Valuation of Systematic Risk in the Cross-section of Credit Default Swap Spreads

Sebastian Löhr [a] Arndt Claußen [b] Daniel Rösch [c]
Harald Scheule [d]

[a] *Institute of Banking and Finance, Leibniz University of Hannover, Königsworther Platz 1, 30167 Hannover, Germany, Phone: +49-511-762-5624, Fax: +49-511-762-4670, mailto: Sebastian.Loehr@finance.uni-hannover.de*

[b] *Institute of Banking and Finance, Leibniz University of Hannover, Königsworther Platz 1, 30167 Hannover, Germany, Phone: +49-511-762-19567, Fax: +49-511-762-4670, mailto: Arndt.Claussen@finance.uni-hannover.de*

[c] *Institute of Statistics and Risk Management, University Regensburg, Universitätsstraße 31, 93040 Regensburg, Germany, Phone: +49-941-943-2588, Fax: +49-941-943-4936, mailto: Daniel.Roesch@wiwi.uni-regensburg.de*

[d] *Finance Discipline Group, University of Technology, Sydney, PO Box 123, Broadway NSW 2007, Australia, Phone: +61-2-9514-7722, Fax: +61-2-9514-7722, mailto: harald.scheule@uts.edu.au*

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Abstract

This paper analyses the pricing of systematic risk factors in credit default swap contracts in a two-stage empirical framework. In the first pass, we estimate contract-specific sensitivities to several systematic risk factors by time-series regressions using quoted credit default swap (CDS) spreads of 339 U.S. entities from 2004 to 2010. We find that the credit market climate, the cross-market correlation and the market volatility explain CDS spread changes. In the second pass, we examine by cross-section regressions whether the contract-specific sensitivities to these systematic risk factors are priced in the cross-section of swap contracts by controlling for individual risk factors such as credit ratings, liquidity and leverage. We find that our basic risk factors explain about 83% of the CDS spreads prior to the crisis and about 90% during the crisis.

Key words: Credit Derivatives, Cross-section of Credit Default Swap Spreads, Systematic Risk,

JEL classification: C 16; C 50; G 21; G 24;

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1 Introduction

During the Global Financial Crisis (GFC) the spreads of Credit Default Swaps (CDS) heavily increased across most CDS dealings on corporate debt claims, which was triggered by high numbers of corporate defaults on bonds and loans.[1] While 31 Moody's-rated corporate issuers defaulted in 2006 on a total of 10.4 USD billion of loans and bonds, the number of defaulted issuers increased to 261 in 2009 on a total of 328.9 USD billion (Moody's 2010). In fact, the CDS spreads on high-rated debt claims, e.g., 'AAA'-rated bonds, increased much more rapidly than those on lower-rated credit assets, which may indicate a mismatch between credit ratings and the related default risk.

On the corporate debt market this phenomenon takes part in the so-called credit spread puzzle which is already addressed by several authors (Amato & Remolona 2003, Hui 2010). Apart from addressing corporate default risk (Giesecke et al. 2011), several empirical studies recently looked beyond theoretical contingent claims and accounted for other pricing factors such as liquidity (De Jong & Driessen 2011, Dion Bongaerts 2011, Friewald et al. 2012). As suggested by Collin-Dufresne et al. (2001), Hui (2010) and Iannotta & Pennacchi (2011) for corporate debt, other authors also identified systematic risk factors driving CDS spreads (e.g., Amato 2005, Blanco et al. 2005, Gala et al. 2010, Gandhi et al. 2012).

Most of the recent studies analyze time-series properties of credit spreads

[1] Similar to insurance contracts, CDS – as credit derivatives – are linked to credit-risky assets such as corporate bonds, loans etc. In their role as protection seller, CDS investors periodically receive premium payments for covering losses in the underlying credit assets. These losses may be due to default events such as interest shortfalls or principal impairments, see Gandhi et al. (2012). Thus, in the absence of arbitrage, the fair CDS spread (risk premium) theoretically compensates for the default risk of the underlying credit asset.

or credit spread changes by focusing on time-series regressions. An exception are Friewald et al. (2012) who use Fama-Macbeth cross-sectional regressions to show that liquidity is priced in bond markets after controlling for other factors such as credit ratings. In summary, the current literature on both bond and CDS markets focuses on the identification of credit spread drivers and aims to answer the question how these determinants are priced.

Our paper contributes to credit spread determinants in several ways. Firstly, we explicitly address systematic risk exposures of CDS contracts and identify at least three systematic risk factors beyond Merton's (1974) structural theory as important drivers for CDS spread changes. Thus, we suggest the *Credit Market Climate*, the *Market Volatility* and the *Cross-market Correlation* as common determinants of CDS spread changes.

Secondly, based on our CDS database from 2004 to 2010 containing weekly spread data of 339 U.S. firms we show that credit ratings do not sufficiently cover the overall credit risk priced in CDS spreads. We find that systematic risk is generally priced beyond the ratings of U.S. firms located in numerous economic sectors, e.g., financials, industrials and consumer goods.

Thirdly, we extend the current literature by applying a two-pass regression approach to CDS markets (similar to Fama & MacBeth 1973) and thus we show that systematic risk exposures are cross-sectionally priced in swap markets.[2] In the first pass, we identify common determinants of credit spread changes and provide contract-specific sensitivities (betas) to common risk factors by time-series regressions. In the second pass, we examine by cross-section regressions how these betas are cross-sectionally priced in CDS spreads after

[2] The initial two-pass regression approach was proposed by Fama & MacBeth (1973) to evaluate the cross-section of stock returns.

controlling for i) several individual factors such as credit ratings, contract liquidity and firm leverage and ii) sectoral influences. Thus, we calculate premiums for these systematic risk betas, similar to the CAPM's beta premium. [3] We find that these determinants of CDS spread changes are priced across several economic sectors, particularly in times of financial distress. Especially, common risks related to the *Credit Market Climate*, the *Market Volatility* and the *Cross-market Correlation* are rewarded in the cross-section of CDS spreads, even after controlling for other important pricing elements such as credit ratings and liquidity. The results of the cross-section regressions show that our set of variables – composed of systematic and non-systematic risk measures – allows us to explain about 80% of the observed CDS spreads in normal market environments. Even in times of financial turmoil, our model setup achieves an explanatory power of about 90%. Furthermore, the OLS regression results are robust with respect to the inclusion of the Fama-French factors and other firm-specific factors such as the firm's leverage ratio and market capitalization. Our findings suggest that systematic risk is a decisive pricing factor, even if we control for individual risk factors and sectoral influences.

Our empirical findings are important for at least three fields. Firstly, the contributions are relevant for asset pricing as they identify variables which determine spreads of swap contracts referring to credit risky assets. While previous literature analyzes price impacts of credit ratings (e.g., Ederington & Goh 1993, 1998), we explicitly address price impacts of systematic risk in CDS spreads beyond ratings. Extending the current literature related to CDS

[3] According to the Capital Asset Pricing Model (CAPM), market participants can fully diversify idiosyncratic risks, but not market (systematic) risk which is therefore compensated by a risk (beta) premium (compare Sharpe 1964).

and corporate debt, our findings are not only relevant for the valuation of CDS, but may also provide further insight into the pricing of corporate bonds, as bonds are also exposed to systematic risk (see Collin-Dufresne et al. 2001, Hui 2010).

Secondly, the results are important for the regulation of financial markets. As pointed out by Iannotta & Pennacchi (2011), there is a mismatch between regulatory capital for banks derived from credit ratings and credit spreads, as the latter might account for systematic risk, while credit ratings do not appropriately reflect systematic risk. Current regulatory capital requirements for banks primarily focus on credit ratings, and therefore banks – or financial investors in general – are subject to misaligned incentives if systematic risk is priced: within a specific rating grade, banks may choose those investments with highest systematic risk exposures due to the higher risk premiums linked to these products. This might be a threat to financial institutions, or even the whole financial system. By providing empirical evidence for the pricing of systematic risk on CDS markets beyond ratings, our paper also contributes to this discussion.

Thirdly, our findings might be important for pricing structured finance securities such as Collateralized Debt Obligations (CDOs). Since, for example, synthetic CDOs such as single-tranche CDOs (STCDOs) take on credit exposures through including CDS contracts, this work may also provide first insight into the valuation of such structured products, which are particularly exposed to systematic risk (see Coval et al. 2009). [4]

[4] Popular STCDOs are tranches of credit indices such as the North American CDX and iTraxx Europe index families. Each credit index represents a basket of the 125 most liquid CDS contracts on corporate names which exhibit an investment grade rating.

The remainder of the paper is organized as follows. In Section 2, we provide the theoretical framework for our empirical analysis by introducing systematic and rather firm-specific spread determinants. Further, we describe the database and briefly discuss the proxies used. In Section 3, we firstly introduce the regression models within the two-pass approach and secondly provide the methodology to test whether corporate ratings appropriately reflect systematic risk. Thirdly, we provide our results and check the robustness of our findings by expanding our model framework, e.g., to i) the Fama-French factors, ii) further firm-specific factors and iii) a principal component analysis. Section 4 concludes.

2 Determinants of Credit Default Swap Spreads

2.1 Theoretical Framework

Black & Scholes (1973) and Merton (1974) introduced an intuitive option-pricing framework for valuing corporate equity and debt. This structural framework by Merton (1974) provides an attractive approach to credit risk. In structural models the default event is usually triggered when the firm's assets fall below a critical threshold.[5] The value of a firm's asset follows a simple random walk (firm value process) and the default threshold is a function of the amount of debt outstanding.

The values of debt claims are determined under the risk-neutral measure by computing the present value of their expected future cash flows discounted

[5] Structural models were further investigated by Black & Cox (1976), Leland (1994), Longstaff & Schwartz (1995), Briys & de Varenne (1997), Gordy (2000), Collin-Dufresne & Goldstein (2001) and Gordy (2003).

at the risk-free rate. Since a credit default swap extracts and transfers the default risk of corporate debt, CDS investors – in their role as protection seller – periodically receive a premium payment (premium leg) for covering losses in underlying debt claims (protection leg). In the absence of arbitrage and in the presence of risk-neutral valuation, the present value (PV) of the premium leg equals the PV of the protection leg. Hence, depending on the underlying debt claim future expected cash flows – namely the protection and premium payments – of the related CDS are analogously discounted to determine the fair CDS spread.[6]

Motivated by the structural framework, we uniquely define the CDS spread $S_{\vartheta,t}$ of contract ϑ at time t through 1) the price of underlying debt claims, 2) its related contractual cash flows, 3) the time-specific risk-free rate r_t, 4) common state variables $\mathcal{Y}_t$, which are affecting cross-sectionally all credit spreads simultaneously and 5) individual state variables $\mathcal{V}_{\vartheta,t}$, which are firm-specific. Thus, we define credit spreads similarly to Collin-Dufresne et al. (2001) extended by the common state variables $\mathcal{Y}_t$. This leads to

$$S_{\vartheta,t} := S_{\vartheta,t}\left(C_{\vartheta,t}(F_{\vartheta,t}), r_t, \mathcal{Y}_t, \mathcal{V}_{\vartheta,t}\right) \tag{1}$$

with contractual payments $C_{\vartheta,t}$ depending on the firm value $F_{\vartheta,t}$.[7] Based on this theoretical framework, credit spread changes are determined given the current values of the time-specific variables $\mathcal{Y}_t$ and $\mathcal{V}_{\vartheta,t}$ respectively. Referring to the structural framework, we may predict i) determinants of CDS spread changes, and ii) whether changes in these variables should be positively or negatively correlated with changes in the CDS spreads.

[6] For more detailed information compare Amato (2005).
[7] See Collin-Dufresne et al. (2001) for more detailed information.

