back, Laitinen, Sere & van Wezel 1995.)

2.2.2. Market-based models

The first credit risk model based on equity market information was introduced by Merton (1974), soon after Black-Scholes option pricing formula had been presented. The main idea behind Merton's model is that the value of corporate debt is fundamentally depended on the risk-free rate, the bond indenture, such as maturity and coupon rate, and the probability of failure. This allows using the same basic approach of Black-Scholes formula with observable equity market variables. Thus, the resulting model is theoretically attractive, although it has a number of assumptions included. However, this Merton-type pricing model is widely used and accepted, and there are a number of redeveloped applications based on the grand idea, such as commercial Moody's KMV model.

In the theoretical framework of structural models, a firm is supposed to have different classes of claims, a single class debt and equity as a residual claim. Furthermore, the firm has promised the bondholders to make a specified payment on a specified date. Hence, in the event that the firm does not meet its obligations, that is, the payment is not met, the debtholders immediately take over the company and the shareholders receive the residual claim, in this case nothing. Given these assumptions, the value of the equity can be written as a European call option on firm's assets, where today's firm asset value corresponds to stock price and the face value of debt corresponds to the exercise price. The value of the debt is an increasing function of asset value and promised payment to bondholders, and decreasing function of time to maturity, asset volatility, and risk-free rate. (Merton 1974.)

This reasoning allows that the risky debt of the firm can be viewed as a risk-free debt plus a short put option on the firm's assets. In this form, the strike price equals to the same face value of the debt as mentioned before and the risk-free debt is the face value of debt discounted at the risk-free rate.

As a direct consequence of Merton's (1974) framework, the probability of default can be expressed as a distance-to-default measure, which is specified as the distance of firm's future asset value from the default threshold (level of debt) in normal cumulative density function. Hence, the model provides a measure of distance (standard deviation) of how far the firm is from the default, which is a direct result of the assumptions behind the model. The following equations are based on the theoretical framework of Merton's (1974) credit risk model and the presentations below follow the presentations of Crouhy et al. (2000) and Giesecke (2002) regarding the underlying model.

The value of firm's assets at time t, V_t, is assumed to follow a standard geometric Brownian motion, that is:

(3) $$V_t = V_0 \exp\left[(\mu - \sigma^2/2)t + \sigma\sqrt{t}Z_t\right] \qquad \text{with } Z_t \sim N(0,1)$$

where V_t = Firm's assets value
μ = Mean of the instantaneous rate of return on the assets (drift)
σ^2 = Variance of the instantaneous rate of return on the assets (volatility)

Furthermore, V_t is log-normally distributed with expected value at time t:

(4) $$E(V_t) = V_0\, e^{\mu t}$$

As mentioned, the default occurs when the value of assets is less than the promised payment to the debtholders, given that the balance sheet of the firm is simplified as in Merton's (1974) framework. This structural relationship between firm's risky assets V_t, level of debt F and maturity T is illustrated in Figure 2, where the shaded area below F denotes the probability of default. Hence, for the probability of default, it can be written as follows:

(5) $$p_{Def} = \Pr[V_t \leq V_{Def}]$$

$$= \Pr\left[\frac{\ln\left(\frac{V_{Def}}{V_0}\right) - \left(\mu - \left(\frac{\sigma^2}{2}\right)\right)t}{\sigma\sqrt{t}} \geq Z_t\right]$$

$$= \Pr\left[Z_t \leq -\frac{\ln\left(\frac{V_0}{V_{Def}}\right) + \left(\mu - \left(\frac{\sigma^2}{2}\right)\right)t}{\sigma\sqrt{t}}\right] \equiv N(-d_2)$$

where V_{Def} is the critical asset value and Z_t is the threshold in the standard normal distribution corresponding to default probability p_{Def}. Hence, the equation can be transformed into raw distance-to-default measure:

(6) $$d_2 = \frac{\ln\left(\frac{V_0}{V_{Def}}\right) + \left(\mu - \left(\frac{\sigma^2}{2}\right)\right)t}{\sigma\sqrt{t}}$$

As can be noted from Equation 6, the distance-to-default depends on the critical asset value, expected return on assets and asset volatility, and time to repayment. Thus, by using risk-free rate instead of expected return on assets, risk-free default probabilities can be derived from Equations 5 and 6.

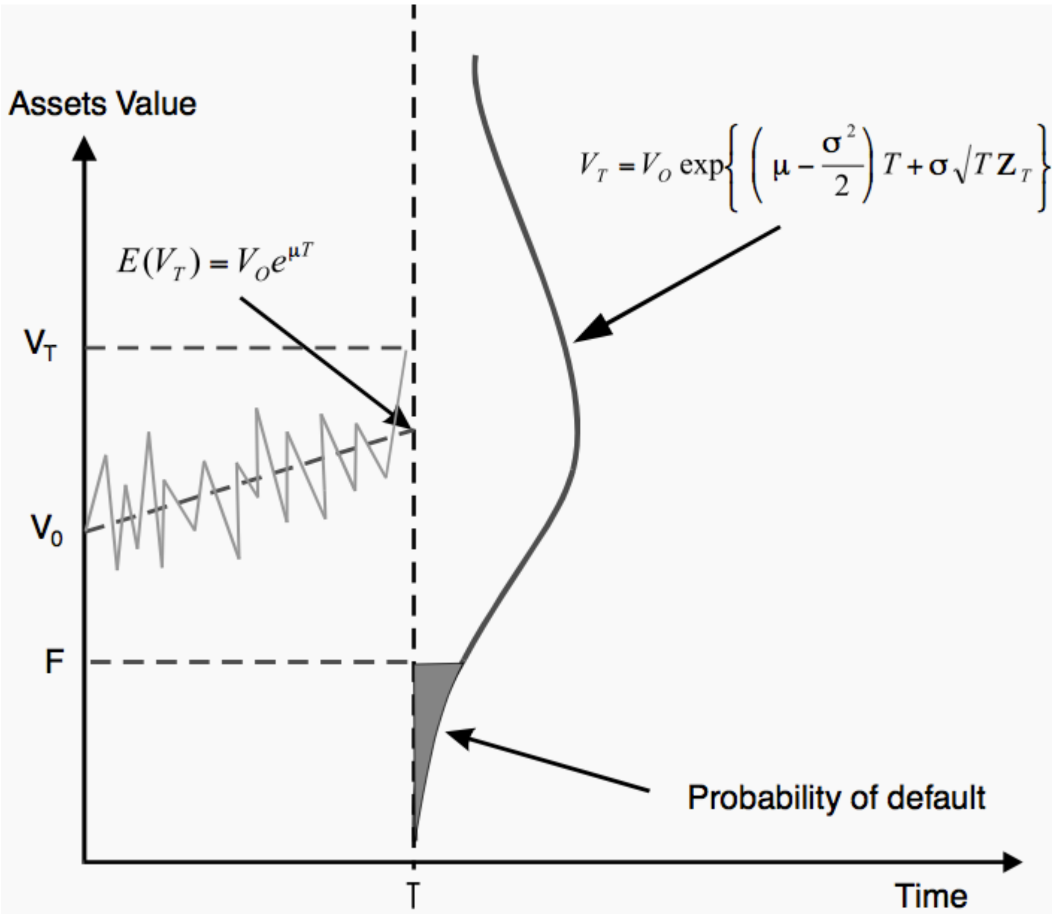

Figure 2. Distribution of the assets of the firm at maturity of the debt obligation. (Crouhy et al. 2000.)

However, the naïve assumptions of Merton's (1974) model cause the model to work only on theoretical level rather than be extremely accurate in practice. Bharath and Shumway (2008) find that a simplified predictor utilizing only the form of the Merton's model performs better than the actual Merton's model itself. The results suggest that the functional form of the Merton's model is more important than the actual solution employed. The results have real practical contribution, because Merton's model and its further commercial applications are considered feasible practices in risk management purposes for banks (Basel Committee on Banking Supervision 1999).

A comparative analysis between default forecasting models that are structurally the same but use different data inputs shows that the model with simple approximations of the same information captured by the original model outperforms the accurately estimated model. In the simplified model, the market value of the debt is approximated to the face value of the debt, the volatility of debt is approximated to one quarter of the firm's equity volatility plus five percentage points, and the expected return on assets equals to the firm's stock return over the previous year. Both the true Merton's model and the simplified model perform rather well when compared to Moody's KMV, correlations being 79 % for both models, respectively. However, when comparing the estimates of the firm volatility, the simplified model volatility has remarkably high correlation of 87 % with Moody's volatility estimate, whereas the volatility computed from Merton's model has only 57 % correlation. (Bharath & Shumway 2008.)

When combining the two default forecasting models with the information included in the models, Merton's model seems to lose its predictive power. Moreover, the simplified model remains as a significant contributor to default risk estimation when dealing with actual bankruptcy cases, even when the components are included separately to the hazard model. This suggests that the functional form of the model overrules the estimation output for default forecasting. Again, the same conclusion is made when estimating CDS spreads with implied probability of default: the simplified model keeps dominating and incorporates more explanatory power than the original Merton's model. The same conclusion is made using bond spreads to predict bankruptcy: the simplified model outperforms the Merton's model and remains highly significant even when combined with the separate components of the model. This truly confirms the structural and functional usefulness of the model rather than the applicability of the resulting default probability. (Bharath & Shumway 2008.)

3. CREDIT DEFAULT SWAPS

Credit default swaps are derivative products with debt as an underlying asset. As the name suggests, their purpose is to trade the possible default on credit to a more certain and secured outcome, and limit the borrower's exposure to credit risk. By nature they are insurance products to hedge from the default on underlying debt and, thus, the deal involves long credit risk for one side and short credit risk for the other. Credit default swaps can be used for number of reasons, such as reducing credit exposure, managing portfolio cash flow, obtaining capital relief and arbitrage. Typically, the protection buyer has a long position on the underlying debt and needs to reduce the credit exposure by purchasing credit protection, hence obtaining a short position on the debt, which works exactly as the opposite of long position on the debt. Therefore, credit default swap markets offer a natural and more easily accessible stage to trade credit risk for desired periods of time or desired (or sometimes required) amounts of capital than, for example, shorting bonds.

However, credit default swaps, like any other derivative, can be also used in speculation. This is particularly dangerous when speaking of credit default swaps, because unlike insurances, they do not require for reserves, which makes the situation problematic in the case of default. For example, a car insurance can be bought by anyone who owns a car, but a credit default swap can be bought by simply anyone without owning the underlying. In that same fashion, one could buy car insurance for every car there exists and benefit from any triggering event, such as car wreck, without even owning a car. From insurance seller's point of view, this could lead into numerous payment events and, thus, unexpectedly large obligations, should the triggering occasions actualize.

In respect to their primary purposes, credit default swaps are considered as tools for hedging purposes and the speculation aspect is left mainly unnoticed in this thesis. The remainder of this chapter is constructed as follows: First, the basic functions and mechanisms of credit default swaps are introduced along with the typical features of a CDS contract. Second, CDS markets and the evolution of credit default swaps are briefly introduced. Finally, the composition of credit default swaps is examined together with CDS pricing and theoretical relationship between corporate bond yield spread and CDS spread. Also, arbitrage opportunities with credit default swaps are briefly discussed at the very end of this chapter.

3.1. Mechanism of credit default swaps

Credit default swaps are contracts between two parties and, essentially, they are simply an insurance policy, in which the policy actualizes when the issuer of the underlying debt defaults on its obligations. The terms and definitions considering the triggering event, usually referred to as credit event, are determined in the agreement between the buyer and the seller of the protection. Should a credit event occur, the seller of the protection is obliged to compensate the buyer with a predetermined settlement.

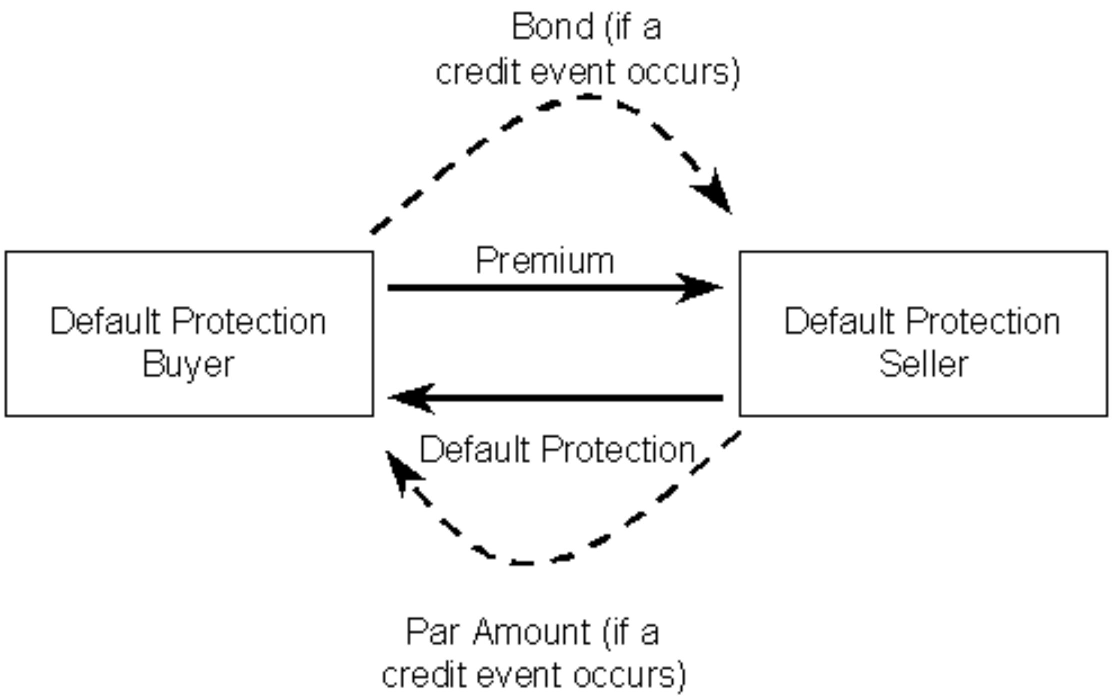

Figure 3. Cash flows involved in a regular CDS contract. (International Swaps and Derivatives Association 2013.)

The transactions between CDS contract parties are illustrated in Figure 3 by International Swaps and Derivatives Association (later ISDA). The buyer of the protection pays a periodic fee, usually on a quarterly basis, to the protection seller during the term of the CDS. Should the reference entity default or meet the specified terms of credit events, the protection seller is obligated to pay the protection buyer for the loss, that is, the face value of the underlying bond. Earlier, the CDS contracts used to specify that the protection buyer should deliver the defaulted bond to the protection seller in order to get the par value of the bond, but, as the contracts have developed, most agreements are settled in cash nowadays. In this situation, the protection seller returns only the difference between the par value and the market value or recovery value, which is typically determined in a CDS settlement auction. Moreover, this allows market participants to speculate on default without owning or getting involved with the actual debt itself. (ISDA 2013.)

The triggering credit events are defined by ISDA and, as mentioned above, the terms are usually included in the CDS agreement by contracting parties. The six credit events under ISDA definitions are:

1. Bankruptcy
2. Obligation Acceleration
3. Obligation Default
4. Failure to Pay
5. Repudiation/Moratorium
6. Restructuring

The most commonly incorporated credit events for corporate reference entities are failure to pay and bankruptcy, whereas obligation acceleration and obligation default are rarely included as they are referring to more technical defaults, like violation of covenants, and include considerations. Furthermore, restructuring of the debt is often included as a credit event. Restructuring by definition covers situations, in which the terms of the obligation have become less favorable to the bond owners than they have previously been, such as a cutback in the principal amount or interest, a postponement of payment, or a change in seniority or priority of payment. Repudiation or moratorium is related to situation where government reference entity disclaims or otherwise challenges the legitimacy of the obligation and, thus, it is not commonly incorporated in contracts regarding corporate reference entity. (ISDA 2003.)

Because CDS contracts are traded over the counter (OTC), the terms are widely negotiable, and thus there are a wide range of unique agreements with diverse terms and conditions. The traditional view has been that the hedge buyer holds a CDS to expiration and, furthermore, the negotiated terms correspond to the mutual agreement between the buyer and the seller. However, as the markets have evolved, CDSs have become more and more like tradable assets with a standard form and terms. A typical CDS contract is $10 million in protection with maturity of five years and includes the quotation for the protection premium per annum.

3.2. Credit default swap market structure

As explained earlier in the thesis, the CDS markets have exploded since the first CDS developed in 1997, and in mid 2013, the notional CDS amounts outstanding were over \$25 trillion. Single-name instruments, that is, CDS contracts on single reference entity, accounted for \$12,5 trillion, whereas multi-name instruments including index products accounted for the remaining \$10,7 trillion. Of the \$12,5 trillion, about 70% of the reference counterparties were rated investment grade, 20% non-investment grade, and, interestingly, 10% were non-rated. On the other hand, the corresponding net notional amount, that is, the sum of the net protection bought, totaled \$907 billion for single-name CDSs. Generally, the net notional positions are the worst case scenarios and represent the maximum potential settlements, should the credit events occur. This makes the net notional amount substantially smaller than the gross notional amount, which indicates the aggregate values for contracts bought or sold. (BIS 2013; Securities Industry and Financial Markets Association 2013.)

