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Modelling Term Structure Dynamics of Credit Default Swaps

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Abstract

We analyse dynamics and determinants of the term structure for different North American credit default swap (CDS) indices. While previous studies on the determinants of CDS spreads have typically been restricted to five year contracts, we aim to examine the dynamics of the entire term structure by fitting a dynamic semi-parametric factor model (DSFM) to the data. We find that the CDS term structure can be decomposed into two factors, level and slope, that explain a high percentage of the total variation in the term structure. Variations of the level factor can be explained by equity volatility, leverage, and interest rates. The slope factor reflects the overall market environment, and can be related to GDP growth and the slope of the yield curve. We find the CDS term structure for investment grade firms and high risk firms to be upward sloping in a healthy market environment, while it is inverted during more severe market conditions. Interestingly, factors impacting on the CDS term structure do not differ significantly for low-risk and high-risk firms. Our findings provide evidence that the determinants of structural models for credit risk can also be applied to explain shifts in the entire term structure of the CDS market.

JEL Classification: C14, C58, G01, G15

Keywords: *Credit Default Swaps, Term Structure, Dynamic Semiparametric Factor Model (DSFM), Financial Crisis*

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1. INTRODUCTION

The credit default swap (CDS) market has experienced rapid growth since its inception in 1992. Since then, many studies have analysed the determinants of CDS spreads (see Collin-Dufresne and Goldstein, 2001; Huang and Huang, 2003; Zhang et al., 2009 and Arora, 2012). The intuition of these studies is often derived from the literature on credit spreads of bonds, since both credit spreads and CDS spreads reflect the credit risk of a company. Therefore, it should be possible to apply models that have been derived for credit spreads also to CDS spreads.

The majority of existing studies on credit spreads or CDS spreads are either based on the structural model by Merton (1974) or on the reduced-form model by Black and Cox (1976). While structural models assume that the probability of default is endogenous, reduced-form models use an exogenous variable to model the probability of default.

Merton (1974) finds that the main determinants of a firm's default risk are equity volatility, leverage, and the yield of the risk-free asset. Reduced-form models show that a CDS spread is determined by the probability of default, the recovery rate and the risk-free asset's yield.

In the recent past, several studies have analysed the explanatory power of structural and reduced-form models, and find that neither are able to fully explain the CDS spread variations (see Black and Cox, 1976, p.351; Kim et al., 1993,p.118; Collin-Dufresne and Goldstein, 2001, p. 1931; Huang and Huang, 2003, p.4).Some studies have explained the residual spread by a liquidity premium while others have found counterparty risk to be an additional determinant of the CDS spread (see Longstaff et al., 2005, p. 2243; De Jong and Driessen, 2006, p. 21; Jorion and Zhang, 2009, p.2065; Pu et al., 2011, p.69; Arora, 2012, p.288).

However, all of these studies restricted themselves to a 5-year CDS spread. Therefore, the results are not representative of the overall CDS market. The CDS term structure incorporates information on the credit risk of a firm over time and on different maturities.

The literature on the term structure of CDS is relatively rare. Further, the results concerning the shape of the credit risk term structure are ambiguous. Some studies find that the term structure of high-risk firms is downward sloping (Sarig and Warga, 1989, p. 1356; Fons, 1994, p. 29). Others predict an upward sloping term structure for non-investment grade firms (see Helwege and Turner, 1999, p.1875; Huang and Zhang, 2008, p. 62).

Several studies argue that the variables suggested by the structural model may also determine the whole CDs term structure. Han and Zhou (2011b) and Fonseca and Gottschalk (2013) analysed the impact of the equity volatility on the CDS term structure, and found a strong positive relation. Furthermore, Han and Zhou (2011) find that financial leverage and the risk-free asset determine the CDS term structure. Other studies point out that the explanatory power of the structural variables is insufficient (see Han and Zhou, 2011, p.19). For example, Pan and Singleton (2008) and Augustin (2012) find that macroeconomic risk such as the gross domestic product affects CDS term structure as well.