Similar to other authors, we propose some common state variables reflecting systematic risk:[8]

(1) *Changes in the Spot Rate.* In theory, the static effect of a higher spot rate is to increase the risk-neutral drift of the firm value process (Longstaff & Schwartz 1995, Duffee 1998). The higher drift reduces the firm's probability of default and thus the price of related derivatives offering protection against default losses. We therefore expect that CDS spreads are negatively correlated with the risk-less interest rate.

(2) *Changes in the Slope of the Yield Curve.* Independent from the structural framework, some authors argue that the interest term-structure is upon other factors mainly driven by i) the interest level and ii) the slope characteristics (Blanco et al. 2005).

    Often, the slope of the yield curve is seen as an indicator of economic wealth: while a positive slope indicates a prosperous economy, a negative one reflects expectations of an economic downturn. Hence, the CDS spread may decrease if an increasing slope of the interest curve indicates higher expected short rates, as also argued by Collin-Dufresne et al. (2001) for credit spreads.[9] By contrast, a decreasing term-structure may indicate an economic downturn leading to higher losses given default since recoveries are assumed to be negatively correlated to the macroeconomy (Frye 2000, Altman 2008, Bade et al. 2011). In this way, the liquidation risk for corporate debt may be higher leading to widening CDS spreads.

(3) *Changes in the Market Volatility.* Since debt claims exhibit characteristics

[8] Since systematic risk affects all market participants simultaneously, we aim to approximate this kind of risk by common risk variables. Note that state variables are generally not necessary in Merton's structural approach.

[9] Note that rising future short-term rates may lead to lower default probabilities and thus to lower CDS spreads.

similar to a short position in a put option, it follows from the option-pricing framework that option prices increase with increasing volatility. Intuitively, with an increase of volatility the firm's default probability increases and thus the related CDS spread increases due to the higher default risk.

(4) *Changes in the Credit Market Climate.* The *Credit Market Climate* may reflect the market view of the overall credit risk. If the global economy is turning down in line with decreasing recoveries, the weakening market conditions should increase the firms' default risk as well as related losses. Thus, the increased credit risk on credit markets may lead to an increase of the overall credit spread level. The *Credit Market Climate* can be seen as a common market factor similar to the market index in the CAPM. It should be strongly affected by economic conditions. Therefore, we expect a cross-sectional increase of default risk due to weakening economic conditions leading to increased CDS spread levels. Hence, the CDS spreads should be positively correlated with the *Credit Market Climate*.

(5) *Changes in the Cross-market Correlation.* Foresi & Wu (2005) argue that downside movements in any equity index are likely to be highly correlated with those in other markets as a result of global contagion. Expanding this argument to credit markets, we expect higher CDS spreads if cross-market correlations increase, because the prospects for risk diversification on global markets decrease. In turn, we expect lower CDS spreads if the dependencies across various markets – such as credit, equity, and exchange markets – decrease.

Lastly, non-systematic and thus rather individual spread determinants are proposed and discussed individually.

(1) *Physical Default Probability.* Within the structural framework, the difference between the physical probability of default (PD) and the risk-neutral PD indicates the risk aversion of market participants. Under the risk-neutral measure, the drift parameter μ of the asset value process is changed to the risk-less rate r from which it follows that the risk-neutral PD is composed of the physical PD plus a correction term accounting for the risk aversion. By controlling for the physical PD, we quantify the premium for pure default risk apart from other major determinants. In line with intuition and ceteris paribus, the higher (lower) the firm's physical PD, the higher (lower) the CDS spread should be.

(2) *Swap Liquidity.* Analogously to other authors who show that liquidity is priced in credit spreads of corporate bonds, we assume that CDS investors also claim a premium compensating for liquidity risk. Transferring these empirical findings to CDS markets, the contract's liquidity is expected to determine the CDS spread. Intuitively, CDS spreads should rise if the contracts' liquidity, for example, measured by its trading volume, decreases and vice versa. Eventually, we expect a negative relationship between *Swap Liquidity* and swap spread.

2.2 Empirical Data

Our empirical study refers to a comprehensive data set of single-name CDS spreads provided by Markit. Overall, we analyze dollar-denoted CDS spreads of 339 U.S. American entities from January 6^{th}, 2004 to December 27^{th}, 2010.[10] By splitting the entire period into two different subsamples, we ac-

[10] The contracts' document clause is MR. The seniority is SNRFOR (senior unsecured debt). For more information compare Markit (2008). Thereby, we select only contracts which have at least 47 weekly spread notations in each year.

count for different market conditions before the GFC and in times of market turbulences during the GFC. Firstly, we define the period from January 6^{th}, 2004 to June 18^{th}, 2007 as time prior to the GFC (Pre-GFC). Secondly, we define the period from June 19^{th}, 2007 to December 27^{th}, 2010 as times of financial distress during the GFC.[11]

Table 1 summarizes the sample periods for the time-series regressions (TSR) and for the cross-sectional regressions (CSR).[12] The amount of related CDS spread observations and the number of considered entities are also denoted.

[Insert Table 1 here]

Overall, we investigate 124,413 weekly CDS spreads from 339 different issuers in the entire period, in which the number of CDS spreads per entity is 367. The Pre-GFC sample contains 180 weekly spreads per entity, which leads to 61,020 weekly observations in total. In the GFC sample, we examine 63,393 weekly CDS spreads with 187 observations per entity.

The U.S. companies are divided over ten economic sectors, e.g., financials (16.81%), industrials (14.16%) and consumer goods (13.57%). Table 2 summarizes the amount of firms located in each sector and provides the sector-specific average spreads by sample.

[Insert Table 2 here]

Since we investigate a wide range of U.S. firms, we may obtain a broad insight into the cross-sectional determinants of CDS spreads. The sector-specific

[11] On June 18^{th}, 2007 it is reported for the first time that Merrill Lynch seizes collateral from a Bear Stearns hedge fund invested heavily in subprime loans, which may have caused strong spread increases on credit markets over the following days.
[12] The corresponding regression models are introduced in the next section.

average spreads clearly vary by sample and even across sectors. In order to account for sector-specific influences, we implement sector dummies in our CSR model.

Furthermore, all underlying contracts of the CDS are rated on a rating scale from 'AAA' to 'CCC'.[13] In Figure 1, we plot the time series of average CDS spreads per rating grade from January 6^{th}, 2004 to December 27^{th}, 2010 (x-axis). The y-axis denotes the average CDS spreads.

[Insert Figure 1 here]

The average spread level generally varies depending on the rating grades: the average CDS spread of 'AAA'-rated underlyings (black line) is below all other grade-specific average spreads throughout, as theoretically assumed above. By contrast, 'CCC'-rated contracts (dashed line) exhibit the highest average CDS spreads since they reflect the highest default risk. All grade-specific functions show that average spreads are rapidly increasing across all rating grades during the turmoil of the GFC.

Next, we choose the following proxies for the identified systematic state variables.

(1) *Spot Rate*. The spot rate (SP) is approximated by changes in government bonds, as also suggested by other authors in the recent literature (compare Blanco et al. 2005, Avramov et al. 2007).[14] We use 5-year Treasury

[13] The rating scale contains average ratings referring to Moody's and S&P ratings. For more details compare www.markit.com.

[14] However, due to several reasons, e.g., taxation treatment, scarcity premiums and benchmark status issues, it is often criticized that government bonds are no ideal proxy for the unobservable risk-free rate. In this concern, 5-year swap rates for dollars and euros are often proposed as a better proxy. For an insightful discussion see Blanco et al. (2005). We also incorporate corresponding swap rates for robustness.

bill rates provided by the U.S. Department of the Treasury.[15]

(2) *Slope of the Yield Curve.* Analogously to Collin-Dufresne et al. (2001), among others, we define the slope of the term structure (STS) as the difference between the long-term and the short-term Treasury bill rate. To capture slope effects, we use changes in spread differences on U.S. Treasury bills with 2-year and 10-year maturity. The slope may be interpreted as an indicator of the economic health and expectations of future short rates. Respective Treasury bill rates are also provided by the U.S. Department of the Treasury.

(3) *Market Volatility.* As benchmark for the *Market Volatility*, we assume the VIX index provided by the Chicago Board Options Exchange. The VIX measures market expectation of near-term volatility conveyed by stock index option prices.[16] By using a wider range of strike prices rather than just at-the-money series, the VIX index is additionally incorporating information from the volatility 'skew'. Thus, the VIX may not only reflect investors' consensus view of future expected stock market volatility: since out-of-the money put options as well as in-the-money call options are considered for short maturities, the index may also be seen as an indicator for negative jumps in the S&P 500 index causing investors' fear. According to Collin-Dufresne et al. (2001), an increasing probability and magnitude of large negative jumps in the firm value should increase credit spreads, and thus CDS spreads (Blanco et al. 2005).

(4) *Climate of Credit Markets.* As S&P 500 index returns are suggested to approximate the overall state of the economy (see Collin-Dufresne et al.

[15] Other maturities such as 1 year, 2 years and 10 years are also investigated, but not reported since they lead to similar results.

[16] The VIX uses a weighted average of options with a constant maturity of 30 days to expiration. The options refer to the S&P 500 index.

2001, Blanco et al. 2005), we analogously assume the index spread changes of the 5-year (5Y) CDX NA IG credit index (CDX) as proxy for the credit market conditions. The CDX is one of the most popular CDS indices covering a cross-sectoral basket of the 125 most liquid North American (NA) investment grade (IG) single-name CDS.[17] Index spreads of the CDX are provided by Markit.

(5) *Cross-market Correlation*. We consider the average of quarterly cross-correlations referring to returns on numerous i) exchange, ii) equity and iii) credit markets. In this context, we suggest some indices to calculate the applied *Cross-market Correlation* (CMC), e.g., S&P 500, DAX 30, 5Y CDX NA IG, Dow Jones Industrial Average, Nikkei 225.

Figure 2 shows the times series of the systematic state variables from January 6^{th}, 2004 to December 27^{th}, 2010 (x-axes). The y-axes denote the states of the respective proxies. The dashed vertical lines divide the entire sample period into the samples Pre-GFC and GFC.

[Insert Figure 2 here]

Time series of the *Cross-market Correlation* (upper-left chart) fluctuated within the entire period in a moderate range between 0.13 (min) and 0.63 (max) with mean 0.36 and standard deviation (STD) 0.09.

As intuitively expected, the index spread of the CDX (upper-right chart) was moving sideways with relatively low volatility before the GFC. Indeed, during the GFC the volatility of the CDX strongly increased as well as its spread level. While its mean was denoted at almost 47 basis points (bp), its

[17] The composition of the basket is fixed until maturity and included CDS contracts are equally weighted. For a detailed description of the numerous CDX indices refer to www.markit.com.

STD was at 9.8 bp prior to the crisis. In contrast to the Pre-GFC, the mean of the CDX was three times higher (136 bp) during the GFC, while its STD was six times higher (59 bp). The maximum spread was observed at the end of 2008 denoting at 280 bp, the minimum spread of 29 bp in January 2007, a few months before the GFC began.

The VIX index (mid-left chart) moved sideways from January 2004 until June 2007 with moderate volatility (index mean 13.6 and STD 2.2), increased clearly in the beginning of the GFC and reached its historical peak at around 80.9 in December 2008. Similarly to the other systematic risk factors, the mean of the VIX was clearly higher in times of crisis (2.3 times higher) than in moderate economic conditions and also its related STD (6.1 times higher). In the beginning of 2009, the VIX index clearly turned back on the index level reached in January 2008.

The *Spot Rate* in terms of the 5-year Treasury bill rate (mid-right chart) was about 3% in January 2004, moved to around 5% in June 2007 and then decreased rapidly to 1.5% in 2009 due to the market turbulences on the credit markets.

A decreasing *Slope of the Term-structure* (lower-left chart), which we observed before the global financial crisis began in June 2007, indicates expectations of an economic downward movement (compare BIS 2009). Increasing slope values as observed during the turmoil on financial markets, in turn, may have predicted an economic up-turn in the aftermath.