CDS markets have a role as alternative trading venues for trading credit risk, regardless of whether the position is used for hedging or speculaton. Although, economically the same result could be acquired using bonds of the underlying firms, the CDS markets function as an alternative, more direct and comprehensive, marketplace for credit risk trading. The hedging argument is supported by the findings, that the net notional CDS outstanding is positively related to both firm's assets and debt, thus, revealing that they both are significant determinants of CDS market existence and composition. Especially, the positive coefficient on debt variable suggests that the CDS markets are truly founded on hedging purposes on underlying debt, and that the emerging credit risk exposure is protected by CDS. This is also supported by the finding that the net notional CDS outstanding is negatively related to ratings AA or higher, the coefficient being about 50 % stronger than for the debt outstanding. Moreover, the lost of investment grade rating in the last five years is also heavily related to the net notional CDS outstanding, referring to the overpowering effects of ratings on credit risk assessment. (Oehmke & Zawadowski 2013.)

The impacts of hedging and speculation using CDS rather than bonds should be directly reflected to the liquidity of the reference entity's bonds. The incentive to choose between CDSs and bonds is the cost of the trade and, thus, the liquidity measures should be affected by the choice. To examine the hedging effects, the reference entities that lost investment grade rating are investigated. The lost of investment grade status raises an incentive, sometimes even a requirement, for investors to unload the credit risk exposure and acquire more hedge by purchasing CDS protection, hence, causing the net notional CDS to increase. The effect of downgrade depends on the liquidity of the reference entity's bond, measured in number of bond trades. For high liquidity firms, the increase in net notional CDS reaches 103,6 %, where the downgrade for medium liquidity firms accumulates net CDS by an additional 27,6 % and for low liquidity firms, the downgrade from investment grade is associated with an increase of additional 178 %, respectively. The results show evident importance of the CDS markets as an alternative credit risk trading venue with respect to corporate bonds, driven by the degree of illiquidity in the corporate bond market, and confirm the strong relationship of the number of outstanding bonds and the existence of CDS markets and the amount of net CDS outstanding. (Oehmke & Zawadowski 2013.)

3.2.1. Market regulation and further discussion

In the aftermath of the financial crisis of 2007–2009, discussion about CDS market structure and regulation, and whether they should be regulated and overseen, arose radically. It is very true that the opaque and obscure market structure and lack of regulative action in these bilateral agreements ultimately lead to reducing social welfare. However, CDSs, likewise insurance products, allow for more optimal allocation of risks in the economy, resulting in increased welfare, if and only if, the risks of the CDS seller are minimized properly. Thereby, by "oiling the wheels" and preparing the system to allow some volatility, optimal and economically safe use of CDSs can be achieved. All in all, even during the financial crisis the CDS markets worked well and the OTC agreements themselves did not cause any economically dramatic occasions. (Jarrow 2011; Stulz 2010.)

Some economic improvements to the CDS market structure and regulation are presented and combined by Jarrow (2011). The effects of the regulatory propositions are processed independently and their advantages are evaluated from both economic and social point of view. Since financial institutions are regulated by Basel II –regulations and are under capital requirements imposed by a Value At Risk (VaR) constraint on the equity capital, there are some differences compared to the equity capital computations for insurance companies. First, whereas conventional insurance events are independent and identically distributed (i.i.d.), credit defaults tend to correlate across firms and across time. Second, because of this non-independent quality, the law of large numbers will not apply across periods and, moreover, the realized losses of a large sample of

CDS agreements will differ from the expected losses of such sample, resulting in higher uncertainty and realized losses. Thus, the higher uncertainty should be accounted for CDS sellers in VaR calculations, unlike for insurance sellers. Finally, the default correlation across firms is conditional on the health and state of the economy: during economic boom or expansion, the default correlation is lower, that is, the systematic risk is lower. The correlation between defaults increases as the economy slides into depression. Again, this will essentially lead to more and more complex capital equity calculations for CDS sellers. (Jarrow 2011.)

As pointed out, there are complex restrictions to account for the hidden risks in CDS contracts and consequently, there needs to be alternative solutions to improve and strengthen the CDS sellers risk position and the system comprehensively. One alternative to reduce all counterparty risk to the minimum is the 100 % collateral structure. On one hand, this arrangement would protect against comprehensive market failures and negative externality of systemic risk. Also, it is easy to implement and take into account in calculating capital requirements for protection sellers. On the other hand, the CDS trading activity would be reduced remarkably, as the capital requirements would skyrocket. In spite of the requirement, the trading would not be certainly eliminated: in reinsurance markets, a 100 % collateral is required for the reinsurance trading participants. (Jarrow 2011.)

Moreover, exchange-traded CDSs are presented to increase monitoring of CDS traders. The exchange could monitor the aforementioned collateral requirement as well as the equity capital requirements of the both CDS buyers and sellers. At the same time, lower transaction costs would improve the liquidity of CDS contracts with improved monitoring. Also there would be more transparency in the market transactions; pricing and trading of CDSs. However, the diversity of CDS contracts with different terms and conditions complicates the centralized exchange of CDSs. One possibility is to have standard contracts traded in the exchange, whereas the unique bilateral agreements are traded OTC with 100 % collateral. (Jarrow 2011.)

In addition, close to the current market situation, the role of central clearing parties is proposed to be expanded and developed to cover all of the trades between CDS parties. Presently there are some clearinghouses already clearing CDS trades, but the operations have remained somewhat moderate thus far compared to respective size of the CDS markets. Alternatively, instead of regulating the actual CDS trading process, the central clearing parties could focus on centralized clearing of collateral, which would fortify the protection against the systematic risk and market failures. At the same time, any imbalances and disturbances in collateral would be monitored by a central authority, providing more transparency as well as regulative robustness and protection to CDS markets. (Jarrow 2011.)

3.3. Composition of credit default swaps

A simple way to approach the T-year CDS spread is to observe the yield of T-year bond for the reference entity and subtract the T-year risk free rate (the choice of the adequate proxy for risk-free rate is discussed later in the Data segment). Essentially, the CDS valuation is based on this arbitrage condition and more intuitively, buying an underlying bond and protection for the bond should yield the same net return as risk-free rate. On the other hand, buying a risk-free bond and selling CDS should result to equal cash flows as owning the underlying bond. The relationship between risk-free bond (R_t), defaultable bond (R_t + S) and CDS spread (S) is presented in Figure 4. In the case of default at time t, the settlement of CDS equals 100 − Y(t), where Y(t) is the market value of the underlying note. Thus, the settlement 100 − Y(t) represents the difference between the face value and the market value of the underlying. Again, this residual is the lawful part secured and settled for the protection buyer in the case of default. (Duffie 1999.)

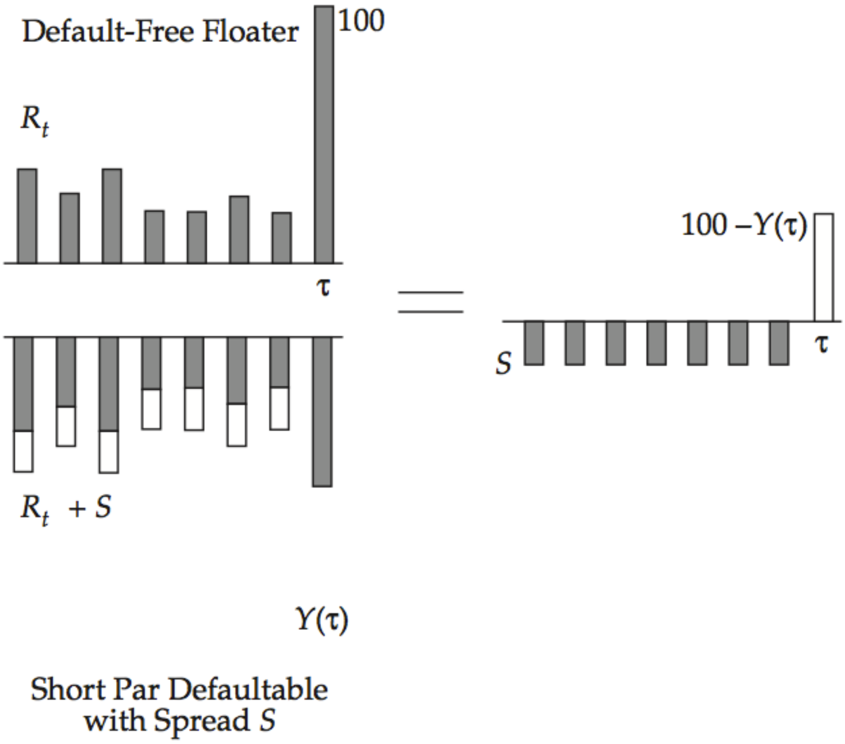

Figure 4. Theoretical cash flows of CDS under arbitrage condition. (Duffie 1999.)

From the expression above, the risk-neutral default probability can be conducted for the reference entity. Furthermore, the present value of the expected loss is a function of the present value of both risk-free bond and defaultable bond, and risk-neutral probability of default. Thus, it can be written that

(7) $$Xpe^{-\mathrm{Rt\,T}} = Xe^{-\mathrm{Rt\,T}} - Xe^{-(\mathrm{Rt}+\mathrm{S})\mathrm{T}}$$

where X = face value of underlying bonds
R_t = yield of risk-free bond
$R_t + S$ = yield of defaultable bond
T = maturity
p = probability of default

On the left-hand side of Equation 7, the present value of the expected loss given the default is presented. The rates are expressed with continuous compounding and the model assumes that there are no recoveries in the default event. On the right-hand side, the present value of the cost of default is expressed, again, using continuous compounding and assuming that the underlying bonds are zero-coupon bonds. (Hull & White 2000.)

For example, suppose that risk-free zero-coupon bond yields 4 % and corresponding zero-coupon defaultable corporate bond yields 6 %, both with a maturity of five years and a face value of 100. Thus, the present value of the cost of default using continuous compounding is

$$100e^{-0,04 \times 5} - 100e^{-0,06 \times 5} = 7,7913$$

And the risk-neutral probability of default is therefore

$$100pe^{-0,04 \times 5} = 7,7913$$

with $p = 0,09516 = 9,52\ \%$.

However, the default probabilities implied in bond prices usually differ from this theoretical approach. One reason is that the recovery rate is typically not zero, that is, the debtors receive some fraction of the face value through the bankruptcy or insolvency procedures. Second, this approach assumes that the bonds are zero-coupon bonds, which is not the usual case in practice. (Hull & White 2000.)

Furthermore, the difference between CDS prices and bond yield spreads over the risk-free rate holds only if the maturities meet and bonds trade at par. As mentioned earlier, the most common CDS contracts have the maturity of five years as from the moment the deal is made, which complicates the examination since the corresponding bond with equal maturity is rarely available (Duffie 1999). In practice, there are a number of elements other than default risk that cause these deviations between CDS spread and bond yield spread, such as liquidity (Longstaff et al. 2005; Huang & Huang 2002), differences in market structure and systematic risk (Elton et al. 2001). Also the choice of risk-free rate can affect this so called basis spread, as discussed in Data segment.

Additionally, the basis spread, that is, the spread between the CDS price and bond yield, is nonlinearly connected to the credit rating class of the underlying company and to the general market conditions, as well. During normal, economically stable times, the basis spread lies around or very close to zero, usually on the positive side, if anything. However, during the financial crisis the basis spread shows significant negative plunges in the time-series pattern, which makes the arbitrage opportunities more convenient than for the positive basis spread. Essentially, investor is required to buy the bond and simultaneously buy protection, i.e., CDS for the underlying bond. Thus, the resulting "risk-free" cash flows equal theoretically to the bond yield minus the CDS price, but in practice, there are several risks that are needed to be accounted for, such as funding risk and counterparty risk. (Bai & Collin-Dufresne 2011.)

The basis spread widened dramatically after the bankruptcy of Lehman Brothers in the fall of 2008, and the arbitrage opportunity became very lucrative, especially with the firms below investment grade rating. The CDS-bond spreads after the Lehman Brother collapsed drop from near zero or slightly positive to negative 250 basis points for investment grade firms and down to 650 basis points for high yield firms, respectively. However, as mentioned, there are several limits to arbitrage included in the case of negative basis trade. First, the counterparty default probability should be revised, since the CDS expires worthless should the seller of the protection default. Ultimately, the counterparty risk is explicitly related to the correlation between default risk of the reference entity and the protection seller, and it should be considered carefully, especially in turbulent market conditions. Second, funding cost risk or funding liquidity risk should be considered in the arbitrage trade risks, unless the investor has very deep pockets. Finally, the quality of the collateral pledged by the borrower can affect the CDS-bond basis arbitrage. The better the collateral quality of the reference entity, the lower the funding costs and, thus, the more profitable the basis trade. (Bai & Collin-Dufresne 2011.)

The cross-sectional analysis implies that all the aforementioned risk factors are significant and mostly of expected sign in explaining CDS-bond basis. Counterparty risk and funding cost risk both have negative sign, whereas the collateral quality has positive sign in the whole sample period spanning from January 2006 to September 2009. Furthermore, the sample is divided into subsamples consisting of investment grade and high yield subsamples and sub-periods before the financial crisis, the crisis period before the bankruptcy of Lehman Brothers, and the crisis after Lehman Brothers collapse. Interestingly, the risk factors experience a notable jump as does the total variation explained by the model: After the Lehman Brothers bankruptcy, the R-squared increases from less than five to around 20 % for high yield firms and around 10 % for investment grade firms, which is remarkably higher than in the crisis period prior to Lehman collapse. Considering the dynamics regarding the basis trading, one can see that the economic contribution of the risk factors is driven by seriousness and depth of the uncertainty and market conditions, and also, by the risk characteristics of the firm, such as credit rating. The behavior of these risk factors between high yield and investment grade is nonlinear and unbalanced, driven by counterparty risk and “flight-to-quality” for investment grade firms, and counterparty and funding risk together with collateral quality for below investment grade firms, respectively. (Bai & Collin-Dufresne 2011.)

Blanco, Brennan and Marsh (2005) study basis spread and CDS price discovery before the financial crisis, using data of both US and European CDS contracts from January 2001 to June 2002. The empirical results are multidimensional and arise many questions. First, the average basis spread seems to be very close to zero or, if anything, positive when using swap rates as a risk-free proxy for interest rate. In turn, the CDS-bond basis turns negative for almost every reference entity when using government bond yields (5-year Treasuries or German government bonds) as a risk-free rate. The finding that during normal market conditions the basis spread is close to zero or slightly positive is consistent with Bai and Collin-Dufresne (2011).

Second, CDS markets lead the bond markets in price discovery of credit risk and changes in credit conditions, providing timely information. Creating an upper bound to credit spread (at least on normal times), the CDS markets contribute around 80 % of price discovery, before the credit risk is priced in bond prices (lower bound of spread). Finally, the lead-lag relationship between the credit risk determinants and CDS prices and credit spreads are examined. Because the CDS prices lead credit spread in how fast the information is incorporated, the credit spreads react much greater to the changes in credit determinants, such as long-term interest rates, slope of the yield curve, equity market returns. Although the magnitude of these macro-variables is much greater for credit spread than for CDS spread, the firm-specific variables, such as implied volatilities and equity returns, act conversely. The results show no statistical nor economical significance to firm-specific determinants and credit spreads, giving some support to structural credit risk models. However, the unequal effects of the credit risk determinants can lead to unequal results in basis spreads, leading ultimately greater to arbitrage opportunities. (Blanco et al. 2005.)

Together with the price discovery element, the dynamic effects of the risk determinants could also lead to converse arbitrage opportunities, as recognized earlier by Bai and Collin-Dufresne (2011). Combining the impact of market conditions and empirical findings of Blanco et al. (2005) on the nonlinear lead-lag effects of risk determinants and CDS spreads could open up more and more negative basis arbitrage opportunities, which are easier to access and, on occasion, more profitable than positive basis arbitrage trades.

4. RELATIONSHIP BETWEEN CREDIT RISK AND CREDIT DEFAULT SWAPS

The literature on the structural approach on CDS spread is rather covered, since the subject is both theoretically appealing and, thus, academically more approved. The effects of solely theoretical determinants of default risk in CDS premia is studied by Ericsson, Jacobs and Oviedo (2009). The linear relationship between actual market CDS spread and leverage, volatility and risk-free interest rate is investigated using both bid and ask quotes of credit default swaps on senior debt in 1999–2002, which was truly booming growth period for CDS markets. Both cross-sectional and time-series dimensions are covered, meaning that the effects can be estimated between companies and also in time for a given company.