The purpose of this study is to analyse the dynamics of the CDS term structure. Our data captures CDS spreads of the North American CDS market, which is the largest CDS market in the world. Using CDS spread data of the CDX.NA.IG, the CDX.NA.XO and the CDX.NA.HVOL from December 8, 2008 to September 30, 2010; we estimate and compare the major determinants of three CDS term structures, which are characterized by different levels of credit risk.

In a first step, we decompose the CDS term structure dynamics into two major factors, which explain approximately 95% of the term structure variations. The factors are obtained by fitting a dynamic semiparametric factor model (DSFM) proposed by Fengler et al. (2007) to the data. The DSFM model is similar to an ordinary factor analysis, and makes it possible to reduce the dimensions of complex data sets. We find that the first DSFM-factor reflects shifts in the level of the term structure, whereas the second factor mirrors the slope of the term structure. In a second step, we analyse the determinants of the two factors extracted by the DSFM. We show that the variations of the level factor can be explained by the variables equity volatility, leverage, and interest rate as suggested by the structural model by Merton (1974). Further, we find evidence that the residual is driven by the systematic counterparty risk.

The slope factor reflects the overall market environment and can be explained by the GDP growth, and by the slope of the yield curve. We also find that in a healthy market environment, the slope of investment grade and high risk CDS term structures is positive, resulting in an upward sloping term structure, whereas the CDS term structure of can be inverted in tensed market situations.

The remainder of this study includes a brief overview of the literature on the determinants of CDS spreads and the term structure of CDS. We then present our data and the sample selection procedure. In section 4 we introduce the DSFM model and the estimation of the variables used in this study, followed by a presentation of the results of the DSFM and regression analysis. Finally, we summarize our major findings in a short conclusion.

2. LITERATURE

2.1 Determinants of the CDS market

As mentioned above, the literature on CDS spread determinants is closely related to literature on the credit spread of bonds. [2] All theoretical models concerning credit spreads or CDS spreads can be classified either as structural models or reduced-form models. The main difference of these two models is the calculation of the probability of default (see Yawitz, 1977, p.581). Structural models are based on the option pricing model by Black and Scholes (1973), and they assume that the default probability of a firm is determined by its financial structure. According to a structural model, a zero bond defaults when the value of a bond at maturity is higher than the firm value resulting in a leverage ratio close to zero. Merton (1974) formulized the structural model, and shows that default risk is determined by financial leverage, equity volatility, and the risk-free asset's yield.

In contrast to this, reduced-form models are based on the intuition that a risk-neutral investor is indifferent between a risk-free treasury bond and a corporate bond if the present values are equivalent. The present value of the corporate bond is calculated from the probability of default, and from the recovery rate of the firm, which need to be determined exogenously in advance (see Yawitz, 1977, p.483; Jonkart, 1979, p.257).Thus, reduced-form models predict that CDS spread variations can be explained by a firm's probability of default, the recovery rate, and the risk-free asset's yield.

However, recent studies argue that neither structural nor reduced-form models are able to fully explain the credit spread variations (see Black and Cox, 1976, p.351; Kim et al., 1993, p.118; Collin-Dufresne and Goldstein, 2001, p.1931; Huang and Huang, 2003, p.4). Some studies tried to explain the residual spread by a liquidity premium or macroeconomic variables, such as the gross domestic product, equity indices or inflation (see Longstaff et al., 2005, p.2243; De Jong and Driessen, 2006, p.21; Koopmann and Lucas, 2005, p.316).

The failure of the structural models and reduced-form models is even more evident for the CDS market. Blanco et al. (2005) shows that the structural variables fail to explain up to 75% of the CDS spread variations. In comparison to the corporate bond market, the CDS market is characterized by many limitations. CDS are individual negotiated OTC contracts and are not usually available for small companies. Therefore, CDS spreads are likely to be affected by a liquidity premium.

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[2] A credit spread is the difference in yields between a corporate bond and a risk-free asset such as a treasury bond; see Friewald et al. (2012), p.19.