Eventually, the time series show that each systematic risk factor clearly moves different before the GFC than during the financial turmoil, as it is indicated by the factors' period-specific means and standard deviations. Basically motivated by the chronology of the GFC, the determination of our subsamples is also confirmed by both CDS spread descriptives and time-series analysis of the systematic state variables.

The correlation matrix in Table 3 refers to changes (Δ) in the systematic state variables identified above and reflects the linear dependency structure across these changes. The upper triangle of the matrix refers to correlations in the Pre-GFC and the lower triangle shows cross-correlations in the crisis.

[Insert Table 3 here]

According to Table 3, the proxy for the *Cross-market Correlation* and the proxies for the interest risk – *Slope of the Term Structure* and *Spot Rate* – exhibit the lowest overall Δ-dependencies on the other systematic risk factors in both samples. Table 3 also shows that the dependencies generally increase during the GFC. Nevertheless, most cross-correlations denote at low levels (about 0.10). We observe the highest correlation between the VIX and the CDX with 0.41 before the GFC and 0.64 during the financial crisis. [18]

In the following, proxies for individual risk are provided.

(1) *Physical Probability of Default.* Since a credit rating generally reflects an opinion of the obligor's creditworthiness, the highest-rated obligors ('AAA'-rated) are assumed to exhibit the lowest probability of default (PD), while lowest rated ones ('C'-rated) exhibit the highest PD. Credit-rating agencies (CRA), for example, link their classical rating grades (ordinal scaled) to historical default rates of corporate bonds (Moody's

[18] Even if the correlations are solely moderate, the presence of multi-collinearity in systematic state variables may generally distort the interpretations of regression results.

2010).[19] Hence, we use average ratings provided by Markit as proxy for the firm's physical default risk, similarly to Friewald et al. (2012).[20]

As already examined by Abid & Naifar (2006), we assume that the absolute CDS spread level is determined by the related obligor rating. The worse the rating of the obligor the higher the CDS spread level and vice versa, all else equal. For simplicity, we apply a shortened rating scale which summarizes the available rating metrics. In our cross-sectional regressions, we account for five different rating classes RC_1 to RC_5, where the latter indicates lowest creditworthiness and RC_1 highest.[21]

CRAs such as Moody's and S&P provide ratings that are rather stable through business cycles (through-the-cycle ratings), see Moody's (1999) and S&P's (2008). Thus, macroeconomic point-in-time information is rather neglected in such a through-the-cycle approach (Moody's 1999).[22] Since CRAs mainly address firm-specific risks in their rating metrics rather than states of the global economy (common risk) (S&P's 2008), we consider credit ratings primarily as proxy for individual risk.

(2) *Swap Liquidity.* As proposed by Gala et al. (2010) and Gandhi et al. (2012), we incorporate the contract's amount of trades (trading depth) to proxy its liquidity. The data were provided by Markit and denoted as

[19] Referring to the three major rating agencies – Moody's, S&P and Fitch – the rating grades are monotonically increasing with the obligor's creditworthiness (compare Moody's 2012).
[20] Recall that Markit's average ratings are based on available Moody's and S&P ratings, see www.markit.com
[21] Due to the number of available ratings, RC_1 includes rating grades 'AAA', 'AA' and 'A' , RC_2 reflects 'BBB' ratings, RC_3 accounts for rating grade 'BB', RC_4 refers to 'B' ratings and RC_5 to 'CCC' ratings. The data set contains only one 'AAA'-rated and six 'AA'-rated entities. Even if we exclude these entities from our regression approach and thus solely group 'A'-rated firms in RC_1, we obtain similar regression results.
[22] More detailed information to CRAs and their rating systems can be found in Krahnen & Weber (2001) or in Löffler (2004), Löffler (2012).

Swap Liquidity (LIQ).

Overall, each single-risk proxy i) reveals for itself significant explanatory power in respective univariate regressions, ii) significantly contributes to the explanation of the endogenous variable in our CSR and iii) has the power to innovate. The latter condition is especially important in terms of multi-collinearity: all of our systematic risk factors provide for themselves additional explanatory power, even if considered lastly in a normalized regression framework. [23] In other words, the explanatory power of each proxy is i) not completely covered by the ensemble of other regressors, independent of the introduction order, and ii) its explanatory power is not the product of the entire ensemble.

3 Empirical Evidence for Pricing Systematic Risk in CDS Spreads

3.1 Models in the Two-pass Regression Approach

In the first step of our two-pass regression procedure (similar to Fama & MacBeth 1973), we estimate the CDS spread sensitivities (betas) to the proposed systematic state variables by multiple time-series regressions (TSR). For each CDS referring to entity $\vartheta \in \{1, ..., 339\}$ with CDS spread $S_{\vartheta,t}$ at time t we estimate the following time-series regression model, which was methodologically proposed by Collin-Dufresne et al. (2001) for credit spreads and also

[23] The order of regressors does not matter in basic OLS regressions, but within OLS regressions based on normalized regressors which were additionally conducted for robustness. Within a normalized framework, the regressors are corrected for observable co-variances. In the end, the regressors' covariance matrix is a diagonal matrix with variances equal to one. The regressors' means are also standardized and equal null. The results accounting for multi-collinearity are not separately reported since they solely confirm the presented findings.

applied by Ericsson et al. (2009) and by Friewald et al. (2012).

$$\Delta S_{\vartheta,t} = \alpha_\vartheta + \beta_\vartheta^{CMC} \cdot \Delta CMC_t + \beta_\vartheta^{CDX} \cdot \Delta CDX_t + \beta_\vartheta^{VIX} \cdot \Delta VIX_t + \beta_\vartheta^{SR} \cdot \Delta SR_t + \beta_\vartheta^{STS} \cdot \Delta STS_t + \varepsilon_{\vartheta,t}. \tag{2}$$

$\Delta S_{\vartheta,t}$ denotes the spread change of the contract related to firm ϑ at time t.[24] α_ϑ describes the intercept, $\beta_\vartheta^{(\cdot)}$ denotes the coefficients of included regressors, Δ refers generally to changes in the state variables and $\varepsilon_{\vartheta,t}$ is the residual.[25]

In the second step, we examine the cross-section of CDS spreads by cross-section regressions, similarly to Friewald et al. (2012) who apply this type of regression to corporate bond spreads. Thus, our TSR beta estimates are used as regressors in the cross-sectional regression (CSR), along with additional variables such as the proposed individual risk factors. In the basic model setup, we consider the firm's ratings and the contract's liquidity. Additionally, we account for firm-specific sectoral influences by sector dummies. In Section 3.4, we add further firm-specific risk factors, e.g., the firm's *Leverage Ratio* and *Market Capitalization*, as well as further systematic risk betas related to the Fama-French factors in order to check the robustness of our findings.

After calculating the entities' average CDS spreads $\overline{S}_\vartheta$ by sample, we esti-

[24] In our TSR regressions, we regress weekly CDS spread changes by weekly changes in the common risk variables. Corresponding regressions are also conducted on a daily database leading to similar results. Due to the noise in high-frequency data, we focus on results related to the weekly database.
[25] Linkage of shortened declarations according to Section 2.2: *Cross-market Correlation* (CMC), *Credit Market Climate* (CDX), *Market Volatility* (VIX), *Spot Rate* (SR) and *Slope of the Term Structure* (STS).

mate the following cross-section regression model for each sample

$$\overline{S}_{\vartheta} = \alpha + \gamma^{CMC} \cdot \hat{\beta}_{\vartheta}^{CMC} + \gamma^{CDX} \cdot \hat{\beta}_{\vartheta}^{CDX} + \gamma^{VIX} \cdot \hat{\beta}_{\vartheta}^{VIX} + \gamma^{SR} \cdot \hat{\beta}_{\vartheta}^{SR} + \gamma^{STS} \cdot \hat{\beta}_{\vartheta}^{STS} + \gamma^{LIQ} \cdot LIQ_{\vartheta} + \boldsymbol{\gamma}^{RC} \cdot \boldsymbol{RC}_{\vartheta} + \boldsymbol{\gamma}^{SI} \cdot \boldsymbol{SI}_{\vartheta} + \varepsilon_{\vartheta}^{CS}, \quad (3)$$

where $\varepsilon_{\vartheta}^{CS}$ denotes the cross-sectional residual. $\hat{\beta}_{\vartheta}^{(\cdot)}$ denotes the parameter estimates of TSR regressors. LIQ denotes the swap's average liquidity, **RC** and **SI** represent the firm-specific *Rating Classes* and *Sector Indicators* respectively, which are included as dummy variables.[26] α denotes the intercept and $\gamma^{(\cdot)}$ are the cross-sectional slope parameters. $\boldsymbol{\gamma}^{RC}$ and $\boldsymbol{\gamma}^{SI}$ represent vectors of estimators referring to the sector-specific and rating-specific dummy variables.

Table 4 gives a brief regressor overview and shows the predicted signs of coefficients related to the TSR and the CSR in line with the theoretical expectations presented in Section 2.1.

[Insert Table 4 here]

For example, the estimates of the TSR which refer to changes in the CDX credit index should be positive since in theory an increase of the CDX index spread should commonly widen the CDS spreads. Alternatively, for the *Swap Liquidity LIQ* we expect a negative relationship to the CDS spread. Hence, an increase of the liquidity should lead to a decrease of the CDS spread and vice versa.

[26] RC_1 (SI_1) represents the reference rating class (sector) included in the intercept.

3.2 Systematic Risk Beyond Ratings

Firstly, we examine whether the firms' ratings have cross-sectional explanatory power with respect to the CDS spreads of 339 entities. Table 5 reports the regression results of rating-based CSRs.

[Insert Table 5 here]

The intercept includes the reference rating class RC_1 referring to 'AAA', 'AA' and 'A' ratings. Thus, the intercept represents the basic spread level of swap contracts related to high-rated obligors. Furthermore, Table 5 shows that the worse the firm's rating the higher is the general risk premium for that CDS contract, which is in line with our expectations. The risk premiums seem to be higher in the financial crisis than prior to the GFC, which holds across all rating classes. The results show that firm ratings represent relevant information for pricing swap contracts cross-sectionally. A comparison of R^2 based on a comparable number of observations (see Table 3) indicates that ratings may explain more of the spread variation in times of financial distress than in moderate economic conditions (45.29% vs. 55.39%). These results may also indicate that market participants, who were involved in pricing swap contracts, relied more intensively on ratings during the GFC than prior to the crisis. Since we observe sample-specific differences in the rating-based spread level, which are 'averaged' out over the entire period, we focus our empirical study in the following solely on the two samples Pre-GFC and GFC.

A simple preliminary test to examine whether CDS spreads are reflecting systematic risk beyond the risks reflected by CRA ratings is to compare the rating-based mean CDS spreads of contracts having different sensitivities to systematic risk.[27] Similarly to Iannotta & Pennacchi (2011), we conduct univariate TSRs for each systematic regressor by rating class ($RC_1 - RC_5$). For each sample period, the sensitivity to systematic risk is measured by the regressor's beta. CDS contracts exhibiting systematic risk sensitivities above or equal to the sample median are defined as contracts with high systematic risk exposures and thus attributed to Portfolio 1. Contracts with sensitivities below the sample median are attributed to Portfolio 2 (low systematic risk exposures). Afterwards, the portfolios' mean spreads are calculated by rating class and tested for equality (t-test).

Table 6 reports the median betas (β), the portfolio-specific mean spreads and the t-test results for each systematic risk factor, rating class and sample.

[Insert Table 6 here]

The median betas are monotonically increasing with rating classes. Hence, contracts related to the worse credit rating exhibit the highest betas to systematic risk. This may be due to the increase in the rating-specific spread level. Thus, swap contracts of poorly-rated firms may not necessarily exhibit the highest sensitivities to systematic risk. Although the sensitivities to systematic risk are not comparable across rating classes, the contracts' systematic risk sensitivities vary widely around the median beta within each rating class. This indicates that systematic risk exposures are underestimated in parts by CRAs. This finding holds for all regressors and both samples.