The time-series estimation results are strongly in line with the underlying theory, suggesting that equity volatility, leverage and risk-free rate are heavily incorporated in CDS spreads. The coefficients for volatility and leverage are always positive, whereas the coefficient for 10-year government bond has a negative sign, as expected. For lower rated firms, the magnitude of estimation coefficients is two to three times stronger than for higher rated firms, which is consistent with the basic nature of structural credit risk models as they are more vulnerable to changes in fundamental footings. For all the companies, 1 % increase in annualized equity volatility inflates the CDS bid quote by 0,8 basis points and ask quote by 1,5 basis points, but the effect increases to between 1,1 and 2,3 basis points for lower rated companies, respectively. Moreover, the leverage effect acts in the same fashion: a 1 % increase in firm leverage causes the CDS spread to widen between 4,8 and 7,3 basis points, whereas for the lower rated firms experience a 6–10 basis points rupture in CDS premium. Interestingly, the level of risk-free interest rate exhibit a great deal of variation across ratings, the estimation coefficient for lower rated firms being more sensitive to interest rate of long maturity government bond than the higher rated firms. Although, the estimate of risk-free rate is strong, reaching to almost -60 basis points for lower rated firms, it can be overestimated and biased because of the choice of 10-year yield as a risk-free proxy. Regardless, the results show robust evidence that the theoretical structural variables perform sufficiently in explaining CDS premia. (Ericsson et al. 2009.)

The relationship between accounting-based models and CDS spread is rather unexplored because of the inconveniences regarding financial firms, although the financial ratio analysis in widely used and easily applied method. Das, Hanouna and Sarin (2009) use CDS spreads of publicly traded non-financial US firms together with quarterly accounting information. In the analysis, a 10-variable approach is used to estimate the accounting-based credit risk. Only sale growth and income growth variables were found insignificant in the model that used only accounting information. Furthermore, equity market information, such as stock return, volatility and distance-to-default measure obtained from Merton's model, was included in the analysis. All market-based variables were found significant in the model that did not include accounting information, suggesting the rather important role of structural credit risk determinants in explaining CDS spread.

A comprehensive model that combined both the accounting and market information yielded different results from the previous models. The most essential differences between the models were found in volatility and 3-month T-Bill rate. The explanatory powers of the models were 64,30 % for accounting model and 63,45 % for market model, respectively, whereas the comprehensive model yielded adjusted R-squared of 71,40 %. Thus, the results indicate that accounting and market information should be considered as complements rather than substitutes. Even though the accounting variables lose some of their economic significance in explaining the CDS spread in comprehensive model, they still retain their statistical significance. This suggests that there are certain misty, opaque part of credit risk left unexplained when dealing strictly with structural, theoretical approach, and, that with meaningful accounting-based determinants, this curtain of obscurity can be revealed and exposed slightly further (Das et al. 2009.)

Benkert (2004) uses accounting and equity information in the examination of CDS prices. The analysis covers past profitability, leverage and interest coverage and includes ratios of earnings before interest and taxes (EBIT) to net sales, long-term debt to total assets, and EBIT to interest expense. EBIT to net sales and long-term debt to total assets were found significant when including only accounting ratios in the regression. When historical volatility was included in the analysis, the ratios were still significant but lost some effectiveness. Furthermore, introducing implied volatility to the model caused the EBIT to net sales variable to lose significance. The results suggest persistently the importance of the structural credit risk determinants and are similar to the findings of Das et al. (2009). When examining the effects of historical volatility and implied volatility in a comparative manner, the implied volatility seems to have slightly more contribution to the CDS spread than the historical volatility: one percent increase in the former leads to 6,3 % increase in CDS spread, whereas for the latter, the effects is around 4,5 %, respectively. Yet, both the volatility measures are statistically very highly significant and give parallel results, again, suggesting the salience of structural determinants.

Interestingly, including credit ratings to the regression leads to a sign change in profitability (EBIT to net sales) measure, while the other variables retain the correct signs. This finding suggests that the credit ratings capture the matter of profitability ratio more effectively. Also the differences between the credit ratings coefficients are remarkable: when moving from investment grade BBB-rating to non-investment grade BB-rating, the coefficients jump from 0,53 to 8,42 with very high significance. In brief, ceteris paribus, the CDS spreads of BBB-rated (investment grade) or BB-rated (non-investment grade) firms are around 53 % or 842 % higher than the reference group of AA rated firms, respectively. This can be as a result of the investment rules of institutional investors; some investors are prohibited from investing in speculative grade bonds and they are obliged to cut down their holdings in the case of a downgrade. (Benkert 2004.)

Bai and Wu (2012) study the usefulness of firm fundamentals in explaining CDS spreads in addition to market-based or “Mertonian” variables. They form different valuation models to determine, which determinants are the most contributable to CDS prices. The models range from distance-to-default raw valuation (RCDS) and risk-adjusted two-variable Mertonian credit risk valuation including leverage and volatility (MCDS) to model including additional firm fundamentals via a Bayesian shrinkage method together with market-based variables (WCDS). The risk-adjusted market-based valuation model (MCDS) reaches rather high explanatory power of 65 %, suggesting that the Merton model provides generally a good starting point for assessing credit risk and CDS spreads. Furthermore, when firm fundamentals are introduced, the overall explanatory power of WCDS model increases to 77 %, the 12 percentage point difference being highly statistically significant, thus, showing strong contribution of additional firm fundamentals.

Not surprisingly, the WCDS model with multiple firm fundamentals outperforms the MCDS valuation model, but the truly meaningful point of interest is the significance and usefulness of the included variables. To study the cross-sectional contribution of firm characteristics, the residuals from Merton model are mapped with characteristics divided into percentiles. First, the major two financial leverage measures, total liabilities to market cap and total debt to total assets, act as anticipated: higher leverage leads to higher CDS spread, especially within the top percentiles (highest leveraged). On the contrary, interest rate coverage has a negative and more linear correlation with CDS spread, as expected. Second, the most influential liquidity measures appear to be EBIT to total assets and retained earnings to total assets, whereas the working capital to total assets has rather small impact on CDS spread. Both of the significant liquidity measures perform similarly as better profitability reduces CDS spread, exceptionally at the tails. Interestingly, low or negative retained earnings, meaning deprived cashflows from firm's investments and business operations, leads to notably wider spread, highlighting the importance of profitability of firm's initial investments. (Bai & Wu 2012.)

Finally, the contributions of the risk characteristics measured by size (total market cap), momentum and implied volatility to realized volatility (crash risk) are examined. The firm risk characteristics are assessed rather highly in the CDS spreads: large size and positive momentum contribute to lower CDS spread, whereas impact of higher implied volatility is oppositely leading to higher spreads. Time series analysis of the variables supports the presented findings, but since the data ranges from 2003 to 2009, some of the heavily market-related variables, such as momentum and total liabilities to market cap, are affected by the stock market turmoil in 2007–2009. On the other hand, ratios of interest rate coverage, EBIT to total assets, retained earnings to total assets, implied volatility to realized volatility and size appear to be also surprisingly robust in time series analysis, supporting their usefulness in contributing to credit risk. (Bai & Wu 2012.)

Economically and practically, different valuation models can be utilized in forecasting the market movements and creating investment strategies for trading CDSs. Bai and Wu (2012) argue that since the firm fundamental-based (WCDS) model reflects the cross-sectional variation significantly well, the remaining fraction not captured by the model is probably driven by non-fundamental elements, for example supply-demand shocks, and, furthermore, the WCDS valuation model could be used in forecasting the future market movements. The correlations between current WCDS valuation and future market CDS quote at one- and four-week horizons were -7 % and -12 %, whereas for the MCDS valuation the correlations were -6 % and -10 %, respectively. The findings suggest that the market quote of CDS will deteriorate in the future if the fundamental valuation models currently suggest lower spread. This mean reversion of the CDS spreads is statistically significant and has economical and practical contribution as it can be utilized in investment strategies, for example, going long in CDSs under the “fundamental par” and going short in CDSs above the fundamental valuation. Based on the WCDS valuation, the presented hypothetical investment strategy yields over 32 % excess returns with standard deviation of 1,97 % (both annualized) in one-week horizon and extending the investment to four-week period the strategy yields still impressive 20,55 % with standard deviation of 3,81 %, respectively.

The regime dependence of CDS spread determinants is documented by Alexander and Kaeck (2008). They use iTraxx CDS indices ranging from June 2004 to June 2007, which covers the time just before the financial crisis period started in 2007, to investigate the effects of different market-based determinants to CDS spreads in diverse market conditions. Without the regime specification, the linear regression model finds only weak explanatory power for determinants, such as stock market volatility, stock market return and interest rate. Most remarkably, the linear approach suggests that the lagged dependent variable is the most significant determinant in explaining current CDS spread, that is, there is first-order autocorrelation in the CDS indices. The results suggest that the CDS indices may behave differently in dynamic market regimes.

The state-dependency, that is, the dynamic relationship between market conditions and different determinants, is studied by using Markov switching regression. The results state clearly, that the determinants evolve in different regimes. For non-financial firms, the impacts of equity market volatility, equity returns and interest rates intensify significantly when moving from low volatility to high volatility regime, whereas the lagged effect remains approximately unchanged. In low volatility periods, an increase in volatility and a decrease in stock index returns are followed by higher CDS spreads, which is supported by theory. However, during high volatility regime, the effect of equity returns turns insignificant, suggesting that the implied volatility is more deterministic during turbulent and uncertain market conditions than the stock market returns. Moreover, the effect of interest rates on CDS spreads increases from low volatility regime -0,41 basis points to -2,83 basis points in high volatility regime for non-financial firms. Again, the finding is backed by theory, as the increasing interest rates lead to narrower spread. Overall, the effect of all CDS determinants seem to accelerate once the volatility and uncertainty have entered the market, augmenting the structural determinants of credit risk. Finally, the escalation of structural determinants in high volatility regimes leads ultimately to over four times higher hedge ratios for non-financials. This regime dependency of equity risk should be considered carefully when entering or hedging a CDS position. (Alexander & Kaeck 2008.)

Avino and Nneji (2012) study the autocorrelation of European iTraxx CDS index and its structural determinants in different volatility regimes during the period 2005–2010, which covers both the low volatility normal market conditions and the high volatility debt crisis period as well. The structural credit risk model components; equity returns, implied volatilities, risk free rate and slope of yield curve, are tested both linearly and nonlinearly, using Markov switching model for different volatility regimes. Both approaches are first order predictive models, that is, the current CDS spread is predicted by changes in previous day's credit risk determinants. A simple first order autocorrelation test of shows that the CDS spread is not serially correlated for non-financials, but there is some evidence of autocorrelation for financial sector. The lagged linear structural model shows some predictive evidence for equity returns and yield curve for non-financial firms, although all of the coefficients are of the correct sign.

The Markov switching regression provides more viable results for both structural model and simple first order autoregressive model. As discussed before, the CDS spreads and credit risk determinants are depended on the underlying market conditions and their relationship is dynamic and nonlinear in respect to predominant market environment, as shown by Alexander and Kaeck (2008) for example. The results support the aforementioned perception of dynamic relationship, suggesting that when moving from low volatility to high volatility state, the risk determinants rebound from their normal backwater and become economically more and more significant. For example, the low volatility regime estimates for equity return and risk-free interest rate are -18,1 and -4,8, whereas during the high volatility regime, the estimates jump up to -61,3 for the former and -14,5 for the latter, respectively. Interestingly, during the suspenseful high volatility regimes, the autoregressive term does not gain any statistical significance and has a negative sign, which is probably due to the sudden retreat from the CDS positions during the deepest period of the European debt crisis. (Avino & Nneji 2012.)

Furthermore, the predictive information of credit risk determinants and their dynamic nature can be turned into trading rules, should the effect be great enough to be explored by investors. By using the Markov switching structural model, the results show that there are some predictable patterns, at least when compared to simple first order autoregressive model. Then again, the random walk model also generates forecasts that are different from autoregressive model, which arises the question of whether there are exploitable patterns that could be utilized economically. The trading rule involves not CDS trading, but bond trading instead, so that the bond price follows the cited basis spread relationship between CDS spread and bond yield: If the forecasted change in the

CDS spread differs negatively from current spread, then the spread is expected to decrease, causing a decrease in bond yield and, thus, an increase in the price of the bond. However, the trading rule concludes to have no economic significance in terms of (risk-adjusted) returns nor applicability. (Avino & Nneji 2012.)

Empirical literature on the anatomy of credit risk determinants and CDS spread during the financial crisis of 2007–2009 is somewhat scarce. The firm-level fundamental variables of stock price, volatility, leverage, size and profitability all tend to strengthen in the period of financial crisis. Size of total assets is negatively associated to CDS spreads in the normal economic conditions but has a positive sign in the crisis period. Financial firms are included in the analysis of CDS spreads in different regimes, which can bias the results. When comparing CDS spread determinants between investment grade and speculative grade firms, the most remarkable differences occur in volatility, leverage and size variables. The estimates for volatility and leverage are much greater for investment grade firms than non-investment grade. Again, the sign of profitability estimate is changed when moving from investment grade to non-investment grade, which confirms that profitability is captured more efficiently by credit rating. Also the size estimate turns sign correspondingly from positive to negative when crossing the rating threshold. (Tang & Yan 2012.)

In contrast to US financial crisis, the CDS spread determinants during the European debt crisis in 2007–2009 differ from previously presented findings. Again, the size estimate changes sign in different regimes, being negative during low volatility regime and, conversely, turning to positive in the time high uncertainty. The significant accounting variables, which are retained earnings to total assets, total liabilities to equity, and interest rate coverage, hold their expected sign and significance in both crisis and pre-crisis periods with minor alterations. The most significant and effective estimate is annualized equity volatility variable, but in contrast to previous findings the impact decreases in the crisis period. On the other hand, investors seem to appreciate liquidity during the turbulent market conditions, whereas liquidity turns out statistically insignificant during pre-crisis period. Similarly, price to cash flow (P/CF) ratio, which is a valuation ratio that is more invulnerable to accounting rules, gains statistical significance in the crisis period, although the economical contribution remains rather modest. (Trujillo-Ponce, Samaniego-Medina & Cardone-Riportella 2012.)

Interestingly, the explanatory power of the model increases considerably in the crisis period with R-squared of 77,41 % (63,16 %) in the crisis (pre-crisis) period. This finding may result from increasing sensitivity of CDS spreads during the periods of high uncertainty. Also, the flatness of CDS spreads before the crisis period may result to lower explanatory power of the credit risk variables. However, the findings provide robust support to the aforementioned nonlinear dynamics of the credit risk and exogenous (market) conditions as well as to the contribution and feasibility of credit risk determinants, structural or accounting-based. Again, the results suggest that the accounting and market models should not be considered as substitutes but as complements. (Trujillo-Ponce et al. 2012.)

Subrahmanyam, Tang and Wang (2012) examine the reverse connection between credit risk, firm characteristics and credit default swaps, and whether the introduction of CDS lead to ultimately higher credit risk. The main incentives to increased credit risk lie in the monitoring hypothesis: once the CDS have been introduced, the creditors may neglect monitoring of the reference firm, since their positions are hedged. Thus, the underlying firm could accept and take on riskier and riskier projects, eventually ending up with increased higher credit risk. Also, since the debt can be protected with CDS, the debtors may expand the supply of credit beyond normally acceptable threshold, making borrowers more vulnerable.

Indeed, several findings arise when examining this reverse relationship between CDS inception and credit risk. First, the probability of bankruptcy increases with the quantity of live CDS contracts outstanding. Hence, the CDS works as a cycle increasing the risk of default and, at the same time, protecting from the default. The effect works also adversely: credit risk decreases as the number of CDS traded is reduced. Second, leverage of the underlying firm seem to increase once the CDS trading begins, supporting the idea of expansion in the supply of credit on the side of debtor. (Subrahmanyam et al. 2012.)

The results suggest that large firms, measured in market value of equity, and firms with high past stock returns have smaller probability of getting downgraded or going default, whereas the leverage and equity volatility affect conversely. Moreover, when controlling for firms with CDS and non-CDS firms, the evidence of the effect on credit risk is rather mixed: In general, CDS firms have an increased likelihood of getting downgraded but decreased probability of bankruptcy compared to non-CDS firms. Once the CDS trading launches, both the chance of downgrade and default increase, implying that the appearance of credit events is more likely after the trading begins: the odds for downgrade are twice as high and for bankruptcy even 10 times as high as they are for non-CDS firms. (Subrahmanyam et al. 2012.)