A particularity of the CDS market is the existence of counterparty risk, which is not present in cash markets (see Pu et al., 2011, p. 62). CDS spreads are affected by individual counterparty risk and systematic counterparty risk. Individual counterparty risk arises from the default risk of a single protection seller. If the protection buyer argues that the protection seller will not be able to pay the promised protection payment when the underlying firm defaults, he will pay less for a CDS contract with this specific protection seller than for a contract with a low-risk counterparty. Thus, individual counterparty risk is negatively linked to the CDS spread (see Arora et al., 2012, p.280). Arora et al. (2012) find that an increase of 645 bps of the dealer's spread results in a decline of 1 bps in the price of credit protection.

Systematic counterparty risk reflects the joint default risk of all counterparties. Typically, protection sellers protect themselves by buying CDS insurances at other counterparties. Due to the cascading conjunction of the counterparties, an unexpected default of a counterparty may create a domino effect of defaults at other protection sellers.

In 2008, the impact of systematic counterparty risk on the financial system became obvious when the US bank Lehman Brothers defaulted. In the aftermath of the Lehman bankruptcy, CDS spreads increased dramatically due to fears of systematic defaults. Lehman was one of the largest CDS counterparties in the US and sold protection to many banks which were in turn protection sellers to other parties. Thus, the US government decided to bailout the US insurance company American International Group (AIG) to prevent further defaults. The bailout of AG was the biggest bailout in American history and marked the climax of the recent financial crisis.

Taylor (2009), Jorion and Zhang (2009) and Pu et al. (2011) find that systematic counterparty risk is positively linked to the CDS spreads. Most of these studies use LIBOR based proxies for the systematic counterparty risk (see Taylor, 2009, p.15; Pu et al., 2009, p.63).

However, due to the recent LIBOR-affair, these proxies are likely to be biased and result in an underestimation of systematic counterparty risk in the markets.

Morkötter et al. (2012) developed an alternative proxy which is based on the mean CDS spread of the biggest CDS dealers. They find a strong impact of systematic counterparty risk on CDS spreads in the North American and European CDS market.

2.2 The Term Structure of CDS

The CDS term structure incorporates information on the credit risk of a firm over time and different maturities. The literature on the term structure of a CDS is relatively rare. Some studies derived their predictions from structural models. Their intuition is that high-risk firms exhibit a downward sloping term structure, because the firm value is close to the default boundary and, therefore, the default risk is more evident in the short run. In contrast to this, for low-risk firms, the term structure is more likely to be upward shaped, because the credit risk of firms with financial strength tend to increase for long maturities.

However, concerning the sloping of the term structure for non-investment grade bonds there are ambiguous results. Sarig and Warga (1989), Fons (1994) and Lando and Mortensen (2005) find that the credit term structure of non-investment grade bonds is downward sloping. This is contrary to the findings of Helwege and Turner (1999) or Huang and Zhang (2008), who report an upward sloping term structure for high-risk firms.

For the structural framework, Merton (1974) finds that the equity volatility of the reference entity can be used as a proxy for the volatility of the underlying firm asset. The volatility of a firm's asset value affects its default probability. Thus, high values of volatility result in high CDS spreads, because the value of risky debt decreases when volatility increases (see Pu et al., 2011, p. 66).

Many studies, e.g. Benkert (2004), Forte and Pena (2009) and Zhang et al. (2009) analysed the interactions between credit risk and equity volatility, and confirmed the strong positive impact of the equity volatility on CDS spreads. However, most of these studies examined the link between 5-year CDS spreads and equity volatility, e.g. measured as the at-the money 1-month implied volatility.

The nexus between the whole term structure of CDS spreads and the stock market is studied less intense. Han and Zhou (2011b) show that the CDS spread term structure explains log stock returns and conclude that equity volatility is relevant for the slope of the CDS curve as well. Fonseca and Gottschalk (2013) analysed the co-movements of the CDS spread term structure, and the entire implied volatility smile. They find a strong cross-market linkage between the credit and the stock market. Han and Zhou (2011) view a CDS contract as an out-of the money put option on a firm and predict that the CDS slope is positively related to the stock volatility. The intuition is that the increasing relation between equity volatility and CDS spreads is stronger for long maturities, because the option's vega increases with maturity. Vega is the derivative of the option value with respect to the volatility of the underlying asset, and measures sensitivity to volatility.