Eventually, most of the portfolio-specific mean spreads significantly differ from each other in each sample and across all regressors. In most cases, we ob-

[27] Iannotta & Pennacchi (2011) provide a similar test for credit spreads on corporate bonds.

serve higher average spreads for portfolios composed of high risk contracts. [28] From these empirical findings we conclude that CDS with higher systematic risk exposures are in general higher priced and that this systematic risk is not sufficiently reflected by the related credit rating.

3.3 Empirical Results of Time-series and Cross-section Regressions

Figure 3 shows boxplots summarizing the estimation results of multiple time-series regressions across 339 entities by regressor and by sample. All of the state variables in regression (2) have some ability to explain changes in the CDS spreads. Further, the signs of the estimated coefficients mostly correspond with our rationale.

[Insert Figure 3 here]

With respect to the GFC (right boxplot in each chart), the regression results show that signs of estimates agree on average with our expectations, except the betas of the *Spot Rate* proxy. These beta estimates are expected to be negative, which is on average only fulfilled prior to the GFC. [29] Hence, in the pre-crisis the SR corresponds to expectations and thus an increase in the SP tends on average to a decrease of CDS spreads across all firms. In times of financial distress, the beta estimates of the *Cross-market Correlation* are on average positive and thus CDS spreads tend to increase with increasing market correlation.

[28] The order of sensitivities is descending for each rating class. Thus, we observe the highest systematic risk concentration in *Portfolio 2*, if the regressor's sensitivity to systematic risk is expected to be negative, as it is the case in terms of the *Spot Rate*. Again, the higher interest risk sensitivity leads in average to higher CDS spreads.

[29] While the median beta is negative, the mean beta is positive due to a few outliers.

Coefficients of the slope proxy (SMT) are mainly negative during the *GFC*. As suggested in theory, positive expectations of the economic health leads to a decrease in CDS spreads across most of the firms. We find further that the betas of the CDX index spread changes are positive throughout all samples. As theoretically expected, there is a positive relationship between CDX spread changes and CDS spread changes.

Regarding the Pre-GFC (left boxplot in each chart), the signs of betas correspond on average to theory except in case of the VIX and the STS. In terms of the VIX (STS), the respective beta estimates are on average negative (positive) before the crisis and thus contrary to our rationale. [30] Analogously to the empirical findings of Longstaff & Schwartz (1995), Duffee (1998) and Blanco et al. (2005) for credit spread changes, we find that an increase in the risk-free rate (SR) lowers the CDS spread for at least 75% of the firms prior to the crisis.

Similarly to other empirical studies (Collin-Dufresne et al. 2001, Ericsson et al. 2009, Friewald et al. 2012), the coefficient of determination R^2 ranges in average between 14.37% and 29.08%, as shown in the lower-right chart of Figure 3. We find that the explanatory power of our applied systematic risk factors depends on the sample period. Our systematic state variables explain CDS spread changes much better in times of market turbulences than in moderate market conditions. This finding may justify the selection of our proxies for systematic state variables.

By contrast, most recent studies (e.g., Collin-Dufresne et al. 2001, Ericsson et al. 2009) primarily consider firm-specific risk factors in their TSR, but

[30] Note that there are still entities whose beta estimates meet our rationale, but not on average.

do not provide a cross-sectional spread examination, except Friewald et al. (2012). In our two-pass approach such individual risk factors are methodically omitted in the TSR (pass one), but explicitly considered in the CSR (pass two).[31] Nevertheless, we achieve comparable explanatory power in our first pass by focusing on systematic risk factors.

In the second step, we run the cross-sectional regressions (3) according to our two-pass regression methodology to identify significant cross-sectional pricing factors and their specified weights or spread premiums (γ) in pricing CDS contracts.

Table 7 shows the gamma estimates of the CSR for the two samples (Pre-GFC and GFC). While the left column in each sample reports results without sector dummies, the right column shows results under consideration of sector dummies which account for sectoral influences. Standard deviations are reported in parentheses and significance levels are marked with asterisks. In contrast to the additional individual variables in the CSR, which are deterministic, the betas of our systematic state variables are statistically estimated. Thus, they are generally stochastic and hence possibly misspecified. To account for related parameter estimation errors, we also report corrected standard deviations and corrected significances for the gamma estimates, as suggested by Shanken (1992).[32]

[Insert Table 7 here]

[31] We are explicitly targeting at the product's sensitivity to systematic risk based on weekly data points. To avoid distortions due to time-constant firm-specific risk factors such as the firm ratings or corporate debt, we omit these factors in the first pass.

[32] The Shanken corrections are separated by slash. For a thorough description of the applied correction procedures compare Shanken (1992), Shanken & Zhou (2007).

While the TSR estimates indicate the firm-specific sensitivity to the systematic risk factors, the CSR estimates may be interpreted as average pricing weights for the systematic risk factors across all CDS spreads. We find that mostly the CSR estimates significantly differ from null. Thus, TSR estimates are either positively ($\gamma > 0$) or negatively ($\gamma < 0$) priced.

For example: given a positive beta (β), we observe with respect to a positive gamma ($\gamma > 0$) that the CDS spread increases if the firm's sensitivity to that common risk factor increases.

In times of financial distress (GFC), all systematic risk sensitivities (TSR-betas) exhibit significant explanatory power to the cross-section of CDS spreads, even if the standard deviations of gamma estimates are Shanken corrected (separated by slash). This means that the contracts' sensitivities to the systematic risk proxies are significantly priced in CDS contracts across all economic sectors. Thereby, the signs of all gamma coefficients correspond to our economic expectations.

In the pre-crisis, we observe a slight mismatch between theory and empirical findings with respect to the interest risk proxies. Prior to the GFC, the gamma estimates indicate that a higher sensitivity to the *Spot Rate* leads to a spread increase, but the corrected t-statistic shows that these estimates are not significantly priced. The *Slope of the Term Structure* also lacks statistical significance in the pre-crisis, but becomes statistically significant in the GFC. Therefore, we infer that market participants view the STS as an indicator of economic wealth, which is particularly priced in economic downturns, but less relevant in moderate economic conditions.

The gammas of the CDX, the CMC and the VIX reach high statistical significance in both samples, even if we control for firm-specific risks, sector dummies and Shanken-corrected t-statistics. Thus, market participants seem to demand a positive risk premium depending on the *Cross Market Correlation*, the *Credit Market Climate* and the *Market Volatility*, independent from the sample period.

As found in previous literature, liquidity is also an economically and statistically significant pricing determinant, which is contract-specific. The estimates of the *Swap Liquidity* proxy are statistically significant across all samples. According to our rationale, market participants claim a risk premium for the market liquidity of the CDS. Thus, in the cross-section an increase of the *Swap Liquidity* leads to a decrease of swap spreads and vice versa.

Regarding the rating classes, our empirical results confirm our expectations and show that the CDS spreads monotonically increase with decreasing firm rating. Again, we observe a strong increase of basic spread levels across all rating classes during the GFC. This general increase in CDS spreads may be due to extremely high default rates of investment grade bonds in this period, which may have caused many rating downgrades of these financial instruments as well. Hence, we suspect that the firms' rating information significantly determines the CDS spread levels across both samples, correction methods and swap contracts. As expected, we conclude that a high-rated firm may benefit from its higher creditworthiness by receiving a reduction in its CDS spread (lower spread level).

Moreover, we find that our empirical results hold across all economic sectors examined, since the inclusion of sector dummies affects our estimation results only slightly. Thus, we conclude that the introduced risk factors have economy-wide impacts on the pricing of swap contracts, beyond sectoral influences.

While the entire ensemble of risk factors account for almost 90.18% of the spread variation during the GFC, the models R^2 is clearly lower prior to the crisis (83.18%). Thus, we find that the explanatory power of the regressor ensemble depends on the sample period and that the regressors best fit CDS spreads in the crisis. This finding also indicates that systematic risk betas of CDS contracts are particularly priced in economic downturns coming along with increasing statistical significances of our systematic risk proxies in the GFC.

In Figure 4, we compare predicted CDS spreads with observed market spreads by sample in order to indicate the accuracy of our CSR model. The x-axes of the two charts denote the predicted CDS spreads and the y-axes denote the market CDS spreads.

[Insert Figure 4 here]

Referring to regression (3), both scatter plots visualize the quality of our proposed CSR model. Since the spread predictions in the lower chart ($R^2 =$ 90.18%) are less scattered than in the upper one ($R^2 = 83.18\%$), we suggest that our CSR model – which explicitly addresses systematic risk – reaches the highest model accuracy in times of global financial distress.

3.4 Robustness

In the following, we extend our basic regression approach in several ways to show the robustness of our empirical findings. Firstly, we test whether our results hold, even if the three Fama-French (FF) factors are included in our basic models. Thereby, we also examine if the FF factors provide additional explanatory power in the cross-section of swap spreads beyond the basic risk components (compare Fama & French 1993). Secondly, we examine euro/dollar swap rates as alternate proxies for the *Spot Rate* and the *Slope of the Term Structure*. Thirdly, we conduct a principal component analysis (PCA) referring to the residuals of the multiple time-series regressions. The PCA may help to identify further potential candidates for systematic risk. Related to the PCA, we conduct new cross-sectional regressions in which we include the eigenvector of the first major component. By this, we test if this unknown systematic risk factor is cross-sectionally priced in the CDS spreads. Fourthly, we add the firm's *Leverage Ratio* and *Market Capitalization* as two more firm-specific risk factors to the basic regression model. Lastly, we provide the regression results of the entire model in which all model extensions are simultaneously considered.[33]

Table 8 shows CSR results referring to the first three model extensions. Estimation results are presented for both sample periods (Pre-GFC and GFC) under consideration of sector and rating dummies. Respective standard deviations are reported in parentheses. Additionally, corrections for the standard deviations and significances are provided as suggested by Shanken (1992), which are separated by a slash.

In the first case (left column), the three Fama-French benchmark returns are included in the TSR. Afterwards, the estimated betas are added to the basic CSR model in Equation (3). The *Fama-French excess Return* (FFR)

[33] Not reported are robustness checks related to i) various window sizes of the cross-sectional regressions, e.g., rolling or fixed, and ii) other alternate proxies for, e.g., the *Slope of the Term Structure*, *Spot Rate* and *Cross-market Correlation*. These analyses lead to similar regression results as the already reported ones.

describes the excess[34] return on the market, *Small Minus Big* (SMB) represents the performance of small stocks relative to big stocks, and *High Minus Low* (HML) denotes the performance of value stocks relative to growth stocks (compare Fama & French 1993). Commonly, the Fama-French factors are used by investors seeking portfolio benchmark returns and by academics to explain the cross-section of stock returns.

We find that there is a negative relationship between the FFR and CDS spreads which is also statistically significant. This empirical result also follows economic intuition since positive excess returns may indicate a prosperous global economy with lower default risk in general. Thus, the CDS spreads should increase if the excess returns decrease and vice versa. In contrast to the FFR, we observe shifts in the signs of estimators with respect to SMB and HML across samples. These sign changes makes further interpretations somewhat difficult, even if the estimates reach statistical significance in both samples.

[Insert Table 8 here]

On the one hand, the R^2 increases from 83.19% to 89.04% through the consideration of the Fama-French factors in the pre-crisis. On the other hand, the R^2 remains on the same level with respect to the GFC (90.18% vs. 90.57%). Thus, we conclude that the Fama-French factors may increase the explanatory power of the basic model in times of moderate economic movements, but that the additional pricing information is strongly limited in times of an economic downturn.

[34] The excess return is defined as the difference between the return of the market portfolio (R_m) and the risk-less rate (r) (compare Fama & French 1993).