Additionally, the reverse relationship between credit risk and CDSs is studied by Peristiani and Savino (2011) by regressing both structural and accounting-based credit risk determinants on distance-to-default measure of non-financial CDS firms. The data spans from 2001–2008, covering the economic downturn of the dot-com collapse in 2001 and the very beginning of the financial crisis of 2007–2009. The results are intriguingly similar to results of Subrahmanyam et al. (2012) presented above, suggesting that during 2004–2008 the CDS firms experienced a remarkable increase in default measured in structural distance-to-default. Exceptionally, year 2008 shows significant increasing effect in default risk (declining distance-to-default) as well as in bankruptcy odds ratio with actual bankruptcies. Furthermore, by studying the relationship between distance-to-default and CDS, the results imply that the main contributors to lower distance-to-default are, unsurprisingly, stock return and volatility as well as market capitalization. Leverage ratio total debt to total assets together with profitability ratio EBITDA to total assets gained also significance in explaining the distance-to-default, leverage being the most dominant. Interestingly, the closing gap of distance-to-default between CDS and non-CDS firms in 2007–2008 does not occur in actual bankruptcy rates in corresponding period: of the 2677 non-CDS firms only 1,23 % went under in 2008, whereas of the 527 CDS firms 3,42 % filed for bankruptcy, respectively. The 2,57 times larger bankruptcy odds for CDS firms present undisputed evidence of the depth of the financial crisis of 2007–2009, particularly for the CDS markets.

On the trading point of view, the probability of CDS trading is positively connected to size of the firm (measured in total assets), leverage, volatility and certain accounting-based variables, such as EBIT to total assets, working capital to total assets, and cash to total assets. Interestingly, profitability ratio return on assets (ROA) does not appear to be significant. In short, firms with generally good credit quality are more prone to have CDS trading. Furthermore, the difference in CDS trading between rated and unrated firms is rather wide, suggesting that firms rated by credit rating agency are more likely to have increased CDS trading than the unrated firms and, moreover, if the given rating is above the investment grade threshold, the CDS trading accelerates remarkably. (Peristiani & Savino 2011.)

5. DATA AND METHODOLOGY

In this chapter the data and the methodology are presented. First section is focused on describing the data and its source, range and format. Later, the econometric models are introduced. Generally, the data spans from December 2007 to the end of 2012 including CDS prices for 207 non-financial US firms listed in the S&P 500 index. Data for CDS prices, accounting and financial ratios, and risk-free rate is collected from Datastream (Thomson Reuters) with the assistance of the department of Accounting and Finance at the University of Vaasa. With more than five years of daily quotes including various sectors, the goal is for the results to be fairly adaptable and general to the CDS prices of most non-financial firms.

5.1. CDS prices

The CDS data consists of the daily CDS price quotes of 207 U.S. non-financial firms presented in Appendix 1. The quotes are mid prices at close of each day and the prices are denoted in basis points (bp), 100 basis points being equal to one percent. As suggested in previous studies, the data is limited to the most traded contract type, that is, single-name five-year contract on unsecured senior debt. Thus, the CDS prices should reflect the effects of explanatory variables in a similar fashion. Another notable matter is the equal maturities of the CDS contracts, which allows the comparison of the results without any adjustments. The CDS prices acquired from the Datastream database are readily quoted in the form of spreads, so no adjustment is required for the quotes.

5.2. Risk-free rate

Rate of the five-year U.S. Treasury note is used as proxy for risk-free rate. The yield is obtained from Datastream and represents daily closing price. The use of Treasury curve as a benchmark riskless curve is motivated by most of empirical tests in finance. A government bond has theoretically no fundamental credit risk, and hence its yield should be equal to the risk-free interest rate. Also, the effects of the changes in risk-free rate to the CDS spreads are estimated in the empirical analysis. Moreover, five-year Treasury curve is easy to match accurately with five-year CDS contracts.

Although the Treasury rate is the most obvious choice, swap rates are also used to proxy the risk-free interest rate (Blanco, Brennan & Marsh 2005). Hull, Predescu and White (2004) argue that the market uses the rate that is 10 basis points less than the swap rate as a benchmark risk-free rate. They point out that swap rates are very low risk (not entirely risk-free), liquid rates and that they are not under any special taxation unlike Treasury bonds. Longstaff et al. (2005) use different benchmark risk-free rates and find that swap rates can overestimate the size credit component as they account for both credit and default components. On the one hand, Treasury rates may be affected by taxation treatment, benchmark status and liquidity, whereas on the other hand, swap rates are not riskless since they include default and counterparty risk components. (Blanco et al. 2005).

However, for the purposes of this thesis, the five-year U.S. government Treasury rate is chosen for benchmark risk-free rate. The aim is to acquire evidence for the effects of the risk-free rate on CDS spreads and credit risk, not the vanishingly small differences in the dynamics of different risk-free proxies, and therefore, the Treasury rate serves the intentions of the credit risk analysis meaningfully. Furthermore, since the analysis is based on quarterly frequency, the quarterly rates are obtained from the initial daily dataset.

5.3. Accounting information

From the substantial set of accounting variables available, the most relevant and quoted ratios are included in the analysis. The selected variables should cover the three dimensions of firm’s health: liquidity, profitability and solidity. In Altman’s (1968) original Z-score, all the dimensions are covered but the extensive analysis can fall short. The ZETA model extends the variables including interest rate coverage, size and capitalization (Altman et al. 1977).

Furthermore, considering the empirical findings of Benkert (2004), Das et al. (2009) and Trujillo-Ponce et al. (2012) about the combination of relevant accounting ratios, equity market information and credit default swap spreads, the following variables are chosen: Return on assets, retained earnings to total assets, interest coverage, current ratio, total debt to total assets, total debt to common equity, working capital to total assets, and size of total assets. Accounting information is acquired from interim statements, i.e., quarterly financial statements in 2007Q4–2012Q4, which leads to total of 21 quarterly observations of each variable for each firm.

5.4. Equity market information

Both equity return and volatility of equity return are obtained from stock market data and they represent the market-model variables in the empirical part. These are the two most important firm-level fundamental market variables along with the leverage (default threshold) according to the structural model of Merton (1974), and thus they are included in the analysis. The equity market performance variables, earnings per share and dividends per share, are also included in the analysis and they represent firm-specific performance ratios similarly to accounting-based variables.

The stock market information of the included firms consists of daily observations of adjusted closing prices for each of the firms. Again, because of the quarterly nature of the interim data, the stock market data is transformed into quarterly returns instead of daily returns. Thus, the returns represent the past quarterly stock performance for the firm, prior to the end of the quarter. However, the volatility measures are presented in annualized form, which is a typical and more informative way of presenting the effects of volatility. The effects of volatility are assessed in a similar fashion to the aforementioned stock return effects.

5.5. Methodology

In the empirical approach, the panel data features of the dataset are exploited, which leads to a sufficient number of observations for each quarter. Moreover, panel data allows controlling for unobservable variation among the sample firms, which should ultimately lead to more reliable and robust estimation results. The ordinary least squares panel regression can be written as follows:

(8) $$y_{it} = \alpha + \beta x_{it} + u_{it}$$

with time series from 1 to T and cross sections from 1 to N. In Equation 8, i subscripts the cross section, whereas t subscripts the time period. Thus, the respective number of $N \times T$ observations is estimated using panel regression. Accordingly, the presented dataset leads to total of $207 \times 21 = 4347$ observations for a single variable. However, due to some missing data points regarding some of the variables, the eventual sample size can vary slightly. Naturally, the number of observations is included in the estimation outputs.

For each firm and quarter a least squares panel regression is estimated to test the first hypothesis, that is, the effects of accounting ratios to the CDS spread. As a dependent variable the natural logarithm of CDS spread is estimated by the accounting variables presented earlier in the data section. The results are compared to the expected signs and evaluated for further estimations. Thus, the most significant accounting variables contributing to CDS spread are chosen into the comprehensive model that includes both accounting and equity market variables. Hence, a comparison between different models can be estimated from the adjusted R-squared, which accounts for the number of variables included. Also, the statistical and economic significance of the variables are considered regarding the comprehensive model. This approach yields three different models: only accounting information, only market information, and comprehensive model.

For accounting based model, the estimation yields the following equation:

$$\text{(9)} \qquad \log(CDS_{it}) = \beta_0 + \beta_1 ROA_{it} + \beta_2 RE/TA_{it} + \beta_3 COV_{it} + \beta_4 CR_{it} + \beta_5 TL/TA_{it} + \beta_6 TL/CE_{it} + \beta_7 \log(TA)_{it} + \beta_8 WC/TA_{it} + \varepsilon_{it}$$

Equation 9 presents the model for accounting-based determinants of CDS spread. Expected signs of the variables are presented earlier in the hypothesis section. Next, the market-based variables are estimated separately as follows:

$$\text{(10)} \qquad \log(CDS_{it}) = \beta_0 + \beta_1 RET_{it} + \beta_2 VOL_{it} + \beta_3 LEV_{it} + \beta_4 EPS_{it} + \beta_5 DPS_{it} + \beta_6 RF_t + \varepsilon_{it}$$

where RET_{it} and VOL_{it} are market-based variables for historical stock return and volatility, EPS_{it} denotes earnings per share, and DPS_{it} denotes dividends per share for firm i and time t, respectively, and RF_t is five-year U.S. Treasury rate.

To account for time-series trend in CDS spreads, both Equation 9 and Equation 10 are adjusted for quarterly development in spreads. As discussed earlier, the connection of high volatility regimes and CDS spreads is dynamic, and as two utterly opposite economic regimes are distinguished in the dataset, this needs to be accounted for. The reference point of time for the adjustment is 2008Q4, which is the highest point of credit risk in the sample and, as well the folding point of the financial crisis period in terms of credit risk. Thus, the distinction between two time periods and economic conditions can be observed in CDS spreads, as suggested in theoretical framework section. The time-series trend variable has also quadratic version that captures the nonlinear development of credit risk.

Furthermore, to test the impact of adding market-based information in explaining credit spread, i.e., creating a comprehensive model, Equation 11 is constructed as follows:

$$(11) \qquad \log(CDS_{it}) = \beta_0 + \beta_1 ROA_{it} + \beta_2 RE/TA_{it} + \beta_3 \log(TA)_{it} + \beta_4 RET_{it} + \beta_5 VOL_{it} + \beta_6 LEV_{it} + \varepsilon_{it}$$

To test the hypothesis 3, the observations are simply divided into to sections by the time regime. Again, a least squares regression is applied to estimate whether the significance and magnitude of explanatory variables are unequal in different economic regimes. To examine the effect of financial crisis on CDS spreads, the advantageous composition of panel data is exploited and the sample period is divided into sub-periods according to the economic conditions. The first sub-period spans from December 2007 to June 2009, and thus represents the period of financial crisis. The second sub-period, covering the time period from July 2009 to the end of 2012, represents the time of recovery and expansion, as per the National Bureau of Economic Research (NBER 2010). Hence, it follows:

$$(12) \qquad \log(CDS_{it}) = \beta_0 + \beta_1 ROA_{it} + \beta_2 RE/TA_{it} + \beta_3 \log(TA)_{it} + \beta_4 RET_{it} + \beta_5 VOL_{it} + \beta_6 LEV_{it} + \varepsilon_{it}$$

Dividing the sample period to sub-periods allows examining the impact of financial crisis on CDS spreads on a general level, as the dataset is strictly twofold in nature: The first period from December 2007 to June 2009 represents the financial crisis and the second period from June 2009 to end 2012 represents the healthy expansion period as a reference period, as suggested by National Bureau of Economic Research (2010). Thus, for crisis period t = 2007Q4, 2008Q1 … 2009Q2, and for recovery period t = 2009Q3, 2009Q4 … 2012Q4 respectively, for every firm i.

Finally, to account for the possible unobserved elements and heterogeneity among sample firms, the panel feature of the data is used to perform cross-section fixed-effects regression. Thus, controlling for unobserved or omitted variables among firms by employing firm fixed-effects regression (together with aforementioned time-series adjustment), the results should supposedly robustify from the initial estimation results. Furthermore, the fixed-effects panel estimation offers many important attributes, such as the contribution of the independent variable on the explained variable and the impact it incurs as it changes. The cross-section fixed-effects regression can be written as follows:

$$(13) \qquad y_{it} = \alpha + \beta x_{it} + [\gamma z_i + u_{it}]$$

where z_i is the unobserved, constant variable for firm i. Incorporating this exclusive constant term into the constant term α for every firm, then the new constant term can be written as $\alpha_i = \alpha + \gamma z_i$. Replacing the unobservable term z_i by α_i and incorporating the composed term into Equation 13, it can be written as follows:

$$(14) \qquad y_{it} = \alpha_i + \beta x_{it} + u_{it}$$

where α_i is the exclusive constant for each firm, cross section fixed effect.

Again, the aforementioned adjustments will contribute to the underlying model and the underlying theory of variables in a practical manner rather than fine distillery between proxies, such as between Treasury rate or swap rate. Thus, the model accounts for overall significance of a given variable in broader perspective, calibrating and specifying it to the effects of credit risk in general level, making it more practical and robust to fine modeling preferences. Certainly, the important credit risk variables show significance in both individual and aggregate level, should the variable have relevance, reliability and validity.

5.5.1. Quantile regression

To examine the asymmetric credit risk distribution and risk dynamics, quantile regression is employed. In general, this approach examines the impacts of given conditioning variables on the quantiles of the dependent variable, providing estimates of linear relationship between explanatory variables and a chosen quantile of the CDS spread. Hence, the unbalanced effects of credit risk determinants on CDS spread can be detected and statistically tested, should there exist asymmetry.

The most attractive attribute of quantile regression is that it makes no assumption regarding the error term normality, and thus there are no strict distributional requirements and assumptions. Obviously, this property offers considerable model robustness compared to the OLS regression and its assumptions of normality. Therefore, quantile regression offers a unique approach to study the credit risk asymmetry as well as unbalanced and dissimilar effects of credit risk determinants on CDS spread. Furthermore, this approach is combined to the periodic distinction between crisis and post-crisis periods for deeper examination of asymmetric behavior of credit risk.

6. EMPIRICAL ANALYSIS AND RESULTS

In this section, the descriptive statistics of CDS data and both the accounting and market-based variables are introduced. Moreover, the estimation results based on the aforementioned estimation methods are presented and analyzed later in the section.

This section will start by presenting the development of CDS spread during the sample period, followed by analysis of the behavior of the general credit risk in the time of crisis as well as post-crisis. This approach will allow for more comprehensive analysis for the estimation results and possible differences in results during crisis period and post-crisis. By recognizing the dynamics of credit risk progression in the sample period, the differences can be examined in a more profound manner and possibly connected to (or distinguished from) the findings of previous literature on CDS spreads.

6.1. CDS spread development

In this section, the descriptive statistics of the data are presented and analyzed before the actual estimation analysis. This approach helps to perceive the behavior of the CDS spreads and credit risk during different states of economy. When the data is described and narrated adequately before the deeper analyses, the reasons and causes behind the credit dynamics are more easily approached and comprehended.

First, the evolution of credit risk is presented in terms of CDS spread description starting from rampaging financial crisis and finishing to recovering end of 2012. Figures 5 and 6 present the CDS spread development, providing both mean and median values for the dataset.

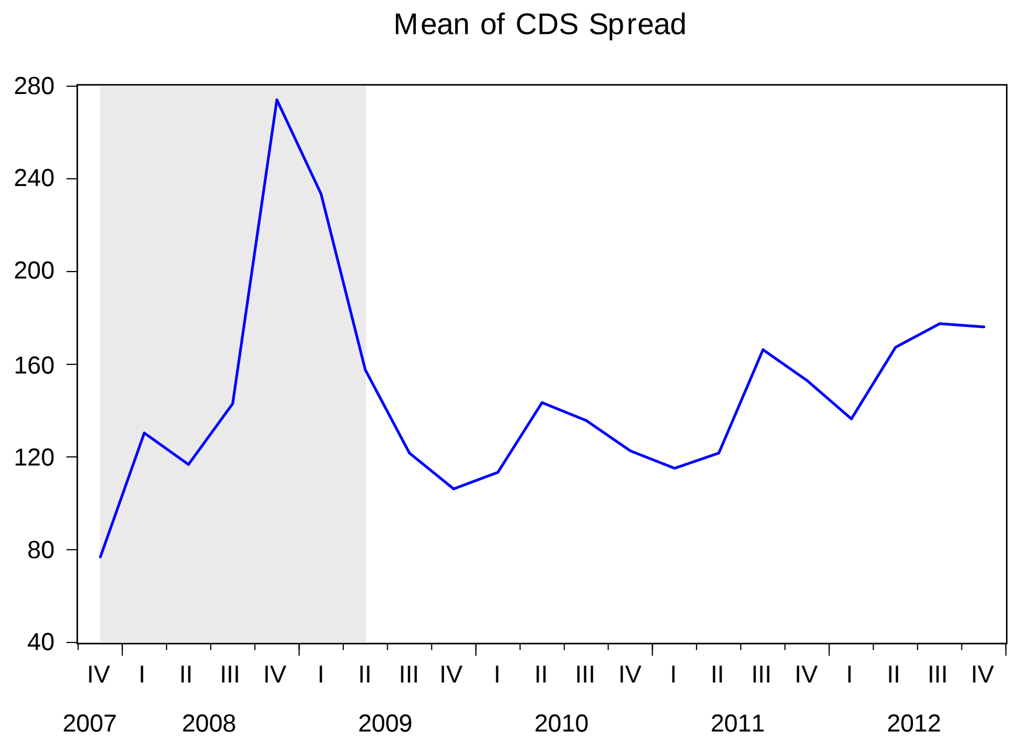

Figure 5. Mean of CDS spreads in 2007Q4–2012Q4 (in bps).