The structural framework by Merton (1974) computes default as a function of the firm's leverage ratio. The leverage ratio reflects the capital structure of a firm. In the case the leverage ratio becomes one, the firm defaults. Thus, several studies analysed the impact of the leverage ratio on the credit risk of a firm, and found a strong positive link (see Collins-

Dufresne, Goldstein and Martin, 2001, p.2184; Blanco, Brennan and Marsh, 2005, p.2275; Avramore, Jostova and Philipov, 2007, p.100).

The impact of the leverage ratio on the CDS term structure can be explained by the option price theory. Precisely, it can be explained by an out-of the money put option's delta. Delta measures the changes of the option value with respect to changes in the underlying asset's price. Further, delta can be used as a proxy for the moneyness of an option, i.e. the probability of an in-the-money expiration. Put options have negative deltas, and the value of delta decreases when it is nearer to maturity. Thus, when the leverage ratio increases, the firm value decreases and the put option price increases, especially for long maturities. Consequently, leverage is predicted to have positive impact on short- and long-maturity CDS spreads. However, the effect is likely to be stronger for long-term contracts (see Han and Zhou, 2011, p. 5).

In the case both, equity volatility, and leverage ratio are high, the CDS term structure can become negative. This combination implies a high short-term default probability. Thus, an improvement in credit risk in the long-run is more likely resulting in a downward sloping term structure (see Han and Zhou, 2011, p.7).

According to the structural approach, the credit risk depends on the individual risk exposure of a firm as well as on macroeconomic risk factors.

The structural approach by Merton (1974) predicts that an increase in interest rates reduces the default risk. The intuition is that increasing interest periods often follow an economic recovery, which implies a decrease in company defaults. Thus, interest rates should have a negative impact on CDS spreads. Many empirical studies confirmed that interest rate is a major determinant of CDS spreads (see Duffee, 1998, p.2240; Annaert et al., 2000, p.6; Düllmann et al., 2000, p.385; Leake, 2003, p.23; Papageorgiou and Skinner, 2006, p.421).

Chen et al. (2012) examine the dynamics between interest rate and the CDS term structure. They find that interest rates affect contemporaneous and future CDS spreads. Moreover, they find that the dynamics depend on the frequency of the interest rates and the CDS sectors (see Chen et al., 2012, p. 436).

In line with the structural models, Han and Zhou (2011) predict a negative relation between the CDS term structure and interest rates. They argue that a higher interest rate increases the risk-neutral drift of the firm value implying a reduction of the default probability and, therefore, reduces the CDS spreads. The effect is more evident for long maturities, because the firm value is expected to grow more in the long run. Thus, interest rate increases are predicted to lower long-term CDS spreads more than short-term CDS spreads and, therefore, to flatten the CDS term structure.

The slope of the yield curve is also a frequently analysed determinant of the credit risk. Following the structural framework, many studies reason that an increase in the slope of the yield curve is related to improving overall economic health, whereas a decreasing slope indicates an economic recession. Therefore, the slope of the yield curve can be used as a proxy for the overall business climate (see Collins-Dufresne, Goldstein and Martin, 2001, p. 2182; Cossin and Hricko, 2001, p.22).

Economic health decreases the default probability of the firms and, therefore, lowers CDS spreads (see Collin-Dufresne, Goldstein and Martin, 2001, p.2183). Several studies show that an economic shock increases the long-term rate more than the short-term rate which leads to a steeper yield curve. Consequently, the firm value growth is more increased in the long-run than in the short-run and long-term CDS spreads are lowered more intensely resulting in flatter CDS term structure.

Similar to the slope of the yield curve, the gross domestic product (GDP) indicates the domestic business climate. Increasing real economic growth lowers the credit risk and, therefore, decreases the CDS spread levels. Several studies confirm a strong negative relation between the credit spread and the real GDP growth (see Koopman and Lucas, 2005, p. 316; see Hackbarth et al., 2006, p. 548). Pan and Singleton (2008) find strong co-movements in the term structure of sovereign CDS spreads of Mexico, Turkey and Korea. They conclude that a common risk factor, which is determined by the global economic risk, affects the CDS term structure of sovereigns. Further, they argue that spillover effects of the U.S real economic growth may explain the global risk factor (see Pan and Singleton, 2008, p. 2382).