In the second case (middle column), we examine the 5-year euro/dollar swap rate as alternate proxy for the *Spot Rate*, since some authors in the recent literature suggest swap rates as interest rate proxies rather than Treasury bills.[35] Furthermore, the *Slope of the Term Structure* is now approximated by the difference of the 10-year swap rate and the 2-year swap rate. The new ensemble of systematic risk factors achieves similarly high R^2, whereat the gamma coefficients are roughly similar to those of the basic model. Since the coefficients of determination vary not more than 0.1% in each sample, we suggest that alternate interest rate proxies provide similar pricing information.

In the third case (right column), we conduct a principal component analysis (PCA) on the residuals of the multiple TSR to identify potential candidates for systematic risk omitted in this empirical study so far. By this, we examine if the TSR residuals are jointly driven by unknown systematic risk factors and we specify these principal components, similar to Collin-Dufresne et al. (2001). To test whether the specified principal components are priced by market participants in our CDS spreads cross-sectionally, we run subsequent second-pass regressions (CSR) in which we additionally include the eigenvector of the first major component.

Results of the PCA are plotted in Figure 5. While the upper chart shows the results of the PCA related to the Pre-GFC, the lower chart contains the PCA results for the GFC. The primary y-axes show the eigenvalues, the secondary y-axes denote the cumulative variance of identified components that are denoted on the x-axes.

[Insert Figure 5 here]

[35] For literature remarks see Footnote 13.

Both charts demonstrate that the PCA leads to similar results in each sample. According to the scree test, the residuals of the time-series regressions are mainly driven by one major risk component that accounts for almost 17% of the cumulated variance prior to the GFC and for almost 25% during the GFC.

The right column of Table 8 summarizes the estimation results of the CSR after adding the first principal component. The results show that the influence of the first component ($PC1$) is negatively estimated in both samples. Moreover, the principal component is significantly priced during the GFC, but not in the pre-crisis. Since the component is unknown, economic interpretations are somewhat difficult. But the coefficient indicates that there may be a source for systematic risk that is negatively correlated with CDS spreads. Thus, the swap spreads increase when the component's value decreases and vice versa.

Overall, the PCA indicates that there are some systematic drivers responsible for the shared variance of TSR residuals, but these drivers are not priced without restrictions cross-sectionally. Therefore, the use of the PCA is strongly limited. From the small pricing impact of the PCA component in combination with the relatively high explanatory power of our basic model framework, one may conclude that our valuation framework already considers the most important systematic as well as individual spread drivers and thus provides valuable insight into the pricing of swap contracts.

Table 9 reports the empirical results related to the CSR based on the last two model extensions. The estimation results refer to the Pre-GFC and the GFC. Standard deviations are reported in parentheses. The shanken-corrected standard deviations and significances are separated by a slash, see Shanken (1992).

[Insert Table 9 here]

Results reported in the left column refer to the basic model under consideration of two more firm-specific factors: the firm's *Market Capitalization* (MC) and *Leverage Ratio* (LR). Independent from Merton's structural framework, we suppose that the firm's size somehow indicates the robustness of the firm against, e.g., economic downturns (compare Blume et al. 1998, Tang & Yan 2007). We suggest that firms characterized by a large and well-diversified asset portfolio exhibit both a higher resistance to external shocks and a greater power to innovate, even in market turbulences (compare Porter 1987, Hitt et al. 1996). Thus, we expect a positive risk premium for firms that are less market capitalized. Finally, we measure the firm size by the natural logarithm of the market value of the firm's equity (market capitalization) (compare Blume et al. 1998) and additionally calculate the book-to-market equity ratio based on a COMPUSTAT database.[36]

According to the structural theory, the default threshold is a function of outstanding debt claims. The higher the leverage, the higher the probability is that the asset value process pass the critical threshold. Hence, the default probability is increasing with increasing leverage. Therefore, we may expect a positive relationship between the leverage ratio and the observed CDS spread. Among others, Welch (2004) found that stock returns capture changes in leverage appropriately. Approximated by stock returns, Avramov et al. (2007) identified leverage as main driver for credit spread changes. We

[36] Since the book-to-market equity ratio reaches no significance in our model framework, we solely focus on the firm's market capitalization.

approximate leverage by the following leverage ratio

$$\frac{\text{Book Value of Debt}}{\text{Market Value of Equity} + \text{Book Value of Debt}}$$

to proxy the firm's health according to Collin-Dufresne et al. (2001). Respective data is provided by COMPUSTAT. As this analysis requires additional data from COMPUSTAT the number of entities is reduced to 225.

According to the left column of Table 9, our main results also hold with respect to the inclusion of these two firm-specific variables.[37] We find that the MC does not provide significant explanatory power – neither prior to the GFC nor during the GFC. By contrast, the firm's LR constitutes a significant pricing determinant in moderate economic conditions which also corresponds to economic expectations: across all economic sectors an increase in the firm's leverage leads to an increase in the swap's risk premium. Overall, the inclusion of these firm-specific risk factors lead to an increase of the R^2 from 83.18% to 91.29% in the Pre-GFC, but causes solely small benefits in times of the GFC, where the R^2 increases only from 90.18% in the basic model to 91.63% in the extended model.

To check whether the effect sizes related to each model extension are complementary or not, we estimate the last model case in which the basic two-pass approach is simultaneously extended to the Fama-French factors, the *Leverage Ratio*, the *Market Capitalitzation* and the first principal component.[38] The respective regression results are reported in the right column of Table 9.

With respect to the models R^2, the entire ensemble of risk factors accounts

[37] Slight differences may be due to the lower amount of entities in this model setup.
[38] Here, Treasury bills constitute the reference interest rates.

for almost 94% of the CDS spread variation in both samples, which is highest compared to the R^2 of all other regression models.[39] We find that the main results are confirmed in the *Entire Model*: again, the OLS regression results show that all estimates of the systematic risk variables reach statistical significance, independent from the sample period.[40] Thus, all systematic risk proxies are significantly priced in the cross-section of CDS spreads. Apart from the *Slope of the Term Structure*, all of these variables additionally meet economic expectations. But even though, e.g., the time-series characteristics of systematic risk variables vary by sample in terms of both their means and standard deviations (compare Figure 2), the quality of the *Entire Model* is almost identical in both samples. Since the *Entire Model* exhibits high explanatory power independent from the sample, this regression model seems to be robust against subsampling in some extent.

Each case-specific model extension confirms for itself the results of the basic approach. Thus, we identify the *Credit Market Climate* (CDX), the *Cross Market Correlations* (CMC) and the *Market Volatility* (VIX) as most important systematic risk factors in the cross-sectional pricing process of swap contracts. The corresponding risk sensitivities (betas) are positively priced across all samples and model cases. This result indicates a positive correlation between these risk proxies and the cross-section of credit spreads. We find that CDS spreads significantly rise if one of these risk factors increases and vice versa which is in line with economic expectations. The applied model extensions may help to increase the model's explanatory power particularly with

[39] Note that the models' R^2 are not directly comparable with each other due to different numbers of entities in the data sets.

[40] The Shanken-corrected t-value of the VIX is not statistically significant in this model setup. Such distortions may generally be due to i) the lower amount of entities, ii) the higher number of regressors or iii) effects of multi-collinearity.

respect to moderate economic conditions. Additionally, we confirm liquidity as a further decisive determinant in pricing swap contracts. Corresponding to expectations, the contract's liquidity reveals a negative relationship to the CDS spread in both samples and we observe significant negative gamma estimates across all models. Hence, the results show that the contract's sensitivity to liquidity risk is compensated through a respective premium widening the spread if the liquidity of the contract decreases. Referring to the rating classes, the estimates are statistically significant in most cases. The empirical results show that market participants claim a higher risk premium for investing in low-rated swap contracts reflecting a lower creditworthiness of the rated obligor. This risk premium is monotonically increasing with rating classes and paid in the cross-section of CDS spreads. All these findings hold, even if we account for the economic sector in which the firm is operating.

Eventually, we conclude that systematic risk generally affects spreads of swap contracts relying on debt assets. Even if it is hard to measure the pricing impact of the systematic risk factors exactly, we demonstrate that specific systematic risk variables such as the *Credit Market Climate*, the *Cross-market Correlation* and the *Market Volatility* may play a major role in pricing credit default swaps. We find that the systematic risk exposures of CDS contracts vary by rating class and even within each rating class. We further show that these systematic risk exposures are priced beyond ratings. Although the explanatory power of our systematic risk determinants may generally vary by regressor and by sample, we find that the influence of most systematic risk factors increases in economic downturns. Overall, we argue in this empirical study from both an economic and a statistical perspective in order to demonstrate the relevance of the provided systematic risk factors for pricing CDS contracts, even in the presence of major firm-specific risk factors, other systematic risk proxies and sectoral influences.

4 Summary

The recent Global Financial Crisis (GFC) has shown that macroeconomic shocks, e.g., caused by the U.S. housing crisis, may have strong impacts on global financial markets, particularly on the credit markets. Indeed, many credit market participants suffered from unexpectedly high default rates on corporate bonds or related financial instruments such as credit default swaps or collateralized debt obligations (compare Moody's 2009, Moody's 2011).

We find that most betas of our systematic state variables are significantly priced in each sample, even if firm-specific risk variables and sector dummies are included. Our basic ensemble of risk factors explains about 83% of the cross-section of CDS spreads before the crisis and about 90% during the crisis. Thus, systematic risk seems to be in economic downturns. Moreover, we identify the firm's rating, *Leverage Ratio* and the contract-specific *Swap Liquidity* as the most important individual risk factors in pricing swap contracts. Thus, our results also correspond to findings of other authors in the recent literature. While the firm's rating is mostly significantly priced and its gamma estimates correspond to economic expectations, those of other risk factors, such as the *Market Capitalization* do not. Results related to the firm's *Leverage Ratio* are plausible from an economic point of view in both samples and this proxy is also significantly priced prior to the GFC.

Related to our systematic risk factors, we find that the sensitivity to the *Credit Market Climate* – approximated by the 5-year CDX NA IG credit index spread – is significantly influencing the cross-section of CDS spreads. From an economic perspective, we observe a positive sensitivity of CDS spread changes to changes in the CDX which leads to a positive risk premium in the contracts' cross-section. If the credit climate gets worse, the CDS spreads significantly increase and vice versa. Hence, our empirical findings show that investors on CDS markets are monetarily compensated for this kind of common risk.

Furthermore, we find that the suggested *Cross-market Correlation* also significantly explains CDS spreads. To approximate the prospects of risk diversification across, e.g., stock, credit and exchange markets, we calculate the average cross-correlation related to specified markets. Both beta and gamma estimates also satisfy economic expectations: the higher (lower) the cross-market correlation the higher (lower) is the related systematic risk since market participants are more (less) constrained in their diversification efforts. Thus, we observe increasing CDS spreads in line with an increasing *Cross-market Correlation* (positive pricing effect) due to a positive sensitivity of CDS spreads to cross-correlation movements.

With the VIX index – indicating the *Market Volatility* – we identify another important determinant for the valuation of systematic risk in CDS spreads. Positive beta as well as gamma estimates, which are also statistically significant, confirm our theoretical expectations and suggest that market participants are positively rewarded for the market risk expressed through the volatility on stock markets. We find that if the volatility on stock markets is high (low) swap investors may receive a high (low) risk premium included in the CDS spread.