Mean of CDS spread over the risk-free rate during 2007Q4–2012Q4 is presented in Figure 5. The shaded area marks the period of financial crisis for easier distinction between different economic regimes within the sample period. As Figure 5 evidently shows, the general level of credit risk rises sky-high during the financial crisis starting from 76,88 basis points at the end of 2007 and winding up at sample-high 274,13 basis points in the last quarter of 2008. Since the turn of the year 2008–2009, optimistic atmosphere and signs of recovery started to show up little by little, leading to remarkable continuous decline in CDS spreads. Although, at the end of the crisis period, the average CDS spread was still 157,59 basis points, over twice as high as at the end of 2007, suggesting that the recovery had indeed started, but not quite finished. The remainder of the sample period suggests the same: On average, the CDS spreads have been increasing and the 100 basis points threshold have not been broken thus far.

Obviously, the financial crisis of 2007–2009 hit the credit risk markets particularly hard, even for non-financial firms. The unraveling opacity in the CDS positions together with the transpiring of the crosswise and uncovered holdings ultimately lead to higher systematic risk in CDS markets and, hence, caused the spreads to widen to the extreme. Furthermore, the credit risk markets have encountered smaller scale shocks as the effects of the European debt crisis in late 2009 and the U.S. government debt limit crisis in mid-2011 shook the markets, although not as severely as the initial financial crisis.

As presented in Figure 6 below, the median CDS spread behaves in the same way and form as the mean CDS spread above. Though, the median spread seems to be significantly lower than the corresponding mean spread, suggesting that the mean is affected by some extreme (high) values. Certainly, there appears radical stretching in the median spread as well, starting from 45,48 basis points of fourth quarter of 2007 and finishing at 157 basis points at the end of 2008. However, as discussed above, the spreads of the upper 75 % quantile spikes significantly, reaching 340 basis points at year-end 2008, whereas the corresponding lower 25 % quantile tops at 105 basis points. This asymmetric behavior drags the mean spread to higher levels, while the median spread tends to stay on moderate levels.

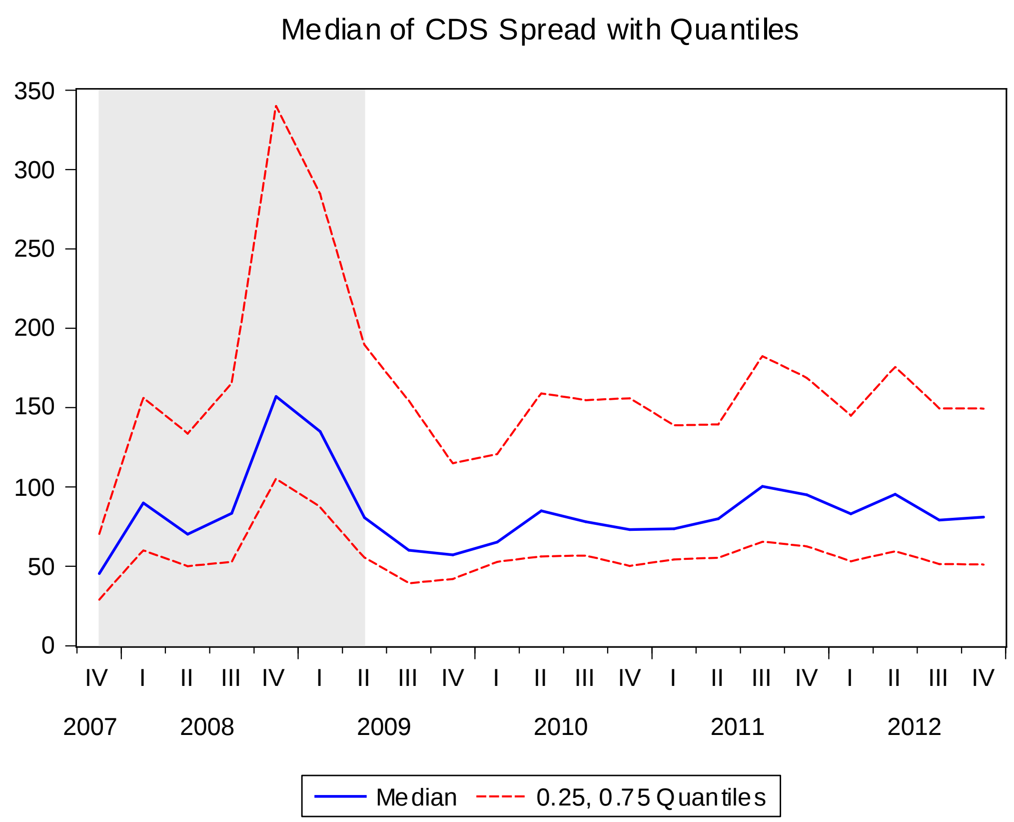

Figure 6. Median of CDS spreads with lower 25 % and upper 75 % quantiles in 2007Q4–2012Q4 (in bps).

As discussed above, the credit risk asymmetry and the persistent uncertainty that had entered the economy and markets will widen the spreads in general, hence, causing broader deviation within the CDS spreads of the sample. In the same manner, as there are more investment-grade rated companies than speculative-grade rated companies, there are also quantitatively more companies in the lower side of average credit risk, according to the sample. Once the uncertainty and volatility enter the economy and credit risk markets, the lower rated companies react almost as explosive to the economic turbulence. The asymmetric risk distribution leads to extreme reactions in the upper tail, as discussed in the previous literature section. During lower volatility periods, that is, between crises, the asymmetry between higher quantile firms and median firms seems to settle and become more or less stationary.

The fluctuated CDS spread, especially for riskier firms, can be as a consequence of many factors, such as initial credit risk increase of the underlying, speculative aspects of CDS, hence, leading into a short-squeeze situation (note that one advantage of choosing CDS over the bond is the viability and ease of stepping into a short position on credit risk), or squeeze as a consequence of (negative basis) arbitrage trading as discussed earlier. Also, the actualization of the systematic risk, particularly after the Lehman Brothers collapse widened the CDS spreads indisputably.

6.2. Descriptive statistics

Descriptive statistics for explanatory variables are presented in Tables 4 and 5. The summary statistics for raw interim variables together with CDS spread statistics are shown in Appendix 2. These numbers form the basis for further calculations of accounting-based financial ratios utilized in the analysis. The descriptive statistics for accounting ratios for the whole sample period of 2007–2012 are presented in Table 4. A quick comparison between descriptive statistics presented below and those of Das et al. (2009), suggests similarities in the size of total assets (TA) and median of interest coverage (COV). The mean and median CDS spread shows notable alteration with mean of 147,71 and median of 83,71 basis points being almost twice as high as from the mean 87,95 and median 48,50 reported by Das et al. (2009) between 2001–2005, respectively. The obvious reason for higher CDS spreads is the severe credit risk jump during the financial crisis of 2007–2009, as shown previously.

Also the liabilities to asset (TL/TA) and retained earnings to asset (RE/TA) ratios show differences between the two samples with mean (median) of 0,28 (0,27) and 0,31 (0,31) of this thesis, and 0,67 (0,67) and 0,18 (0,19) of Das et al. (2009), respectively. As can be noted from Table 4, some variables attain extreme or unreasonable values, such as maximum of interest coverage 7760,58 or minimum of total liabilities to common equity ratio (TL/CE) -3,47. These variables are unbalanced by nature and thus they can show extremely high (or low) for example, if the numerator varies around zero and attains extremely small positive or negative values.

Table 4. Descriptive statistics for accounting-based ratios.

	ACCOUNTING RATIOS						
	RE/TA	TL/TA	TL/CE	COV	WC/TA	CR	ROA
Mean	0,3141	0,2771	0,8922	17,5334	0,1145	1,6143	0,0634
Median	0,3077	0,2656	0,6851	6,5035	0,0821	1,4000	0,0659
Maximum	2,0619	1,2491	9,9955	7760,5810	0,7918	16,4000	0,3834
Minimum	-1,8508	0,0000	-3,4676	-1291,9440	-0,4782	0,0000	-0,7223
Std. Dev.	0,3705	0,1349	0,8063	154,4895	0,1479	0,9181	0,0711
Skewness	-0,7632	0,5625	2,7067	35,6592	1,2386	4,0403	-2,4367
Kurtosis	10,2992	3,9270	16,9805	1638,5770	6,3739	41,6334	19,8611
Observations	4076	4112	4026	4091	4090	4113	4087

Descriptive statistics for market-based variables are presented in Table 5. As can be seen from the table, the mean stock returns are slightly negative for the sample period as consequence of the radical stock price deteriorations during the financial crisis. On the other hand, the median quarterly stock return is notably higher, reaching 1,30 %. Again, compared to the statistics of Das et al. (2009), the only common market variable, annualized volatility, suggests more radical equity price movements for the sample period of this thesis than to the period of 2001–2005. Mean volatility 17,28 % is lower than 28 % of Das et al. (2009), but the maximum of volatility of the sample reaches high, up to 88,16 %. Again, the aforementioned unbalanced nature of variable can be seen from the extreme values of earnings per share (EPS).

Table 5. Descriptive statistics for market-based variables. Equity return (RET) is expressed as quarterly return, volatility (VOL) is expressed as annualized volatility from daily returns of past quarter and leverage (LEV) as risky leverage based on market values of equity and risky assets.

MARKET INFORMATION					
	RET	VOL	LEV	EPS	DPS
Mean	-0,0023	0,1728	0,4409	0,5774	0,2251
Median	0,0130	0,1463	0,4335	0,5800	0,1880
Maximum	1,2540	0,8816	0,9363	22,0700	1,5000
Minimum	-1,5740	0,0000	0,0435	-20,6500	0,0000
Std. Dev.	0,1958	0,1086	0,1714	1,3316	0,1940
Skewness	-0,8046	1,8553	0,2159	-4,3439	0,9880
Kurtosis	8,5702	8,5371	2,3152	84,5040	3,9507
Observations	4334	4334	4172	4200	4133

Interestingly, the risky leverage ratio provided with market information sets on average somewhat higher than the book leverage ratio total liabilities to total asset (TL/TA). The difference between the explanatory power and significance of the two leverage measures in terms of credit risk is truly one of the most interesting aspects of the following analysis.

6.3. CDS spreads and accounting information

The results of the relationship between selected accounting-based variables and CDS spread in 2007–2012 are presented in Table 6. The model follows Equation 9 presented earlier in the methodology section. Column 1 of Table 6 presents the estimation results without controlling for cross-sectional variation or time-series trend, whereas Column 2 controls for cross-sectional fixed-effects and Column 3 for trend in the time series together with firm fixed-effects.

Table 6. Log of CDS regressed with accounting-based variables in 2007–2012.

ACCOUNTING-BASED VARIABLES 2007–2012			
	[1]	[2]	[3]
CONSTANT	7,4905*** (0,2565)	3,7797*** (0,7099)	3,4939*** (0,7694)
ROA	-0,0275*** (0,0021)	-0,0102*** (0,0016)	-0,0096*** (0,0016)
RE/TA	-0,3555*** (0,0410)	0,3228*** (0,0892)	0,3351*** (0,0892)
COV	0,0001 (0,0001)	0,0000 (0,0000)	0,0000 (0,00005)
CR	-0,0242 (0,0287)	0,0123 (0,0307)	0,0066 (0,0307)
TL/TA	0,6213*** (0,1666)	1,0075*** (0,2202)	1,0096*** (0,2198)
TL/CE	0,0243 (0,0235)	0,0257 (0,0204)	0,0278 (0,0203)
log(TA)	-0,1681*** (0,0145)	0,0293 (0,0426)	0,0453 (0,0463)
WC/TA	0,0520 (0,1722)	-0,4928* (0,2547)	-0,6016** (0,2566)
TREND(2008:4)			0,0167*** (0,0047)
TREND(2008:4)^2			-0,0010*** (0,0002)
Adj. R-squared	0,1805	0,7395	0,7411
N	3469	3469	3469

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

Unsurprisingly, all the estimation results in Column 1 are of expected sign. However, Columns 2 and 3 show contrary results for retained earnings to total asset (RE/TA), current ratio (CR) and total assets (TA), arguing against the hypothesis and expected signs. Similarly to previous results of Benkert (2004) and Trujillo-Ponce et al. (2012), the explanatory power of the model measured by adjusted R-squared increases when the fixed-effects are employed. After employing cross-section fixed-effects, leverage measure (TL/TA) gains heavily economic significance together with liquidity ratio working capital to total asset (WC/TA). Additionally, profitability return on asset (ROA) remains statistically significant and economically almost equally important as leverage (ROA has not been scaled, therefore it needs to be multiplied by 100).

Both the trend variables accounting for nonlinear time-series trend within the sample are statistically significant, suggesting lower general credit risk level in the quarters prior to 2008Q4 and marginal deterioration post-crisis. Working capital to total asset ratio (WC/TA) seems to gain importance and statistical significance, while other variables remain mainly the same as in Column 2, when controlling for time-series trend.

Again, compared to the results of Das et al. (2009) and Trujillo-Ponce et al. (2012), the results show differences in magnitude, which depends mostly on the selection and combination of modeled variables. However, the results find support from the results of previous studies regarding the significant accounting-based credit risk determinants.

Table 7 reports the results of accounting-based credit model during the two sub-periods; the financial crisis of 2007Q4–2009Q2 in the first column and recovery period 2009Q3–2012Q4 in the second column. Various observations regarding the credit dynamics can be made. First, the difference in the magnitude of return on asset (ROA) between -3,69 % in the crisis period and -0,38 % in the post-crisis suggest remarkable importance of fundamental profitability during economic uncertainty. Second, the impact of leverage (TL/TA) is almost twice as large in the crisis period than post-crisis, which again highlights the importance of leverage and fundamental cornerstones of firm health triangle. Interestingly, the size variable (TA) is positive and statistically significant for both sub-periods. Also, similar to results discussed above, retained earnings to total asset (RE/TA) remains highly significant and opposite to the expected sign during the crisis period. Finally, the effect of liquidity (WC/TA) seems to be important only in the latter, recovery sub-period. The magnitude of the variable (-0,75 %) is also greater post-crisis than in the initial sample (-0,60 %) with higher statistical significance. The greater importance of the liquidity proxy during healthy economical regime could be explained by different allocation of interest, as the aforementioned profitability and leverage or solidity are more essential and, thus, under strict surveillance, during high uncertainty, while liquidity can be seen as a more of a fine-tuning or performance measure of short-term liabilities and cash management.

Table 7. Log of CDS spread regressed by accounting variables in two time periods.

ACCOUNTING-BASED VARIABLES BY PERIODS		
	2007Q4–2009Q2	2009Q3–2012Q4
CONSTANT	-6,0287**	1,0843
	(2,4877)	(0,8896)
ROA	-0,0369***	-0,0038**
	(0,0044)	(0,0017)
RE/TA	1,8862***	0,0693
	(0,2823)	(0,1115)
COV	0,0001	0,0001
	(0,0001)	(0,0001)
CR	0,0745	0,0230
	(0,0612)	(0,0323)
TL/TA	1,4224***	0,5746***
	(0,5380)	(0,2230)
TL/CE	0,1165**	0,0099
	(0,0512)	(0,0214)
log(TA)	0,5844***	0,2008***
	(0,1500)	(0,0532)
WC/TA	0,0912	-0,7515***
	(0,5393)	(0,2812)
Adj. R-squared	0,7480	0,8300
N	1088	2381

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

A comparison to the results of Tang and Yan (2012) and Trujillo-Ponce et al. (2012) reveals similarities in the behavior of accounting-based variables between crisis and normal periods. Both of the studies support the finding that size of the firm becomes more and more a burden, widening the CDS spread, during the crisis period. Contrary to their findings that size has a negative effect on CDS spread (prior to crisis), the findings in Table 7 find that even after the crisis, larger firms tend to have larger spreads. Furthermore, there are similar observations of the strengthening relationship between profitability (ROA) and CDS spreads between different economic regimes. Additionally, the increasing effect of leverage is reportedly similar than to those of previous studies.

On the other hand, there are distinguishable findings regarding the effect of liquidity and WC/TA ratio. Both Tang and Yan (2012) and Trujillo-Ponce et al. (2012) report increased importance of liquidity and cash ratio during crisis period. Indeed, current ratio (CR) does gain economic magnitude during the crisis period (0,0745) compared to post-crisis sub-period (0,0230), but it does not show statistical significance.