Augustin (2012) analyses the sovereign CDS term structure of 44 countries and finds that both, global macroeconomic risk and country-specific risk, matter for the CDS term structure. When the spread curve is upward sloping, global shocks are the dominant determinant of the CDS spread changes. However, he also shows that country-specific fundamentals explain more spread variation of financial distressed countries, which are characterized by a downward sloping curve. Further, the explanatory power of domestic risk is stronger for increasing time-length of the inverted term CDS structure (see Augustin, 2012, p.34).

Therefore, the CDS term structure is expected to decrease with increasing growth of the real GDP. The effect is likely to be stronger for longer maturities, because economic growth affects the firm value rather in the long-run than in the short-run. Thus, the GDP is predicted to flatten the CDS term structure.

Han and Zhou (2011) analyse the usefulness of structural models for the understanding of the CDS spread term structure. They find that the key determinants of the structural models leverage, volatility, and the risk-free asset's yield, do have some explanatory power for the CDS spread term structure. However, they also highlight that their regression residuals exhibit a common factor which cannot be explained by the variables of structural models (see Han and Zhou, 2011, p. 14).

As mentioned above, a possible explanation for the failure of the structural models may be the existence of systematic counterparty risk in the CDS market. The default of a counterparty leads to the default of the related CDS contracts. Thus, counterparty risk increases CDS spread levels. Systematic counterparty risk reflects the joint credit risk of all counterparties and accounts for the fact that the default of a counterparty may result in defaults of other counterparties.

To our best knowledge, the impact of systematic counterparty risk on the term structure of CDS spreads has not been analysed so far. Pu et al. (2011) and others find a strong positive link between systematic counterparty risk and CDS spreads. As systematic counterparty risk can be measured by volatility correlation of the largest CDS dealers and the reference entity, the systematic counterparty risk may impact the option's vega. As discussed above, an option's vega increases with maturity. Thus, systematic counterparty risk is predicted to increase short-term CDS spreads as well as long-term CDS spreads with the effect being stronger for long-term CDS spreads.

Therefore, systematic counterparty risk is expected to increase the CDS-term structure. We verified our prediction by a univariate regression analysis of a systematic counterparty risk proxy on CDS spreads for different maturities. The results are discussed in section 5, table 3.

3. DATA

This study is composed of three sub samples, which are based on three CDS term structures, which are furthermore characterized by different levels of credit risk. The samples capture the evolution of the CDS term structures for the North American CDS market which is the largest CDS market in the world. We analyse daily CDS spreads at maturities of 2, 3, 4, 5, 6, 7, 8, 9 and 10 years from December 8, 2008 to September 30, 2010. Daily senior secured CDS mid-spread data are obtained from Thomson Reuters Datastream.

The first term structure comprises different maturities of the CDX North American Investment Grade index (CDX.NA.IG) by MARKIT. This index refers to one hundred twenty five of the most liquid North American entities with investment grade credit ratings that trade in the CDS market.

CDS indices are used to benchmark the credit risk in the credit derivate market. They are calculated as baskets of single name CDS. Typically, CDS indices are denoted in bps of the par value. They reflect the annual costs as a function of a proportionate insurance of the face value of the debtors included in the indices. It is crucial to notice that, in contrast to single name CDS, CDS indices are completely standardised credit securities and may, therefore, be more liquid. Consequently, the bid-ask spread is smaller, and it can be cheaper to hedge a portfolio of bonds with a CDS index than it would be to buy many single name CDS.

The second term structure is based on the CDX North American Cross Over index (CDX.NA.XO) provided by MARKIT. This index comprises thirty five North American entities which are on the cross over between investment grade and junk.