In order to check the robustness of our empirical findings, we provide further model extensions: to account for parameter estimation risk related to our two-pass regression approach, to our cross-section regressions, we firstly provide corrected t-statistics for the gamma estimates, as proposed by Shanken (1992). Even if the related significances slightly differ, the primary tendency of our main results hold. Moreover, we extend our analysis to the Fama-French Factors (Fama & French 1993). In both samples, the model accuracy increases in terms of the coefficient of determination (R^2), but this effect is particularly observable in moderate economic conditions. The inclusion of swap rates instead of Treasury bills in order to approximate the interest rate risk in terms of the *Spot Rate* and the *Slope of the Term Structure* leads to R^2, which are similarly as high as in the basic model. Eventually, the R^2 do not differ more than 0.1% in total. Therefore, we conclude that swap rates provide comparable pricing information to Treasury bills. Through a principal component analysis – similarly to Collin-Dufresne et al. (2001) – we identify at least one major component responsible for the shared variance of TSR residuals. We find that this principal component is significantly priced in CDS spreads across all entities during the GFC, but not prior to the crisis. Eventually, the results related to each model extension show that our main empirical findings hold, even in the presence of these additional risk factors or proxy alternatives.

Apart from our findings, further research is suggested in other systematic risk variables such as market recovery risk, or counter-party risk since both factors may represent other relevant determinants of CDS spreads omitted in this study (compare Brigo & Chourdakis 2009, Gandhi et al. 2012). Thereby, both risk variables may be evaluated either referring to credit markets in general (systematic) or explicitly as swap-specific risk factors.

On the one hand, we are aware that there may exist other proxies that more appropriately measure the identified systematic risk variables. On the other hand, results may generally be due in part to 'failure' in the proposed risk proxies since they depend strongly on the measurement technique and the quality of the data source. Even in terms of our *Cross-market correlation*, several other index compilations seem to be economically plausible as well. Thus, modifications of the measurement technique may either confirm or contradict our findings, even in a large set of risk factors, where also multi-collinearity may cause further distortions. Proper interpretations of our empirical findings are even more complicated if single state variables are conversely discussed in the recent literature. This might be the case, for example, in terms of the economic meaning and effect size related to the *Market Capitalization*.

In general, our empirical study provides a valuable insight into the valuation of systematic risk in CDS spreads. We suggest that at least three of our systematic risk factors reflect decisive determinants in pricing credit default swaps in line with economic expectations. These systematic determinants may also play a decisive role in the valuation of synthetic CDOs since this type of asset securitizations consists of CDS contracts. Thus, our empirical study indicates not only the impacts of systematic risk on the valuation of swap contracts, but also offers scope for further research in the valuation of structured securities.

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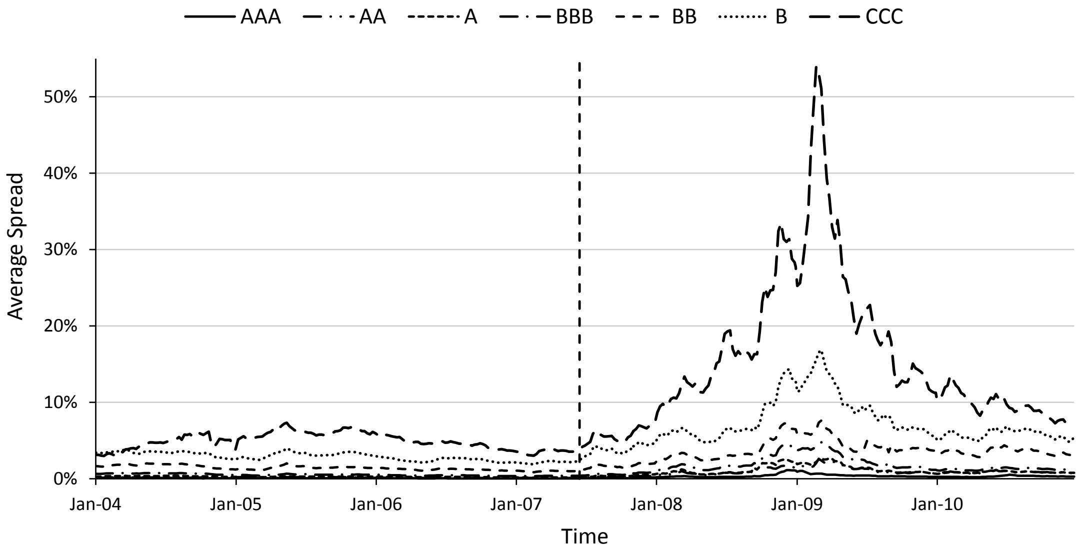
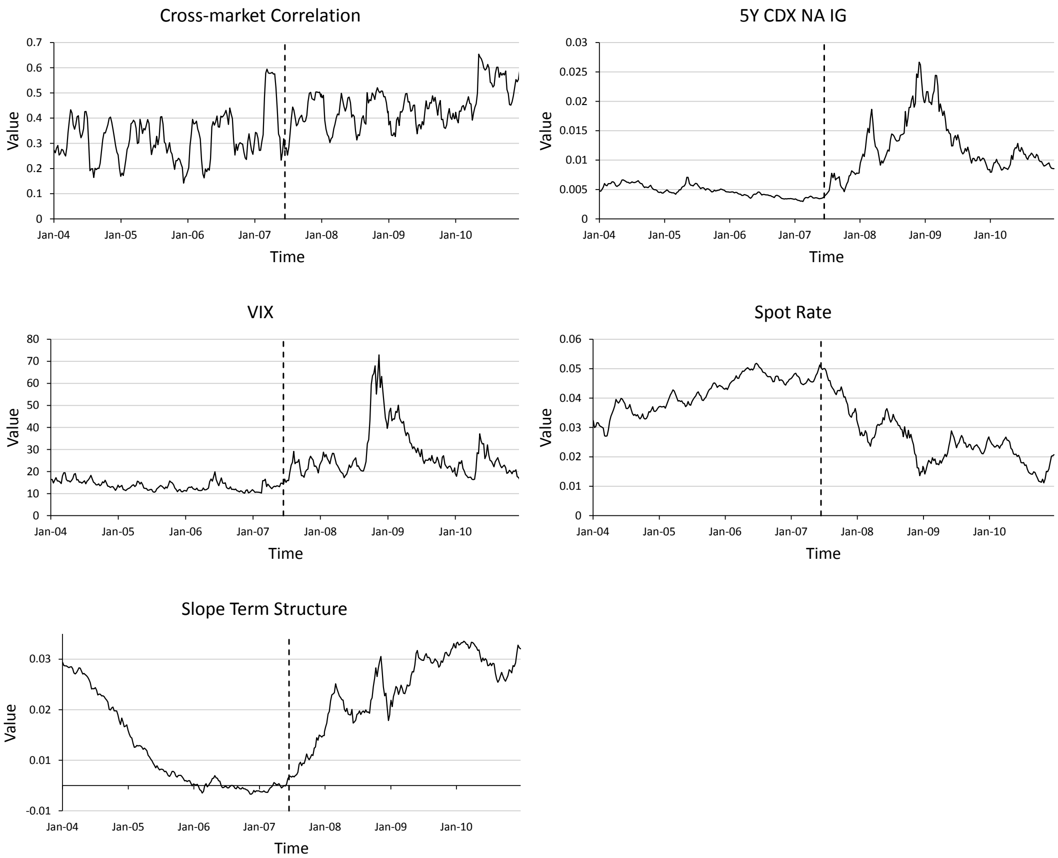
Figures

Fig. 1. Average Spreads by Rating



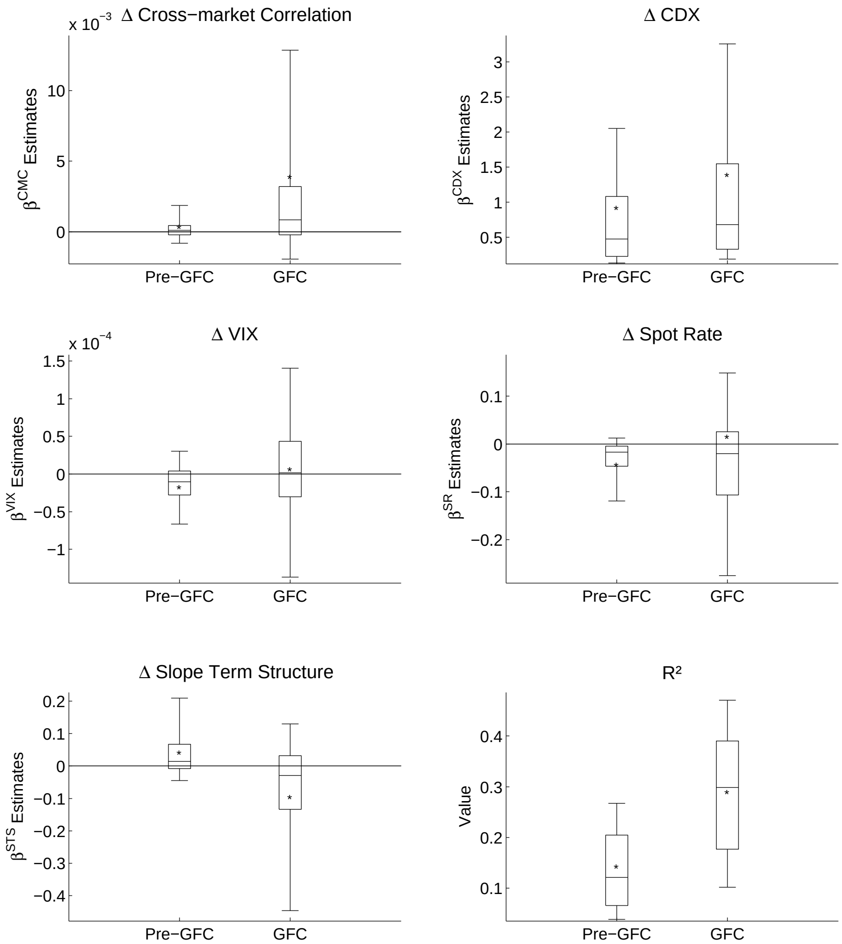
Notes: This figure shows time series of average CDS spreads for various rating grades, e.g., 'AAA', 'AA', 'A', from January 6^{th}, 2004 to December 27^{th} 2010. The spread function of 'AAA'-rated contracts (black line) is below all other spread functions since highest creditworthiness is linked to the lowest risk premium. In turn, the 'CCC'-based CDS spread function (dashed line) is located above all others. The entire sample is divided into the period prior to the financial crisis (Pre-GFC) and the GFC by the dashed vertical line.

Fig. 2. Time Series of Systematic State Variables



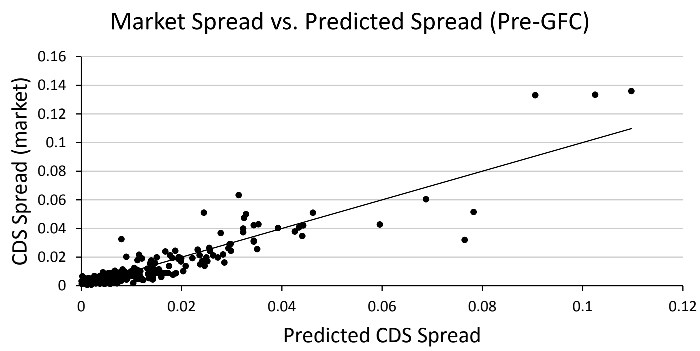
Notes: This figure shows time series of systematic state variables from January 6^{th}, 2004 to December 27^{th}, 2010. The following proxies for the state variables are plotted: the *Cross-Market Correlation* refers to the average cross-correlation across several market indices (upper-left). The time series of the 5Y CDX IG index spread represents the *Credit Market Climate* (upper-right). The *Market Volatility* is indicated by the time series of the VIX index (mid-left). The *Spot Rate* is approximated by the 5Y T-bill rate (mid-right). For the *Slope of The Term Structure*, we present time series of the difference between the 10Y and the 2Y T-bill rate (lower-left). The dashed vertical lines divide the entire sample into the two sub-samples (Pre-GFC and GFC).