6.4. Market-based variables

The relationship between market-based structural variables and CDS spreads is presented in Table 8. As with earlier results, the full sample period results from fixed-effects regression are presented in the first two columns and moreover, the results are divided into sub-samples in the latter two columns. Generally, the explanatory power of market-based model is higher than of the accounting-based model with adjusted R-squared of 82,44 % and 73,95 %, respectively. This finding is supported by several previous studies, as discussed earlier. The Mertonian credit risk variables, that is, equity return and volatility, leverage and risk-free rate, are all statistically significant at 1 % significance level and hold the expected signs. A profitability ratio earnings per share (EPS) does not gain statistical nor economical significance during any of the sample periods. Correspondingly, a unique investor-profitability measure dividends per share (DPS) is not statistically significant in explaining CDS spreads. Interestingly, DPS ratio has both negative and positive signs depending on the prevailing sub-period, signaling mixed relationship between the ratio and credit risk. Certainly, during high uncertainty and economic turbulence, high DPS ratio does not improve firm’s ability to service its liabilities. This proposition is supported by the finding in the third column, as DPS variable has a positive sign. On the other hand, during economic boom, higher dividends can signal stability and wealth, thus narrowing CDS spread, which is precisely what the last column of Table 8 suggests.

Time-series trend variables suggest diminishing general credit risk after the folding point of 2008Q4. Only the marginal effects measuring nonlinear trend variable shows statistical significance, which infers decreasing CDS spreads and credit risk after the financial crisis. This is also supported by increased intercept term during the crisis period (4,90) compared to post-crisis period (4,05).

The most dominant market-based variables are the volatility (VOL) and risky leverage (LEV) with vastly over 1 % effects on CDS spread, respectively. Additionally, the relationship between equity returns (RET) and CDS spread shows very robust evidence for Merton's structural model, though with some variation between the crisis (-0,09 %) and post-crisis (-0,23 %) periods. Risk-free rate (RF) has a negative effect on CDS spreads as supposed according to previous findings on the relationship. Risk-free rate shows statistical significance in all sub-samples and again, its effects seem to strengthen during turbulent market conditions.

Table 8. Log of CDS spread regressed by market-based variables in different regimes. Equity return (RET) is measured as quarterly return and volatility as annualized volatility from daily returns of quarter.

MARKET VARIABLES				
	2007Q4–2012Q4	2007Q4–2012Q4	2007Q4–2009Q2	2009Q3–2012Q4
CONSTANT	4,0294*** (0,0533)	4,4816*** (0,0700)	4,8974*** (0,1133)	4,0454*** (0,0627)
RET	-0,2629*** (0,0292)	-0,2078*** (0,0301)	-0,0911** (0,0374)	-0,2330*** (0,0389)
VOL	1,7212*** (0,0737)	1,1086*** (0,0963)	0,3329** (0,1621)	1,0474*** (0,1215)
LEV	1,1052*** (0,0960)	1,1782*** (0,0973)	1,3903*** (0,1781)	1,1748*** (0,1182)
EPS	-0,0056 (0,0048)	-0,0061 (0,0047)	-0,0044 (0,0061)	0,0000 (0,0064)
DPS	-0,1068 (0,0886)	0,0847 (0,0890)	0,2470 (0,1776)	-0,0629 (0,1137)
RF	-0,1100*** (0,0071)	-0,2493*** (0,0158)	-0,3869*** (0,0203)	-0,0897*** (0,0088)
TREND(2008:4)		-0,0051 (0,0034)		
TREND(2008:4)^2		-0,0012*** (0,0002)		
Adj. R-squared	0,8244	0,8298	0,8796	0,8553
N	3910	3910	1258	2652

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

Again, the magnitudes of structural variables are in line with previous findings of Tang and Yan (2012), Trujillo-Ponce et al. (2012) and Das et al. (2009), supporting the remarkable importance of volatility and leverage in credit risk dynamics. Moreover, the effect of equity return is found significant both economically and statistically, contributing to higher level of equity and, thus, narrower CDS spread.

6.5. Comprehensive model

As described earlier in the methodology section, the comprehensive model is formed on the basis of significant firm credit risk variables from both accounting-based and market-based models. Thus, the final model consists of return on asset (ROA), retained earnings to total asset (RE/TA), size of total assets (TA), equity return (RET), volatility (VOL), and market leverage (LEV). Risk-free rate was not included in the model as it is not strictly endogenous firm credit risk measure, even though it showed significance in the analysis above. Retained earnings to total asset (RE/TA) ratio was included in the model so that the possible changes in the sign could be observed.

Between the two leverage ratios, book leverage (TL/TA) and market-based risky (LEV=total liabilities to risky assets), the latter was chosen to the comprehensive model. The choice was made based on the economic and statistical significance and the explanatory power between the variables. Although, the effects of both leverage measures are similar, the market-based "risky leverage" is also in favor of structural credit risk theory and since the sample firms are publicly traded, it is natural to use the available market-valued data rather than book values.

The estimation results for comprehensive model for the whole sample period 2007–2012 are presented in Table 9. Column 1 presents the estimation results without accounting for firm fixed-effects, while Columns 2 and 3 employ cross-sectional fixed-effects estimation with time-series trend in Column 3. Obviously, as market data is added to the initial accounting-based analysis, the adjusted R-squared of regression jumps from 18,05 % to 30,85 % without employing fixed-effects. This implies that market information does carry a great load of firm specific credit risk information on the top of the accounting information. Furthermore, market information can capture magnitude and significance from initial accounting-based variables, as it is basically more filtered and refined form of interim financial data.

Such effect has occurred in the case of return on asset (ROA): While it was contributing significantly to the CDS spread according to accounting-based model, it shows neither high statistical nor economic significance in the comprehensive model when using fixed-effects approach. However, it holds the expected negative sign, while retained earnings to total asset (RE/TA) ratio changes signs again being statistically significant at the same time. Similar observations can be made for size of total assets (TA) variable between Columns 1 and 2. All in all, accounting-based variables seem to lose some statistical and economic significance, when market information is introduced, except for return on asset, which diminishes in a greater fashion.

On the other hand, market-based variables (equity return, volatility and leverage) hold or even gain magnitude in the comprehensive model. Coefficient of equity return (RET) -0,3256 gains economic magnitude when nonlinear time series trend is added, compared to market-based model coefficient of -0,2078. Similar pattern can be observed for volatility (VOL) coefficient: when time series trend is accounted for, the effect of volatility increases from 1,6983 to 1,9965 in comprehensive model, whereas the effect decreases from 1,7212 to 1,1086 in market model, respectively. The effect of leverage shows robustness and changes fairly modestly between market model and comprehensive model and with time series adjustments.

Time series trend shows statistical significance in Column 3. However, compared to Table 6 or Table 8, the first trend component seems to be somewhat greater (0,023) than of those previously presented. Furthermore, the second trend component, the marginal component, seems to be higher in value than of those earlier marginal components. The changes in the coefficients of selected credit risk variables and in their statistical significance suggests that there is an unobserved nonlinear element affecting the CDS spread, that is not captured by the (accounting) variables. Regardless, the market-based variables show exclusive robustness in contributing to firm CDS spread, whether accounting for time series trend or firm fixed-effects.

Compared to the results of Das et al. (2009), there are similarities regarding the coefficient of volatility, whereas Trujillo-Ponce et al. (2012) and Tang and Yan (2012) report opposite, diminishing findings on differences between comprehensive and market-based models. Analogously with Tang and Yan (2012), the coefficient of firm size (TA) changes signs when employing firm fixed-effects in comprehensive model. Furthermore, both Trujillo-Ponce et al. (2012) and Das et al. (2009) find comparable results about the decreasing effect of accounting-based variables in comprehensive model. In fact, none of the accounting-based risk determinants gain either economic magnitude or statistical significance (but rather the opposite), whereas market-based variables hold their significance in a remarkably robust manner.

Table 9. Comprehensive credit risk model estimation results. The estimation covers time period from 2007Q4 to 2012Q4.

COMPREHENSIVE MODEL			
	[1]	[2]	[3]
CONSTANT	6,3240***	1,5277**	2,9975***
	(0,2108)	(0,6022)	(0,6205)
ROA	-0,0043**	-0,0016	-0,0024*
	(0,0021)	(0,0013)	(0,0013)
RE/TA	-0,2671***	0,2266***	0,1745**
	(0,0344)	(0,0687)	(0,0679)
log(TA)	-0,1526***	0,1269***	0,0385
	(0,0122)	(0,0365)	(0,0376)
RET	-0,2153***	-0,2736***	-0,3256***
	(0,0578)	(0,0306)	(0,0307)
VOL	1,9450***	1,6983***	1,9965***
	(0,1172)	(0,0779)	(0,0823)
LEV	1,2871***	1,3527***	1,0217***
	(0,0832)	(0,1069)	(0,1100)
TREND(2008:4)			0,0234***
			(0,0031)
TREND(2008:4)^2			-0,0008***
			(0,0002)
Adj. R-squared	0,3085	0,8149	0,8205
N	3783	3783	3783

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

Next, the possible explanations for diverse performance of accounting-based credit risk determinants are taken under examination. The significance capturing effect of time series trend variables suggest that the relationship between firm's CDS spread and accounting ratios is not linear. Thus, the asymmetric dynamics need to be explored.

6.6. Credit risk asymmetry

Next, the nonlinear effects of credit risk determinants on CDS spreads are examined with quantile regression approach. Compared to previous studies, for example Benkert (2004), Tang and Yan (2012), in which the effects of credit risk levels are based strictly on credit ratings, the quantile regression approach offers a unique and more unbiased view to credit risk asymmetry. First, asymmetries are examined in a general level to conclude whether there exists asymmetric effects between credit determinants and CDS spreads. Second, quantile regression estimation results are reported and analyzed. Again, the distinction between economic regimes, that is, crisis and post-crisis sub-periods, is applied and the findings are analyzed. Finally, statistical tests are employed to decide whether the asymmetric effects between credit risk determinants and CDS spreads are statistically significant and notable. Note that in this section, the changes in CDS spreads are presented in basis points instead of relative changes.

Graphs of relationships between credit risk quantile estimates and CDS spreads are presented in Figure 7. For the purposes of this thesis, the main point of interest is in the shape of the graphs: The more nonlinear the quantile estimate line (blue line), the more there occurs asymmetric effects. Convex shapes, such as constant (C), volatility (VOL) or leverage (LEV), imply that the effects of the credit risk determinant accelerates when moving to higher credit risk (CDS) levels in a spread widening manner. Concave shapes, such as total assets (TA), return on asset (ROA) or equity return (RET), imply also accelerating effects for higher credit risk levels, but in a contrary, negative (narrowing) fashion. S-shaped slope of retained earning to total assets (RETA) implies accelerating effects for both high and low tails of credit risk, and somewhat uniformly flat effects for around the median risky firms.

As can be observed from Figure 7, most of the acceleration appears to be in the higher quantiles, say, after 70 % or 80 % quantile for almost every variable. Particularly high intensifications of slope can be found from higher quantiles of RET, ROA, RETA and LEV curves. Only RETA curve indicates lower quantile asymmetric effects, while the rest of the curves maintain rather linear shape in the quantiles below the median. Thus, Figure 7 contributes to the presumption that there are asymmetric effects between CDS spreads, at least among the higher risk (spread) firms.

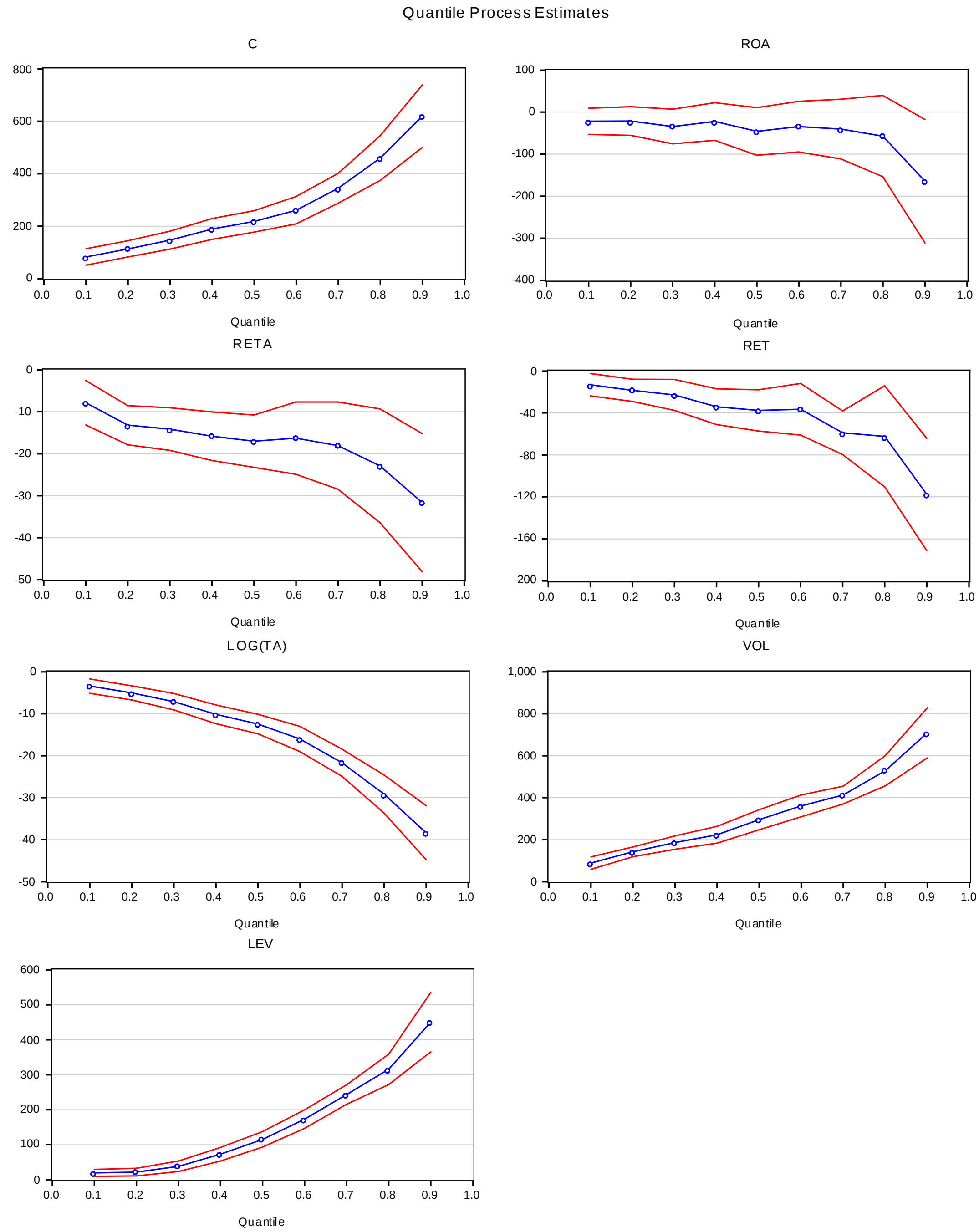

Figure 7. Quantile estimates for comprehensive model variables with CDS spread in basis points. Results for 10-quantiles presented (blue line) in vertical axel in basis points with 95 % confidence level (red lines).

Furthermore, Appendix 3 presents the above-discussed observations in numerical form. The quantile process estimates show statistical significance for every quantile of every variable except return on asset (ROA). As shown in Figure 7, the shape of ROA line is rather flat for quantiles under 80 % until it suddenly drops at the highest risk tail. This finding is also confirmed by Appendix 3, which suggests that ROA appears to be significant only in the 90 % quantile.

Results for symmetric quantiles test are presented in Table 10. Essentially, this asymmetry test examines whether the tail quantile estimations are different from the median estimation results, that is, whether the slope of the credit risk determinant is symmetric and linear. The results in Table 10 cover the whole sample period of 2007Q4–2012Q4 and the results are provided in basis points. The given quantile limits are 10 % and 90 % in the first column ($\tau = 0.1$), and 25 % and 75 % for the second column ($\tau = 0.25$), respectively.

In the second column of Table 10, the differences appear to be statistically significant only for the constant, total assets and leverage. This is vastly confirmed by Figure 7, which suggests that for these variables, there are greater differences within narrower credit risk quantiles. For these credit risk variables the effects are considerably broader in terms of quantile limits and credit risk asymmetry, suggesting that their general significance in contributing to firm's CDS spread is rather recognized.

On the other hand, when the quantile limits are widened to 10 % and 90 %, more variables gain statistical significance and, thus, support the asymmetric effects. Only return on asset (ROA) and retained earnings to total assets (RETA) present symmetric effects between the given quantiles, indicating that their effects on CDS spread are not different from median in the 10 % tails of the distribution. However, the results imply that there is asymmetric, nonlinear behavior between the 10 % tail quantiles for the rest of the credit risk determinants. Aside from constant, the primary asymmetries occur in the effects of leverage (239,04) and volatility (207,03).

Spread-widening variables, such as leverage and volatility, have positive test values, which indicates increasing asymmetry (convexity) in the higher quantiles. For convex curves, positive symmetric quantiles test values indicate asymmetry, and on the contrary, for concave curves, negative test result indicates asymmetry between quantiles. Therefore, spread-narrowing variables, such as equity return or size of total assets, have negative test values, suggesting asymmetric dynamics (concavity). As can be deduced from the symmetric quantiles test results between the two quantile limits presented in Table 10, the asymmetric effects transpire in the very tails, not so much around the median.