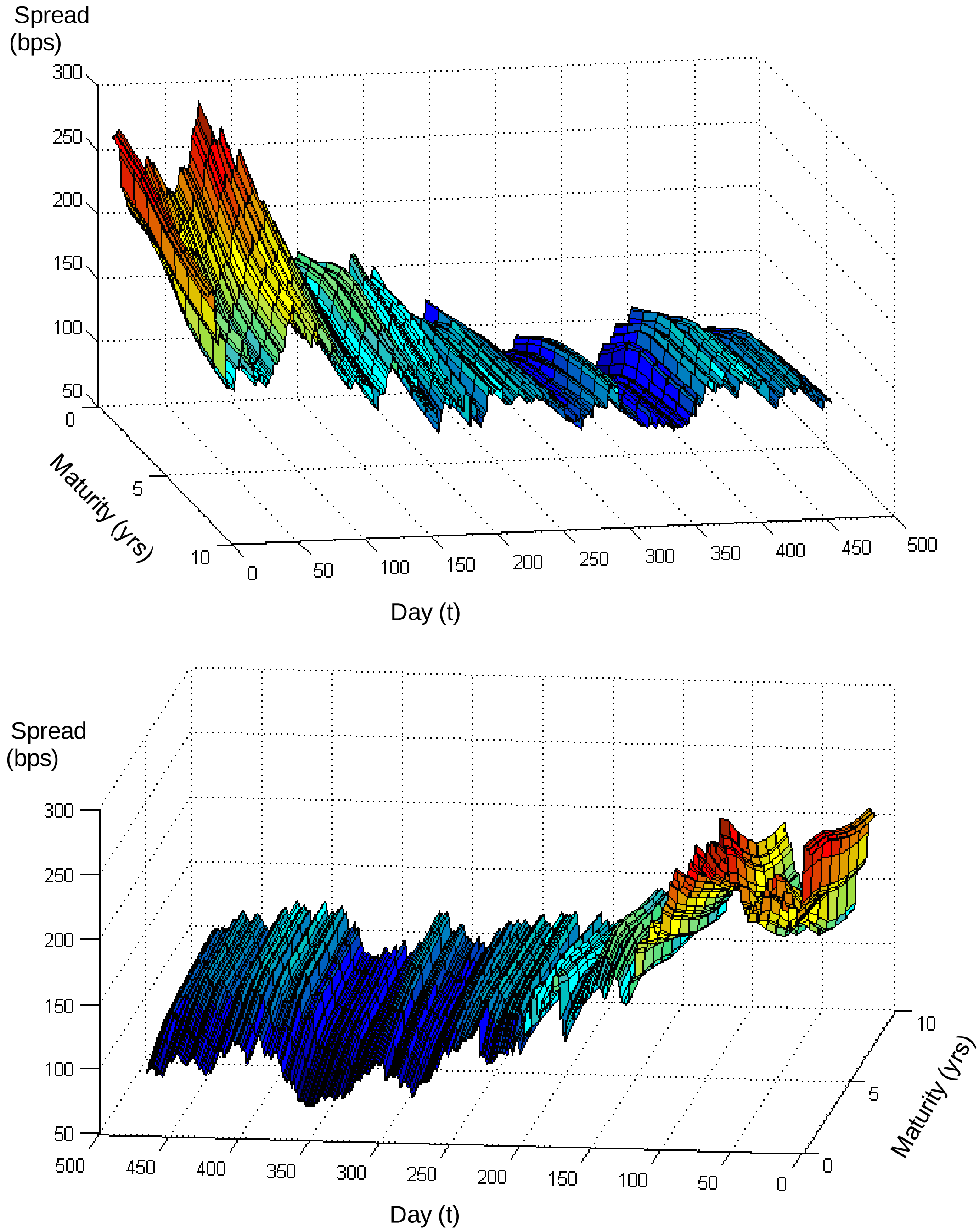
Term structure three is derived from the CDX North American High Volatility index (CDX.NA.HVOL) by MARKIT, which includes CDS spreads of thirty high volatile North American firms.

Figure 1 shows the development of the CDS Investment Grade term structure from December 8, 2008 to September 30, 2010 in bps. In the period from December 8, 2008 to September 30, 2009, the CDS spreads are on high levels for all maturities, and the term structure is downward sloping. This extraordinary shape can be explained by the fact that investors back in 2008 expected credit risk of the firms to decrease in future. Due to the recent financial crisis, many firms were financially distressed, and their risk profiles were above their long-term risk equilibriums.