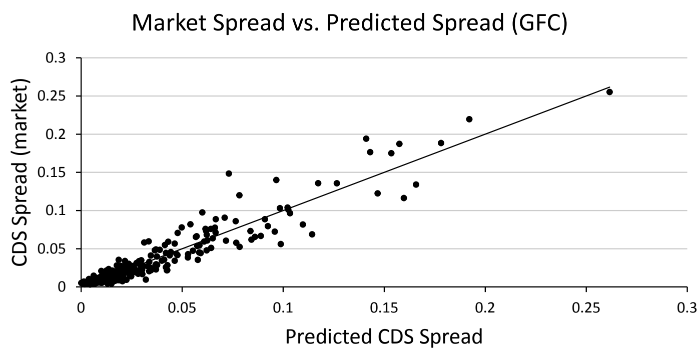
Fig. 3. Estimation Results of Time-series Regressions



Notes: This figure provides boxplots referring to estimates of time-series regressions for the Pre-GFC and the GFC. Additionally, the lower-right chart shows boxplots related to the coefficients of determination (R^2). In each boxplot, the upper whisker$^+$ refers to the 90 percentile, while the lower whisker$^-$ refers to the 10 percentile. Asterisks denote the means.

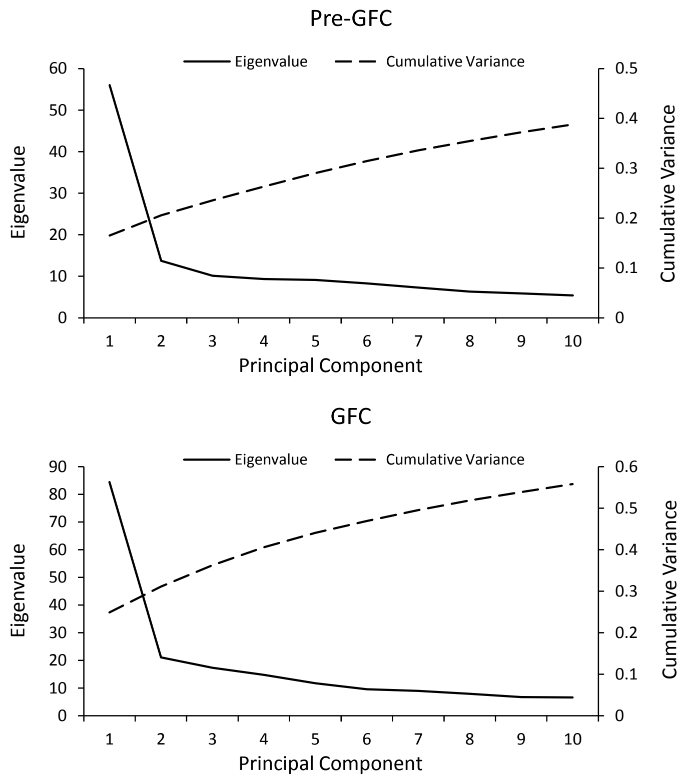
Fig. 4. CDS Spread Comparison (market spread vs. model spread)





Notes: This figure shows the comparison of market CDS spreads (y-axes) and model spreads (x-axes). The spread predictions are based on the estimation results related to the basic CSR model in Equation (3). While the upper chart refers to the period prior to the GFC (Pre-GFC), the lower chart shows the results for the GFC.

Fig. 5. Principal Component Analysis of Time-series Residuals



Notes: This figure shows the results of the principal component analysis (PCA) referring to the residuals of the time-series regressions. The PCA is provided for both subsamples. The upper chart refers to the Pre-GFC, the lower chart to the GFC. In each chart, the x-axis denotes the principal components and the primary y-axis reports the corresponding eigenvalues. The secondary y-axes show the cumulative variance of the principal components.

Tables

Table 1
Sample Period of Multiple Time-series and Cross-section Regressions

Multiple Time-series and Cross-section Regressions				
Sample		Entire period	Pre-GFC	GFC
Maturity	From:	6^{th} of Jan 04	6^{th} of Jan 04	19^{th} of Jun 07
	Until:	27^{th} of Dec 10	18^{th} of Jun 07	27^{th} of Dec 10
Entities	Amount:	339	339	339
	Obs. per entity:	367	180	187
	Sum of obs.:	124,413	61,020	63,393

Notes: The table summarizes the sample maturities as well as the amount of CDS spread observations (obs.) covered by each sample. The period of the Pre-GFC reflects the time interval prior to the financial crisis and the GFC describes the time period during the crisis. Based on each sample, multiple time-series regressions as well as cross-sectional regressions are conducted.

Table 2
Investigated Economic Sectors

			Mean Spread		
U.S. Sector	Count	Count in %	Entire	Pre-GFC	GFC
Basic Materials	22	6.49	0.0184	0.0113	0.0253
Consumer Goods	46	13.57	0.0216	0.0113	0.0316
Consumer Services	58	17.11	0.0320	0.0162	0.0471
Financials	57	16.81	0.0220	0.0042	0.0389
Health Care	16	4.72	0.0137	0.0074	0.0198
Industrials	48	14.16	0.0123	0.0077	0.0168
Oil & Gas	29	8.55	0.0128	0.0082	0.0174
Technology	14	4.13	0.0156	0.0109	0.0202
Telecommunications	12	3.54	0.0291	0.0230	0.0349
Utilities	37	10.91	0.0119	0.0073	0.0163
Overall	339	100	0.0189	0.0107	0.0268

Notes: The table reports the amount of U.S. entities located in ten economic sectors and denotes the sector-specific mean CDS spreads by sample (Entire, Pre-GFC and GFC).

Table 3
Sample-specific Correlation Matrix of Systematic Risk Factors

		Pre-GFC				
		ΔCMC	ΔCDX	ΔVIX	ΔSR	ΔSTS
	ΔCMC		0.0571	0.264	-0.0254	0.0726
	ΔCDX	0.0441		0.4116	-0.1067	-0.0734
GFC	ΔVIX	0.0673	0.6382		-0.1656	0.0219
	ΔSR	-0.0534	-0.4530	-0.3158		0.1949
	ΔSTS	-0.1589	0.0522	0.1152	0.1021	

Notes: The table shows the cross-correlations related to changes (Δ) in five systematic risk variables, namely the *Cross-market Correlation* (CMC), the CDX index, the VIX index, the *Spot Rate* (SR), and the *Slope of the Term Structure* (STS). While the upper triangle of the matrix refers to the cross-correlations of the Pre-GFC, the lower triangle shows the correlations of the GFC.

Table 4
Overview of Common Risk Factors and Predicted Signs

Variable	Description	Predicted Sign β (TSR)	Predicted Sign γ (CSR)
	Systematic Risk Factors in Time-series Regressions		
ΔCMC	Change in the Cross-market Correlation	+	+
ΔCDX	Change in CDX index spread	+	+
ΔVIX	Change in implied volatility of S&P 500	+	+
ΔSR	Change in yield on 5-year Treasury yield	-	-
ΔSTS	Change in 10-year minus 2-year Treasury yield	-	-
	Non-systematic Risk Factors in the Cross-section Regression		
LIQ_ϑ	Liquidity of CDS Contract		-
RC_ϑ	Rating Dummy for Class 1 to 5		+
SI_ϑ	Sector Indicator for Sector 1 to 10		

Notes: The table shows included regressors of both the multiple time-series regressions (TSR) and the cross-section regressions (CSR). The predicted signs for the respective regression coefficients of the TSR (β) and CSR (γ) are also denoted.

Table 5
Cross-section Regressions by Rating Dummies

	Entire Period	Pre-GFC	GFC
Intercept	0.0065***	0.0025*	0.0103***
	(0.0017)	(0.0013)	(0.0028)
BBB-rated	0.0039*	0.0027*	0.005⁻
	(0.0021)	(0.0016)	(0.0034)
BB-rated	0.0217***	0.0116***	0.03***
	(0.0027)	(0.0021)	(0.0043)
B-rated	0.0461***	0.0252***	0.0676***
	(0.0031)	(0.0023)	(0.0049)
CCC-rated	0.0741***	0.0493***	0.1111***
	(0.0048)	(0.004)	(0.0077)
R^2	59.29%	45.29%	55.39%
No. Entities	339	339	339

Notes: The table summarizes the rating-based results of cross-section regressions. The parameters are statistical significant at the 1%-level (***), the 5%-level (**) and the 10%-level (*). R^2 denotes the coefficient of determination. The number of entities (No. Entities) reflects the amount of entities considered in the cross-section regressions.

Table 6
Systematic Risk Indication by Rating Class

		Pre-GFC			GFC		
			Mean CDS Spread			Mean CDS Spread	
	Rating Class	Median Beta	Portfolio 1 (above median)	Portfolio 2 (below median)	Beta Median	Portfolio 1 (above median)	Portfolio 2 (below median)
CMC	1	$\overset{+}{<}0.0001$	0.0024***	0.0025	0.0009	0.0128***	0.0079
	2	0.0001	0.0059***	0.0044	0.0014	0.0182***	0.0125
	3	0.0002	0.014	0.0141	0.0058	0.0518***	0.0293
	4	0.0014	0.0383***	0.0170	0.0187	0.1002***	0.0557
	5	0.0037	0.078***	0.0255	0.0228	0.1315***	0.1112
CDX	1	0.2074	0.0029***	0.0020	0.3926	0.0154***	0.0055
	2	0.4223	0.0063***	0.0041	0.5809	0.0206***	0.0102
	3	11,635	0.0194***	0.0090	11,506	0.0606***	0.0208
	4	16,865	0.0385***	0.0168	23,389	0.0984***	0.0574
	5	23,129	0.0781***	0.0254	46,139	0.1571***	0.0856
VIX	1	$\overset{+}{<}0.0001$	0.0029***	0.0020	0.0001	0.0154***	0.0055
	2	$\overset{+}{<}0.0001$	0.0062***	0.0042	0.0001	0.0201***	0.0107
	3	0.0001	0.0189***	0.0094	0.0002	0.0561***	0.0251
	4	0.0001	0.0384***	0.0168	0.0005	0.0977***	0.0582
	5	0.0002	0.0609***	0.0426	0.0011	0.1416***	0.1011
SR	1	-0.0144	0.0024***	0.0025	-0.1502	0.0054***	0.0150
	2	-0.0235	0.0043***	0.0060	-0.2388	0.0096***	0.0206
	3	-0.0632	0.0089***	0.0191	-0.5638	0.0186***	0.0614
	4	-0.0817	0.0219***	0.0333	-0.9909	0.0514***	0.1045
	5	-0.1624	0.0472***	0.0563	-15,973	0.1209	0.1219
STS	1	-0.0076	0.0026***	0.0023	0.0025	0.0117***	0.0090
	2	-0.0075	0.0056***	0.0047	-0.0210	0.0141***	0.0164
	3	-0.0046	0.0156***	0.0126	0.0177	0.0413*	0.0394
	4	0.0501	0.0322***	0.0231	-0.0470	0.0648***	0.0911
	5	-0.0400	0.0472***	0.0563	-0.2102	0.1416***	0.1011

Notes: This table reports mean CDS spreads per rating class depending on the sensitivity of CDS spread changes to five systematic risk factors: *Cross-market Correlation* (CMC), CDX index , VIX index, *Spot Rate* (SR) and *Slope of the Term Structure* (STS). Univariate regressions are conducted on CDS contracts in order to evaluate the median sensitivity (*Median Beta*) to the systematic risk proxies in each rating class. Afterwards portfolios are established in dependence on estimated betas. Portfolio 1 contains all CDS with betas above the median, while Portfolio 2 includes those with betas below the median. The results are reported for both samples, the Pre-GFC and the GFC. ***, **, and * indicate the statistical significance (1%-, 5%-, and 10%-level) of the t-test for equality of mean CDS spreads for contracts with beta estimates below and above the median.