Table 10. Symmetry test for effects of comprehensive model variables (CDS spread in basis points).

SYMMETRIC QUANTILES TEST			
Restriction Detail:	b(tau) +	b(1-tau)	- 2*b(.5) = 0
Quantiles:	0.1 – 0.9	0.25 – 0.75	
CONSTANT	266,0927***	103,5038***	
	(62,0091)	(34,4669)	
ROA	-0,9443	0,2187	
	(0,7773)	(0,4395)	
RE/TA	-5,4527	2,9846	
	(8,7917)	(5,1498)	
log(TA)	-16,8609***	-6,7750***	
	(3,3836)	(1,9013)	
RET	-55,6481**	-13,7867	
	(27,7954)	(15,7790)	
VOL	207,0306***	5,3266	
	(64,6740)	(38,0722)	
LEV	239,0372***	70,6191***	
	(42,1219)	(17,3044)	
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test	491,8070	14	0,0000

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

Compared to the results of Benkert (2004) and Tang and Yan (2012), the relationship between the intercept and credit risk level (denoted in credit rating in their studies) is naturally positive: the riskier the firm, the higher the starting point of CDS spread.

However, when comparing the effects of leverage and volatility between credit risk levels or thresholds, there appears to be opposite observations. Tang and Yan (2012) report diminishing effects for volatility and leverage and increasing effect for equity return, when moving from investment grade to non-investment grade firms. The findings are opposite to the accelerating findings presented in Figure 7 and Appendix 3, and in Table 10. The differences can be explained with unequal information contents of credit ratings and CDS spread levels, as they are essentially two different approaches to firm's credit risk.

All in all, as graphically suggested by Figure 7 and, moreover, statistically confirmed by Table 10, the level of CDS spread predetermines the effect of credit risk determinant to the spread. Hence, there appears to be asymmetric effects on the different levels of CDS spread and furthermore, the magnified effects seem to concern principally higher spread (risk) firms. There seems to be very little asymmetry in the lower quantiles, that is, greater positive changes with lower CDS spread. The high quantile focus of asymmetric effects is very understandable since healthy firms do not require for extraordinary attention, whereas for higher risk firms, the risk needs to be accounted for in a faster and more precise manner.

6.7. Regime dependency of credit risk determinants

Next, the asymmetric effects are examined within the sub-periods in a same fashion, by employing quantile regression. Thus, the quantile regression results can be compared between sub-periods, deepening the analysis on financial crisis and credit risk dynamics. Table 11 presents the quantile regression estimation results for 10 % and 90 % quantiles for the whole sample period and two sub-periods, as described earlier.

There are several interesting observations can be made from Table 11. First, there occur extreme fluctuations in the explanatory power of the models, that is, in the adjusted R-squared. For lower quantile ($\tau = 0.1$) estimations, the adjusted R-squared values are 3,90 % for the whole sample period, 8,93 % for financial crisis period and 2,84 % for recovery period. Unsurprisingly, the explanatory power is the highest during the financial crisis period as general credit risk increased and caused unstable movement in both CDS spreads and credit risk measures. After the crisis, the movement stabilized, probably causing more and more unexplained variation, and hence lower explanatory power for the modeled lower quantile.

Respectively, the explanatory power of the estimated models soars radically when the higher quantile (τ = 0.9) is considered, reaching 22,02 % for the whole sample period, 31,05 % for financial crisis period and 17,87 % for post-crisis period. Yet again, the higher explanatory power of high quantile estimation compared to low quantile is most probably explained by asymmetric monitoring: Lower risk firms are less prone to sudden, default-leading operations, while for high risk firms, the launching stimulus can occur at any time, causing a vortex ending to default. Hence, monitoring and fine-tuning for smaller incentives can be viewed as more essential and necessary function for higher risk firms than for lower risk firms, that are principally rather far from default.

Table 11. Quantile effects of comprehensive model variables between different regimes (CDS spread in basis points).

COMPREHENSIVE MODEL						
	2007Q4 – 2012Q4		2007Q4 – 2009Q2		2009Q3 – 2012Q4	
Quantile:	0.1	0.9	0.1	0.9	0.1	0.9
CONSTANT	82,7280***	619,5992***	7,7697	558,1702***	140,8738***	490,2371***
	(15,9992)	(60,7460)	(28,1581)	(137,8840)	(16,7747)	(73,5309)
ROA	-21,7648	-164,5122**	-28,5150	-389,9405***	9,2107	107,9941
	(15,8829)	(75,0375)	(32,2995)	(93,4726)	(15,1366)	(97,4300)
RE/TA	-7,8482***	-31,6359***	-12,4131*	-43,8158***	-10,5684***	-42,1314***
	(2,7006)	(8,4022)	(6,4489)	(16,3618)	(2,2908)	(8,4599)
log(TA)	-3,4130***	-38,3456***	0,0793	-33,5377***	-6,1973***	-33,3037***
	(0,8766)	(3,2784)	(1,5415)	(7,6417)	(0,9316)	(3,8058)
RET	-13,1747**	-117,6523***	-14,1752*	-31,4437	-14,3479**	-214,8445***
	(5,4476)	(27,2713)	(8,2433)	(37,1683)	(6,0842)	(31,9358)
VOL	88,4650***	709,0230***	157,2798***	672,7457***	25,5232*	1079,1310***
	(15,1648)	(60,9194)	(17,5314)	(70,6763)	(14,8606)	(78,5413)
LEV	19,1979***	450,2872***	24,3619**	421,4194***	14,5633***	423,7480***
	(5,0010)	(43,4069)	(10,5641)	(72,4942)	(5,1453)	(40,9340)
Adj. R-squared	0,0390	0,2202	0,0893	0,3105	0,0284	0,1787
N	3783	3783	1207	1207	2576	2576

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

As with adjusted R-squared, a similar pattern can be revealed in the estimation results of quantile regression model between time periods and quantiles. For lower quantile (τ = 0.1) estimation results, there are a few variables, most notably volatility and leverage, that intensify remarkably during the crisis sub-period compared to post-crisis or whole sample period. Contrary, some variables, such as size of total assets and return on asset, lose statistical significance during turbulent, high volatility regime. Of these two variables, return on asset does not show significance in any of the estimation periods, while size of total assets behaves as predicted during the post-crisis period. Equity return and retained earning to total assets ratio show robust results with minimal alterations between sub-periods and holding their predicted signs together with statistical significance.

For high quantile ($\tau = 0.9$), there appears to be more radical changes in the credit risk dynamics between estimation periods. First, for the whole sample period, every variable shows statistical significance with predicted signs. Also the magnitude of the effects is remarkable, for example, 709,02 basis points quarterly widening for one percentage increase in annualized volatility and elevation of 450,29 basis points for every one percentage point of (risky) leverage, respectively. On the other hand, the downsizing, narrowing effects show notable strength as well with -164,51 basis points for every one percentage point increase in return on asset, or -117,65 basis points for every percentage point of equity return gained in the quarter. All in all, compared to the lower quantile, the effects of credit risk determinants together with number of significant variables have increased and amplified imposingly.

Again, there are radical changes among the credit risk determinants for higher quantile between crisis and post-crisis sub-periods. For example, the coefficient of return on asset reaches -389,94 during the financial crisis period being statistically significant, whereas during the post-crisis period, it changes signs and jumps to 107,99 without being statistically significant, respectively. Compared to the estimation result for the whole sample, the magnitude of return on asset over doubles from -164,51 to -389,94, suggesting the emphasized effects of essential profitability for high risk firms, especially during economically uncertain periods. Contrary to ROA, there appears opposite phenomena for the effects of equity return and volatility. Instead of decreasing effects during post-crisis period, these variables gain from increased economic certainty in terms of statistical and economic significance: The effects of volatility and equity return accelerate from 672,75 and -31,44 (no statistical significance) to 1079,13 and -214,84, respectively, when moving past the financial crisis to recovery period. Interestingly, these market-based variables become extremely sensitive in explaining CDS spread during the healthy post-crisis period, when at the same time the overall explanatory power (adjusted R-squared) declines from 31,05 % to 17,87 %.

Apart from the aforementioned extreme fluctuations, the rest of the variables (RE/TA, TA, LEV) show robust results with very little alterations between the sub-periods. A quick glance at the standard deviations reveals that during the crisis period, the general deviation of the credit risk determinants was eccentric, even twice as much as in the post-crisis period among the highest quantile.

The spread of risk determinants between the low and high quantiles maintains the corresponding form observed above between sub-periods. For robust variables (RE/TA, TA, LEV), the spread between quantiles holds rather evenly between the sub-periods compared to the initial sample period. Naturally, the spread in the intercept term increases during the crisis period and narrows post-crisis. However, as reported above, the spreads of RET and VOL squeeze exceptionally narrow during the financial crisis period, suggesting an increase in the systematic risk in the CDS markets. The actualization of the systematic risk narrows the essential credit risk determinants and since every firm is more or less in the same boat, their vulnerability and sensitivity to risk determinants converges. Once the pressure and the systematic risk has fallen to its normal stages, the spreads between low and high quantiles widen again, as can be seen from Table 11.

Appendices 4 and 5 present results for symmetric quantiles test for the estimates of two sub-periods. In respect to the test results of initial sample period presented in Table 10, which showed statistically significant asymmetric effects ($\tau = 0.1$) for the intercept, TA, RET, VOL and LEV variables, the asymmetric dynamics within the sub-periods can now be compared between each other and the initial sample period. Again, results are provided for both $\tau = 0.1$ and $\tau = 0.25$, the former in the first column and the latter in the second column, respectively.

First, in Appendix 4, the symmetric quantiles test is employed for financial crisis sub-period. A quick glance in the second column reveals that there is no statistically significant asymmetry between the 0.25–0.75 quantiles, suggesting that the risk dynamics converge and become more and more linear during the financial crisis. However, there appears to be a few statistically significant asymmetries in the first column between the 0.1–0.9 quantiles. As described above, the narrowing of the effects of given credit risk determinants carries on to the results of symmetric quantiles test: Even the tail effects of equity return and volatility become closer to linear and squeeze. Furthermore, positive test result for equity return suggests that the curve flattens and the tail effects converge. This is also supported by the narrowed spread of equity return between quantiles presented earlier in Table 11. Similar observations can be made for volatility, which again shows no statistically significant asymmetric behavior during the crisis due to the narrowed spread between the quantiles.

However, the aforementioned robust determinants total assets and leverage show statistically significant asymmetric dynamics during the financial crisis. As discussed earlier, these variables hold their spread somewhat evenly in different sub-periods, and thus they show asymmetric behavior during the crisis as well. Certainly, firm fundamentals are emphasized during volatile economic conditions, which adds to the robustness of the variables and furthermore, to the significance of the empirical credit risk induction rather than theoretical credit risk approach. The effect of firm size indicates elevated “conciliating halo”; larger firm size signals security and stability during volcanic conditions, which essentially leads to narrower CDS spread and emphasized asymmetric effects between tail quantiles. Additionally, the intercept variable, that is the “model starting point”, seems to capture the asymmetrically distributed credit risk effectively during the crisis, inferring increased systematic risk in the CDS markets. Because the comprehensive model shows increased linearity, i.e. lower asymmetry (also higher explanatory power) during the crisis period, there appears to be an unobserved determinant increasing general credit risk.

Symmetric quantiles test results for post-crisis period are presented in Appendix 5. Compared to crisis period, statistically significant asymmetric effects occur even at 0.25–0.75 quantile limits for firm size and leverage variables, both being very close to the test values of crisis period. Also the intercept term suggests increased asymmetry in 0.25 quantile tails in the post-crisis period. When the quantiles are narrowed to 0.1–0-9 limits, the asymmetric dynamics seem to intensify for most variables. Every credit risk determinant except return on asset shows statistically significant asymmetric effects between the tails and the median. Test values are considerably higher than in crisis period, suggesting increased asymmetric tail effects in post-crisis period. Overall, general asymmetry appears to rise among the credit risk determinants when the crisis has been bypassed. Contrary to the crisis period observations, that is, an increased asymmetry in intercept and decreased asymmetry in determinants, the findings suggest lower systematic risk and, naturally, higher sensitivity to firm-specific risk determinants.

Ultimately, the transformation in risk asymmetry from market risk to firm-specific risk determinants is a consequence of actualization of downside systematic risk occurred in

2007–2009, which eventually lead in upswing in common risk factors. Although the asymmetry diminishes during the financial crisis, the estimation results from both ordinary least squares and (high) quantile regression suggest that the total variation explained by the models increases during the period. Moreover, the estimation results suggest unevenly distributed credit risk dynamics, whereas symmetric quantiles tests employed give somewhat mixed results for different sub-periods, validating asymmetric effects for most determinants during initial sample period and post-crisis sub-period. During the crisis period, asymmetric effects are confirmed only for leverage and firm size (total assets) as well as for intercept term, suggesting increase in general risk level rather than sensitivity to firm-specific credit risk preferences. This is also supported by squeeze between high and low quantiles in most otherwise significant credit risk variables. After the crisis unraveled, the nonlinear effects and firm-specific sensitivity returned to CDS spread dynamics, which is confirmed by symmetric quantiles test (Appendix 5) and quantified by quantile regression (Table 11).

7. CONCLUSIONS

This thesis set out with aims to examine the relationship between credit default swap spreads and different credit risk determinants in dynamic economic regimes by studying the effects of firm-specific variables on corresponding credit default swap spread with 207 U.S. non-financial companies in 2007–2012. The linkage between credit risk determinants and CDS spreads is furthermore decomposed and nonlinear dynamics are studied between different credit risk levels. This asymmetric approach to credit risk and CDS spreads is unique and yet uncovered by previous literature on credit default swaps and credit risk models. Thus, the goal of this thesis is to look deeper into this fundamental relationship between credit risk and CDS spreads, i.e., "price of default insurance".

First, the relationship between firm-specific accounting- and market-based credit risk variables and CDS spreads are examined by conducting linear regression with CDS spreads and chosen risk determinants. The accounting-based empirical components provide some confirmation to the findings of earlier research and, respectively, to the first hypothesis, while market-based structural variables seem to control the credit risk assessment, as suggested by previous studies. The main findings are that during the financial crisis, the most essential and robust accounting variables, such as leverage (TL/TA) and profitability (ROA), intensify, referring to the increased sensitivity and emphasis on fundamentally important firm health factors. Similar observations can be made for effect of leverage from market model approach, although both equity return and volatility show diminishing effects during the financial crisis. Thus, null hypothesis regarding the relationship between economic regimes and credit risk determinants is rejected. Additionally, a comprehensive model consisting of both significant accounting-based empirical components and market-based structural components performs overall better than accounting-based model, which is again suggested by previous studies. Hence, the second hypothesis regarding improving effects of market-based variables is supported.

Second, asymmetric effects of credit risk determinants on different levels of credit risk are studied. Compared to earlier research, controlling for levels of CDS spread rather than credit rating is a unique property and provides robust results, unbiased from credit rating. To examine the asymmetric dynamics, a quantile regression is conducted with comprehensive model variables. Moreover, the variables are tested with symmetric quantiles test in different sub-periods for statistical confirmation. The results are an achievement of the goals set out, providing evidence for hypothesis of asymmetric effects for higher and lower risk firms, that is, top and bottom 10 % quantiles. Furthermore, the nonlinear dynamics are examined in different economic regimes, suggesting decreased asymmetry during crisis period and correspondingly increased asymmetry during post-crisis sub-period. Although the asymmetry diminishes during the crisis period, the model provides robust results for the chosen variables and suggests significant effects particularly for high quantile (risk) firms for every sub-period.

A distinction between robust credit risk determinants and volatile, unstable determinants can be made based on the spreads of the estimated coefficients in different sub-periods. Robust variables, such as retained earnings to total asset, size of total assets and leverage, perform very similarly in dynamic economic conditions maintaining their asymmetric effects (except retained earnings to total assets during the crisis). On the one hand, during economic uncertainty, higher risk firms tend to benefit relatively more from larger size (measured in total assets) than lower risk firms. On the other hand, the spread-widening effect of increased volatility is also significantly greater for the top 10 % riskiest firms than for lower risk firms, respectively.

In the post-crisis period, the asymmetric effects spread to broader range of risk determinants, considering every comprehensive model variable except return on asset. Once the general uncertainty had faded away from CDS markets and recovery had begun, the firm-specific asymmetric effects accelerated. The (firm-specific) credit risk asymmetry seems to develop inversely to systematic market risk, highlighting general uncertainty and effects of essentially important risk determinants (such as leverage) during volatile conditions. In lower volatility conditions and lower systematic risk, the individual differences are emphasized and the performance discrete sensitivity increases.

The results suggest that the most remarkable credit risk determinant is leverage, whether it is measured by using book or market values. This finding is naturally inducted from the very nature of default: once the level of liabilities exceeds the level of assets the firm is in default. Unsurprisingly, the pronounced significance of leverage is empirically supported and stated regarding both cases of actual bankruptcies and CDS spreads, and empirical build up and theoretical structural models. Furthermore, profitability displays great significance in credit risk assessment, which again highlights the importance of impact of essentially vital cornerstones of healthy company.