However, the CDS spread term structure has recovered its normal shape in the more recent years. In general, the CDS spreads are on lower levels and the term structure is increasing for increasing maturities. Since a credit default swap can be regarded as an insurance contract against the default of the reference firm, it is rational that a long term insurance is more expensive than a short term insurance.

Table 1 shows the descriptive statistics for the CDS indices used in this study. As it can be seen from the table, CDS spreads of entities with low credit risk are lower than CDS spreads of high-risk entities, for example: The mean spreads of the CDX.NA.IG are always below the mean spreads of the CDX.NA.XO. The CDX.NA.HVOL represents high volatile entities. According to Merton (1974), high volatile firms are more likely to default and, therefore, they have a higher credit risk than less volatile companies. Thus, it is not surprising that the mean CDS spread of the CDX.NA.HVOL ranges above the mean of the CDX.NA.IG for all maturities. However, the shape of the term structure is less obvious. As mentioned above, the term structure is inverted for the years 2008 and 2009 due to the recent financial crisis. Thus, the mean CDS spread term structure for all observations between December 8, 2008 and September 30, 2010 is not increasing but flat.

Figure 1: CDS Term Structure of the CDX.NA.IG



Notes: Figure 1 reports the CDS term structure of the CDX.NA.IG index provided by MARKIT. The CDX.NA.IG index includes 125 North American entities that are traded in the CDS market. The daily observations range from December 8, 2008 to September 30, 2010.The term structure is analysed for 3,4,5,6,7,8,9,10 year CDS.

Table 1: Descriptive Statistics

Maturity	2y	3y	4y	5y	6y	7y	8y	9y	10y
CDX.NA.IG									
mean		143.29	145.76	147.28	145.95	142.82	141.18	140.27	139.55
std. dev.		63.85	54.55	45.89	38.95	33.60	30.00	27.32	25.37
skewness		0.76	0.73	0.72	0.74	0.81	0.90	0.98	1.04
kurtosis		-0.83	-0.79	-0.65	-0.43	-0.06	0.27	0.57	0.81
CDX.NA.XO									
mean	312.83	326.24	335.76	343.79	340.54	332.07	326.08	321.74	318.02
std. dev.	215.63	180.81	155.22	136.56	121.71	110.20	101.96	95.76	91.00
skewness	1.23	1.14	1.10	1.10	1.06	1.08	1.09	1.10	1.11
kurtosis	0.13	-0.07	-0.14	-0.16	-0.23	-0.21	-0.19	-0.16	-0.12
CDX.NA.HVOL									
mean	411.94	385.00	366.64	354.79	341.26	327.32	317.60	310.56	304.85
std. dev.	201.71	167.24	142.02	123.67	108.95	97.96	89.75	83.29	78.23
skewness	0.47	0.45	0.47	0.52	0.55	0.57	0.60	0.64	0.68
kurtosis	-1.05	-1.09	-1.04	-0.93	-0.88	-0.83	-0.75	-0.66	-0.56

Notes: Table1 reports the descriptive statistics of the indices used in this study between December 8, 2008 and September 30, 2010. Maturities range from 2 to 10 or 3 to 10 years. All statistics are based on daily data. The mean CDS spreads are denoted in bps.

4. METHODOLOGY

In order to analyse the term structure of the CDS portfolios, a dynamic semiparametric factor (DSFM) model is fitted to the data. The DSFM model was developed by Fengler et al. (2007) who studied the dynamics of implied volatility surfaces. Park et al. (2009) extended the model by implementing a series based estimator. Similar to an ordinary principal component analysis (PCA), the DSFM enables to reduce dimensions of complex data sets. It allows explaining variations over time of high dimensional time series through a small number of factors.

The basic principle of all factor analysis is the fact that a J-dimensional random vector $Y_t = (Y_{t,1}, \dots Y_{t,J})$ can be represented by an L-factor model composed of L<<J common factors:

$$Y_{t,j} = m_{0,j} + \sum_{l=1}^{L} Z_{t,l} m_{1,j} + \varepsilon_{t,j}$$

The factor coefficients or factor loadings $m_{l,j}$ and error terms $\varepsilon_{t,j}$ explain the remaining proportion.