Table 7
Table of Cross-section Estimates:

	Pre-GFC		GFC	
Intercept	0.0098***/***	0.0095***/***	0.0165***/***	0.0164***/***
	(0.0014/0.0016)	(0.0017/0.0016)	(0.0033/0.0021)	(0.0036/0.002)
CMC	2.4531***/***	2.5994***/***	0.3227***/**	0.3335***/**
	(0.2492/0.8104)	(0.2455/0.8938)	(0.0673/0.1546)	(0.0678/0.159)
CDX	0.0074***/***	0.0075***/***	0.0127***/***	0.0126***/***
	(0.0004/0.0015)	(0.0004/0.0015)	(0.0006/0.0014)	(0.0006/0.0015)
VIX	41.1653***/***	41.1929***/**	33.0365***/***	32.8229***/***
	(5.7257/15.8017)	(5.6241/16.4716)	(3.6158/8.0606)	(3.674/8.5242)
SP	0.0072*/−	0.0077**/−	-0.0144***/***	-0.0144***/***
	(0.0039/0.0104)	(0.0039/0.0108)	(0.0018/0.003)	(0.0019/0.003)
STS	-0.0002−/−	0.0002−/−	-0.009***/***	-0.0093***/***
	(0.0013/0.0061)	(0.0013/0.0062)	(0.0012/0.0022)	(0.0012/0.0023)
LIQ	-0.0008***/***	-0.0008***/***	-0.0021***/***	-0.0019***/***
	(0.0001/0.0001)	(0.0001/0.0001)	(0.0004/0.0003)	(0.0004/0.0003)
BBB-rated	-0.0001−/−	-0.0002−/−	0.0027−/***	0.0029*/***
	(0.001/0.0003)	(0.001/0.0004)	(0.0017/0.0005)	(0.0017/0.0005)
BB-rated	0.0017−/*	0.0012−/−	0.0122***/***	0.0129***/***
	(0.0013/0.001)	(0.0013/0.0011)	(0.0022/0.001)	(0.0023/0.0012)
B-rated	0.0077***/***	0.0066***/***	0.0258***/***	0.0258***/***
	(0.0016/0.0014)	(0.0016/0.0015)	(0.0028/0.0023)	(0.003/0.0024)
CCC-rated	0.0125***/***	0.0108***/***	0.0445***/***	0.0457***/***
	(0.0028/0.0032)	(0.0028/0.0034)	(0.0043/0.0051)	(0.0045/0.0056)
Sector Dummies	No	Yes	No	Yes
R^2	81.70%	83.18%	89.89%	90.18%
No. Entities	339		339	

Notes: This table shows the estimation results referring to the cross-section regressions (CSR) of Equation (3) under consideration of both systematic and individual risk factors. Systematic risk factors are the *Cross-market Correlation* (CMC), the CDX index, the VIX index, the *Spot Rate* (SR) and the *Slope of the Term Structure* (STS). Non-systematic or individual risk factors are represented by the *Swap Liquidity* (*LIQ*) and the firm's rating. Sector dummies account for the sector in which the firm is operating. The results are provided for each subsample based on weekly CDS spread data. The parameters are statistical significant at the 1%-level (***), the 5%-level (**), and the 10%-level (*). Values in parenthesis describe the parameters' standard deviation (STD). Shanken-corrected STDs and significances are separated by a slash. R^2 denotes the coefficient of determination. The number of entities (No. Entities) refers to the amount of entities considered in the CSR.

Table 8
Table of Case-specific Cross-section Estimates:

Case	Fama-French Factors		Alternate Interest Rates		Principal Component	
Sample	Pre-GFC	GFC	Pre-GFC	GFC	Pre-GFC	GFC
Intercept	0.0085***/***	0.0155***/***	0.0098***/***	0.0155***/***	0.0098***/***	0.0221***/***
	(0.0014/0.001)	(0.0036/0.0021)	(0.0017/0.0015)	(0.0037/0.002)	(0.0019/0.0017)	(0.0042/0.0029)
CMC	1.3524***/***	0.3823***/***	2.3556***/***	0.3015***/**	2.6067***/***	0.3237***/**
	(0.222/0.2979)	(0.0768/0.132)	(0.256/0.7025)	(0.0687/0.1521)	(0.2465/0.9009)	(0.0673/0.1578)
CDX	0.0062***/***	0.0114***/***	0.0073***/***	0.0121***/***	0.0075***/***	0.0126***/***
	(0.0004/0.0008)	(0.0007/0.0012)	(0.0004/0.0013)	(0.0006/0.0015)	(0.0004/0.0016)	(0.0006/0.0015)
VIX	32.3192***/***	27.8042***/***	49.522***/***	33.5933***/***	41.4919***/**	32.8809***/***
	(4.8401/9.7092)	(3.9545/6.1847)	(5.445/17.3408)	(3.6465/8.393)	(5.6819/16.6877)	(3.6428/8.5889)
SR (T-bills)	-0.0059*/−	-0.0152***/***			0.0076*/−	-0.0148***/***
	(0.0033/0.0051)	(0.0019/0.0033)			(0.0039/0.0108)	(0.0019/0.003)
STS (T-bills)	0.0047***/−	-0.0081***/***			0.0002−/−	-0.0096***/***
	(0.0013/0.0035)	(0.0012/0.0025)			(0.0013/0.0062)	(0.0012/0.0024)
SR (Swap Rate)			0.0025−/−	-0.0165***/***		
			(0.0042/0.0084)	(0.0018/0.0029)		
STS (Swap Rate)			-0.001−/−	-0.0093***/***		
			(0.0013/0.0058)	(0.0012/0.002)		
FFR	-0.065***/**	-0.075***/***				
	(0.0106/0.0265)	(0.0083/0.0257)				
SMB	0.0213**/*	-0.0128**/−				
	(0.0085/0.0124)	(0.0056/0.0105)				
HML	0.0151**/−	-0.0262***/***				
	(0.0066/0.0131)	(0.0033/0.0072)				
LIQ	-0.0007***/***	-0.0017***/***	-0.0008***/***	-0.0019***/***	-0.0008***/***	-0.002***/***
	(0.0001/0.0001)	(0.0004/0.0003)	(0.0001/0.0001)	(0.0004/0.0003)	(0.0001/0.0002)	(0.0004/0.0003)
PC 1					-0.0075−/−	-0.0863**/**
					(0.0189/0.0164)	(0.0338/0.04)
Dummies (Rating & Sector)	Yes	Yes	Yes	Yes	Yes	Yes
R^2	89.04%	90.57%	83.22%	90.08%	83.19%	90.38%
No. Entities	339	339	339	339	339	339

Notes: This table shows the estimation results referring to the cross-section regressions under consideration of three different cases: in the first case, three Fama-French Factors are added as regressor to the basic model of Equation (2). Thus, the explanatory power of betas related to the Fama-French excess return (FFR), *Small Minus Big* (SMB) and *High Minus Low* are tested in the presence of the basic risk factors (*Cross-market Correlation* (CMC), CDX index, VIX index, *Spot Rate* (SR), *Slope of the Term Structure* (STS) and *Swap Liquidity* (LIQ)). In the second case, runtime equivalent swap rates are considered in the basic CSR model instead of Treasury bills. In the third case, the basic model is expanded to the first component (PC 1) of the principal component analysis. In all three cases, dummy variables account for both the firm's rating and economic sector. The results are provided for each sample (Pre-GFC and GFC). The parameters are statistical significant at the 1%-level (***), the 5%-level (**), and the 10%-level (*). Values in parenthesis describe the parameters' standard deviation (STD). Shanken-corrected STDs and significances are separated by a slash. R^2 denotes the coefficient of determination.

Table 9
Table of Cross-section Estimates Including Additional Risk Factors

Case	Firm-specific Risk Factors		Entire Model	
Sample	Pre-Crisis	GFC	Pre-Crisis	GFC
Intercept	$0.0029^{-/-}$	$0.0125^{-/*}$	$0.0026^{-/-}$	$0.0184^{**/**}$
	(0.0037/0.0024)	(0.0079/0.0071)	(0.0032/0.0016)	(0.0071/0.0089)
CMC	$2.8977^{***/***}$	$0.5783^{***/*}$	$1.8085^{***/***}$	$0.7574^{***/**}$
	(0.2552/1.0955)	(0.0775/0.3461)	(0.2538/0.3952)	(0.0817/0.3358)
CDX	$0.0056^{***/***}$	$0.0138^{***/***}$	$0.0052^{***/***}$	$0.0092^{***/***}$
	(0.0004/0.0017)	(0.0007/0.0032)	(0.0004/0.0012)	(0.0008/0.0024)
VIX	$48.5248^{***/**}$	$23.6418^{***/-}$	$50.5089^{***/***}$	$12.4364^{***/-}$
	(6.4512/19.9699)	(4.6039/14.6251)	(5.6951/15.5018)	(4.6586/9.3532)
SR (T-bills)	$0.0172^{***/-}$	$-0.0052^{-/-}$	$-0.0072^{*/-}$	$-0.0126^{***/*}$
	(0.0035/0.0207)	(0.0032/0.0057)	(0.0042/0.0083)	(0.0029/0.0069)
STS (T-bills)	$-0.0006^{-/-}$	$-0.0105^{***/*}$	$0.0058^{***/-}$	$-0.0045^{***/-}$
	(0.0016/0.0093)	(0.0015/0.0055)	(0.0016/0.0058)	(0.0014/0.0075)
FFR			$-0.1065^{***/**}$	$-0.0518^{***/-}$
			(0.0142/0.0522)	(0.0084/0.041)
SMB			$0.0035^{-/-}$	$-0.0299^{***/-}$
			(0.0141/0.022)	(0.0069/0.0285)
HML			$0.0206^{**/-}$	$-0.0402^{***/***}$
			(0.0083/0.0223)	(0.0037/0.0134)
LIQ	$-0.0008^{***/***}$	$-0.0017^{***/***}$	$-0.0008^{***/***}$	$-0.0007^{*/-}$
	(0.0001/0.0002)	(0.0005/0.0007)	(0.0001/0.0002)	(0.0004/0.0006)
MC	$0.0003^{-/-}$	$0^{-/-}$	$0.0002^{-/*}$	$-0.0002^{-/-}$
	(0.0003/0.0002)	(0.0006/0.0007)	(0.0002/0.0001)	(0.0005/0.0007)
LR	$0.0055^{**/***}$	$0.0034^{-/-}$	$0.0064^{***/***}$	$-0.0013^{-/-}$
	(0.0027/0.002)	(0.0054/0.0048)	(0.0023/0.0015)	(0.0045/0.0063)
PC 1			$0.0223^{*/-}$	$-0.0768^{***/*}$
			(0.013/0.0151)	(0.0274/0.0419)
Dummies (Rating & Sector)	Yes	Yes	Yes	Yes
R^2	91.29%	91.63%	93.87%	94.43%
No. Entities	225	225	225	225

Notes: This table shows the estimation results referring to the cross-section regressions under consideration of two different cases: in the first case, two more firm-specific risk factors – the firm's *Market Capitalization* and *Leverage Ratio* – are added to the basic CSR model of Equation (3). The *Entire Model* (case two) contains the basic risk factors (*Cross-market Correlation* (CMC), CDX index, VIX index, *Spot Rate* (SR), *Slope of the Term Structure* (STS) and *Swap Liquidity* (LIQ)), the three Fama-French factors (Fama-French excess Return (FFR), *Small Minus Big* (SMB) and *High Minus Low* (HML), additional firm-specific risk factors (*Market Capitalization* and *Leverage Ratio*) and the first component (PC 1) of the principal component analysis as further systematic risk factor. Dummy variables are included to account for both the firm's rating and economic sector. The results are provided for both samples (Pre-GFC and GFC) based on weekly CDS spread data of 225 entities. The parameters are statistical significant at the 1%-level (***), the 5%-level (**), and the 10%-level (*). The values in parenthesis describe the parameters' standard deviations (STD). Shanken-corrected STDs and significances are separated by a slash. R^2 denotes the coefficient of determination.