Interestingly, the size coefficient (size of total assets) has a signaling effect on firm's credit risk and CDS spread. There are mixed empirical results regarding the effect of firm size: Das et al. (2009) report only negative relationship between firm size and CDS spread, while Trujillo-Ponce et al. (2012) and Tang and Yan (2012) report spread-narrowing effects for pre-crisis period and oppositely spread-widening effects for crisis period. Furthermore, Tang and Yan (2012) find similarly, that when fixed-effects are employed size has a positive linkage to CDS spread, whereas the effect is negative (narrowing) without fixed-effects. On the other hand, size coefficient appears to be negative (or very close to zero) in every sub-period when quantile regression is employed. For riskier firms, the sense of stability and security brought by larger firm size is evident. Perhaps the underlying presumption is that larger firms (even the riskier ones) are safer because of heavier monitoring, increased amount of information and publicity, or better reputation and prestige.

In turn, market-based structural variables show great explanatory strength, as described earlier. Arguably, some of the information content contributed by equity market variables leads to diminishing effects in accounting-based variables. The double information causes usually the initial variable to lose significance, as equity market information is based on the firms' financial data, such as financial statements, analytics' predictions or firms' press releases and inside information. Furthermore, the underlying data is filtered and processed into equity market information that can be utilized in structural credit risk assessment. On the other hand, equity market information contains also a lot of information nonrelated to credit risk of the firm, which causes greater deviations of the estimation values as seen in the spreads of volatility and equity return between high and low quantiles.

All in all, the results provide evidence on both the importance of accounting-based variables and also market-based variables. It can be concluded that there should be a golden path in the middle of these two approaches, as also suggested by earlier studies. Moreover, the effects of credit risk determinants can be concluded as nonlinear in respect to prevailing economic regime. Asymmetric effects among credit risk determinants are observed in different levels of CDS spread. These asymmetries narrow during turbulent economic conditions, whereas they appear significantly strong in post-crisis period. As a conclusion, there can be observed an intensifying survival phenomenon in CDS markets and asymmetric credit risk dynamics.

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APPENDICES

Appendix 1. List of firms included in the sample.

COMPANY	TICKER
AmerisourceBergen Corp.	ABC
Abbott Laboratories	ABT
Affiliated Computer Services	ACS
Archer Daniels Midland	ADM
Automatic Data Processing Inc.	ADP
Ameren Corporation	AEE
American Electric Power	AEP
AES Corporation	AES
Aetna Inc.	AET
Allergan Inc.	AGN
AK Steel Holding Corp.	AKS
Advanced Micro Devices	AMD
American Tower Corporation	AMT
Apache Corp.	APA
Anadarko Petroleum Corporation	APC
Air Products & Chemicals	APD
Ashland Inc.	ASH
Allegheny Technologies Inc	ATI
Avon Products	AVP
Avery Dennison Corp.	AVY
AutoZone Inc.	AZO
Baxter International Inc.	BAX
Best Buy Co. Inc.	BBY
Black & Decker Corp.	BDK
Becton Dickinson	BDX
Baker Hughes	BHI
BJ Services Company	BJS
Ball Corp.	BLL
Bemis Company	BMS
Bristol-Myers Squibb	BMY
Burlington Northern Santa Fe Corp.	BNI
Boston Scientific	BSX
Peabody Energy	BTU
ConAgra Foods Inc.	CAG
Cardinal Health Inc.	CAH
Cameron International Corp.	CAM
Caterpillar Inc.	CAT
CBS Corp.	CBS
Coca-Cola Enterprises	CCE
Constellation Energy Group	CEG
Chesapeake Energy	CHK
Clorox Co.	CLX
CMS Energy	CMS
CenterPoint Energy	CNP
Campbell Soup	CPB
Computer Sciences Corp.	CSC
CSX Corp.	CSX
CenturyTel Inc	CTL
Centex Corp.	CTX
CVS Caremark Corp.	CVS
Chevron Corp.	CVX
Quest Diagnostics	DGX
D. R. Horton	DHI
Danaher Corp.	DHR
Walt Disney Co.	DIS
Dover Corp.	DOV
Dow Chemical	DOW
Dr Pepper Snapple Group	DPS
Darden Restaurants	DRI
DTE Energy Co.	DTE
DIRECTV Group Inc.	DTV
Duke Energy	DUK
DaVita Inc.	DVA
Devon Energy Corp.	DVN
Equifax Inc.	EFX
Edison Int'l	EIX
EMC Corp.	EMC
Eastman Chemical	EMN
Emerson Electric	EMR
EOG Resources	EOG
Eaton Corp.	ETN
Entergy Corp.	ETR
Exelon Corp.	EXC
Freeport-McMoran Cp & Gld	FCX
FedEx Corporation	FDX
Fidelity National Information Services	FIS
Fluor Corp.	FLR

Flowserve Corporation	FLS	3M Company	MMM
Gannett Co.	GCI	Merck & Co.	MRK
General Mills	GIS	Marathon Oil Corp.	MRO
Corning Inc.	GLW	Murphy Oil	MUR
Gap (The)	GPS	MeadWestvaco Corporation	MWV
Halliburton Co.	HAL	Mylan Inc.	MYL
Hasbro Inc.	HAS	Noble Energy Inc	NBL
Hess Corporation	HES	Nabors Industries Ltd.	NBR
Honeywell Int'l Inc.	HON	Newmont Mining Corp. (Hldg. Co.)	NEM
Starwood Hotels & Resorts	HOT	NIKE Inc.	NKE
Hewlett-Packard	HPQ	Northrop Grumman Corp.	NOC
Block H&R	HRB	National Oilwell Varco Inc.	NOV
Harris Corporation	HRS	Norfolk Southern Corp.	NSC
Hospira Inc.	HSP	Nucor Corp.	NUE
The Hershey Company	HSY	Newell Rubbermaid Co.	NWL
Humana Inc.	HUM	New York Times Cl. A	NYT
International Bus. Machines	IBM	Office Depot	ODP
International Game Technology	IGT	Omnicom Group	OMC
Interpublic Group	IPG	Occidental Petroleum	OXY
Iron Mountain Incorporated	IRM	Pepsi Bottling Group	PBG
ITT Corporation	ITT	Pitney-Bowes	PBI
Illinois Tool Works	ITW	PG&E Corp.	PCG
Jabil Circuit	JBL	PepsiCo Inc.	PEP
Johnson Controls	JCI	Pfizer Inc.	PFE
Penney (J.C.)	JCP	Progress Energy Inc.	PGN
Johnson & Johnson	JNJ	Pulte Homes Inc.	PHM
KB Home	KBH	PerkinElmer	PKI
Kraft Foods Inc-A	KFT	Pepco Holdings Inc.	POM
Kimberly-Clark	KMB	PPG Industries	PPG
Kohl's Corp.	KSS	PPL Corp.	PPL
Leggett & Platt	LEG	Pactiv Corp.	PTV
Lennar Corp.	LEN	Pioneer Natural Resources	PXD
L-3 Communications Holdings	LLL	Reynolds American Inc.	RAI
Lilly (Eli) & Co.	LLY	Rockwell Automation Inc.	ROK
Lockheed Martin Corp.	LMT	Range Resources Corp.	RRC
Lowe's Cos.	LOW	Donnelley (R.R.) & Sons	RRD
LSI Corporation	LSI	Republic Services Inc	RSG
Southwest Airlines	LUV	RadioShack Corp	RSH
Lexmark Int'l Inc	LXK	Raytheon Co.	RTN
Masco Corp.	MAS	SCANA Corp	SCG
Mattel Inc.	MAT	Sealed Air Corp.(New)	SEE
McDonald's Corp.	MCD	Schering-Plough	SGP
McKesson Corp.	MCK	Sherwin-Williams	SHW
Medtronic Inc.	MDT	Smith International	SII
Massey Energy Company	MEE	Snap-On Inc.	SNA
Medco Health Solutions Inc.	MHS		

Sempra Energy	SRE
Constellation Brands	STZ
Supervalu Inc.	SVU
Stanley Works	SWK
Safeway Inc.	SWY
Sysco Corp.	SYY
Molson Coors Brewing Company	TAP
Integrys Energy Group Inc.	TEG
Target Corp.	TGT
Tenet Healthcare Corp.	THC
TJX Companies Inc.	TJX
Thermo Fisher Scientific	TMO
Tyson Foods	TSN
Tesoro Petroleum Co.	TSO
AT&T Inc.	TTT
Time Warner Inc.	TWX
Texas Instruments	TXN
Textron Inc.	TXT
United Health Group Inc.	UNH
Union Pacific	UNP
United Parcel Service	UPS
United Technologies	UTX
V.F. Corp.	VFC
Valero Energy	VLO
Vulcan Materials	VMC
Walgreen Co.	WAG
Wisconsin Energy Corporation	WEC
Whirlpool Corp.	WHR
Windstream Corporation	WIN
WellPoint Inc.	WLP
Williams Cos.	WMB
Wal-Mart Stores	WMT
Wyeth	WYE
Wyndham Worldwide	WYN
Exxon Mobil Corp.	XOM
Xerox Corp.	XRX
XTO Energy Inc.	XTO
Yum! Brands Inc	YUM
Zimmer Holdings	ZMH
N	207

Appendix 2. Descriptive statistics for interim data. CDS spreads are in presented basis points, interim figures are in thousands ($1000).

	INTERIM VARIABLES							
	CDS	EBIT	INT	RE	REV	TA	TL	WC
Mean	147,41	645360,30	81944,97	9245898,00	6320764,00	26493412,00	15782080,00	1929640,00
Median	83,71	329000,00	50000,00	3895999,00	2813000,00	15001384,00	8879500,00	1093451,00
Maximum	8798,30	24187000,00	952000,00	366000000,00	128000000,00	345000000,00	181000000,00	49792000,00
Minimum	10,50	-22580000,00	0,00	-99780000,00	119273,00	1807400,00	925500,00	-21893000,00
Std. Dev.	266,72	1595846,00	103100,00	26454269,00	12047301,00	37735131,00	21476491,00	4134172,00
Skewness	18,82	3,69	3,81	7,20	6,02	4,32	4,01	3,03
Kurtosis	557,27	72,86	23,48	81,12	48,03	26,36	23,45	26,57
Observations	4143	4120	4124	4076	4183	4180	4180	4090

Appendix 3. Quantile process estimates of CDS spread in basis points.

QUANTILE PROCESS ESTIMATES					
	Quantile	Coefficient	Std. Error	t-Statistic	Prob.
CONSTANT	0.100	82,7280***	15,9992	5,1708	0,0000
	0.200	113,4170***	15,7958	7,1802	0,0000
	0.300	146,7334***	17,5169	8,3767	0,0000
	0.400	189,3366***	20,2811	9,3356	0,0000
	0.500	218,1173***	20,8594	10,4565	0,0000
	0.600	260,8318***	26,6900	9,7726	0,0000
	0.700	344,3375***	29,0039	11,8721	0,0000
	0.800	459,4207***	43,5059	10,5600	0,0000
	0.900	619,5992***	60,7460	10,1998	0,0000
ROA	0.100	-21,7648	15,8829	-1,3703	0,1707
	0.200	-21,3091	17,3842	-1,2258	0,2204
	0.300	-34,2995	21,0482	-1,6296	0,1033
	0.400	-22,2650	22,9079	-0,9719	0,3311
	0.500	-45,9238	28,9059	-1,5887	0,1122
	0.600	-34,6128	30,8271	-1,1228	0,2616
	0.700	-40,3587	36,2187	-1,1143	0,2652
	0.800	-57,0946	49,3504	-1,1569	0,2474
	0.900	-164,5122**	75,0375	-2,1924	0,0284
RE/TA	0.100	-7,8482***	2,7006	-2,9061	0,0037
	0.200	-13,2053***	2,3828	-5,5419	0,0000
	0.300	-14,1223***	2,5975	-5,4368	0,0000
	0.400	-15,8196***	2,9483	-5,3657	0,0000
	0.500	-17,0157***	3,1897	-5,3345	0,0000
	0.600	-16,2920***	4,3908	-3,7105	0,0002
	0.700	-18,0514***	5,2927	-3,4106	0,0007
	0.800	-22,8730***	6,9078	-3,3112	0,0009
	0.900	-31,6359***	8,4022	-3,7652	0,0002
LOG(TA)	0.100	-3,4130***	0,8766	-3,8934	0,0001
	0.200	-5,0301***	0,8660	-5,8083	0,0000
	0.300	-7,1307***	0,9920	-7,1882	0,0000
	0.400	-10,1194***	1,1398	-8,8779	0,0000
	0.500	-12,4489***	1,1796	-10,5537	0,0000
	0.600	-16,0152***	1,5284	-10,4787	0,0000
	0.700	-21,6446***	1,6456	-13,1531	0,0000

	0.800	-29,1022***	2,3105	-12,5956	0,0000
	0.900	-38,3456***	3,2784	-11,6965	0,0000
RET	0.100	-13,1747**	5,4476	-2,4185	0,0156
	0.200	-18,5085***	5,4243	-3,4122	0,0007
	0.300	-22,8620***	7,5081	-3,0450	0,0023
	0.400	-34,1105***	8,6684	-3,9351	0,0001
	0.500	-37,5895***	10,0073	-3,7562	0,0002
	0.600	-36,5626***	12,5571	-2,9117	0,0036
	0.700	-58,9551***	10,5681	-5,5786	0,0000
	0.800	-62,3299**	24,5585	-2,5380	0,0112
	0.900	-117,6523***	27,2713	-4,3141	0,0000
VOL	0.100	88,4650***	15,1648	5,8336	0,0000
	0.200	142,1309***	11,7725	12,0731	0,0000
	0.300	185,8915***	16,2689	11,4262	0,0000
	0.400	223,8664***	20,4512	10,9464	0,0000
	0.500	295,2287***	24,3914	12,1038	0,0000
	0.600	361,0671***	26,3149	13,7210	0,0000
	0.700	412,7501***	21,6355	19,0774	0,0000
	0.800	528,6114***	36,7148	14,3978	0,0000
	0.900	709,023***	60,9194	11,6387	0,0000
LEV	0.100	19,1979***	5,0010	3,8388	0,0001
	0.200	21,7685***	5,6111	3,8796	0,0001
	0.300	38,2383***	7,7010	4,9654	0,0000
	0.400	72,6919***	9,9462	7,3085	0,0000
	0.500	115,2240***	11,2227	10,2671	0,0000
	0.600	173,1543***	13,5878	12,7434	0,0000
	0.700	243,3662***	14,2745	17,0490	0,0000
	0.800	315,3784***	22,1751	14,2222	0,0000
	0.900	450,2872***	43,4069	10,3736	0,0000

Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

Appendix 4. Symmetry test for effects of comprehensive model variables in 2007Q4–2009Q2 (CDS spread in basis points).

SYMMETRIC QUANTILES TEST 2007Q4–2009Q2

Restriction Detail:	b(tau) +	b(1-tau)	- 2*b(.5) = 0
Quantiles:	0.1 – 0.9	0.25 – 0.75	
CONSTANT	361,4128***	134,2297*	
	(137,3467)	(78,8866)	
ROA	-51,2212	-103,9304	
	(130,5386)	(119,3958)	
RE/TA	-12,6275	-14,0353	
	(21,3813)	(15,7251)	
log(TA)	-21,7833***	-6,4772	
	(7,6553)	(4,5833)	
RET	35,5669	19,1193	
	(41,5106)	(29,5974)	
VOL	21,8074	-15,2085	
	(89,5927)	(70,2354)	
LEV	297,7078***	59,8075	
	(72,7269)	(49,1934)	
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test	204,8211	14	0

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.

Appendix 5. Symmetry test for effects of comprehensive model variables in 2009Q3–2012Q4 (CDS spread in basis points).

SYMMETRIC QUANTILES TEST 2009Q3–2012Q4			
Restriction Detail:	b(tau) +	b(1-tau)	- 2*b(.5) = 0
Quantiles:	0.1 – 0.9	0.25 – 0.75	
CONSTANT	141,5200*	93,9216**	
	(75,9660)	(40,7705)	
ROA	36,4233	23,9192	
	(96,0030)	(48,6428)	
RE/TA	-20,8750**	-1,1515	
	(9,2737)	(5,9071)	
log(TA)	-10,1168**	-5,5867**	
	(4,0393)	(2,2306)	
RET	-141,1389***	-7,6363	
	(33,5226)	(22,6319)	
VOL	471,1178***	-55,4202	
	(94,0888)	(62,7091)	
LEV	181,4239***	61,7868***	
	(40,7329)	(19,1891)	
Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Wald Test	483,6977	14	0,0000

Standard errors are reported in the parentheses. Significance levels are indicated as follows: ***–significant at the 1 % level, **–significant at the 5 % level, *–significant at the 10 % level.