In contrast to an ordinary factor analysis, the DSFM involves estimating factor loadings $m_{l,j}$ as nonparametric functions of the covariates, which yields to the following model:

$$Y_{t,j} = m_0(X_{t,j}) + \sum_{l=1}^{L} Z_{t,l} m_l(X_{t,j}) + \varepsilon_{t,j}$$

In this study $Y_{t,j}$ represent the CDS spreads on day t = 1,…,T for different maturities j = 1,...,J and $X_{t,j}$ denotes the corresponding maturity dates. We analyse j = 2,...,10 for the CDS portfolios based on the CDX.NA.XO, and the CDX.NA.HVOL and j=3,...,10 for the CDX.NA.IG portfolio.

In a first step, the $Z_{t,}$ and m_l are estimated from the data. The factor loadings m_l reflect the time invariant factor structure. $\widehat{m}_l$ is a nonparametric estimator which can be directly obtained from the data. Z_t describes the dynamic behaviour and is typically unobservable. Thus, the dynamics are analysed via the estimator $\hat{Z}_t$. Fan et al. (2003) and Yang et al. (2006) found that the DSFM model is different from varying-coefficients models, even if it can be compared to a regression model with embedded time evolution, because the time series Z_t is usually not observable.

However, Haerdle et al. (2007) showed that the differences in the inference based on $\hat{Z}_t$ instead of the true unobservable Z_t are asymptotically negligible (see also Park et al. , 2009, p.294).

In order to get estimates for $Z_{t,l}$ and m_l, Fengler et al (2007) propose to minimize the following kernel estimator:

$$\sum_{t=1}^{T} \sum_{j=1}^{J_t} \int (Y_{t,j} - \sum_{l=0}^{L} Z_{t,l} m_l(u))^2 K_h(u - X_{t,j})\, du$$

where K_h represents a two dimensional product kernel,$h = (h_1, h_2)$, with a one dimensional kernel $k_{h.}(v) = h_.^{-1} k(h_.^{-1} v)$.

The kernel smoothing procedure can be replaced by a series estimator (see Borak and Weron, 2008, p. 6; Trueck et al., 2012, p. 9).Thus, the factor loadings in this study are estimated by a series estimator which linearizes the loading functions with B-splines of the following equation:

$$m_l(X_j) = \sum_{k=1}^{K} a_{l,k} \psi_k(X_j)$$

where K denotes the number of knots, $\psi_k(X_j)$ are the splines and $A = a_{l,k}$ is the coefficient matrix. The loading functions $m_l(X_j)$ and common factors $Z_{t,l}$ are determined by a least squares criterion:

$$\mathrm{S(A, Z)} \equiv \sum_{t=1}^{T} \sum_{j=1}^{J_t} (Y_{t,j} - \sum_{l=0}^{L} Z_{t,l} \sum_{k=1}^{K} a_{l,k} \psi_k(X_j))^2 = min_{A,Z}!$$

The estimation procedure is iterative and the solution to this optimization problem is not unique. Similar to the factor ordering in a PCA, the $\widehat{m}_l$ can be choosen to be orthogonal and then be ordered with respect to the proportion of variation explanation of Y_t. In contrast to a PCA, which maximises the expected variance, the DSFM minimizes the squared residual and, therefore, maximises the in-sample fit with respect to a score function (see Ramsay and Silverman, 1997, p.150).

The DSFM model is most efficient when a high portion the variations of Y_t can be explain by very few common factors $Z_{t,l}$. The number of factors L has to be determined in advanced. For the choice of L we follow Trueck et al. (2012) and calculate the proportion of the variation explained by the model compared to the simple invariant estimate given by the overall mean:

$$1 - RV(L) = 1 - \frac{\sum_t^T \sum_j^{J_t} (Y_{t,j} - \sum_{l=0}^{L} \hat{Z}_{t,l} \widehat{m}_l (X_{t,j}))^2}{\sum_t^T \sum_j^{J_t} (Y_{t,j} - \bar{Y})^2}$$

We repeat the procedure for different values of L until the explanatory power of the model reaches the sufficient level. Subsequent to the calculation of the dynamic factor model, we examine the main determinants which predominantly affect the Z-factors of the three DSFM models.

Based on the literature concerning the determinants of credit risk and CDS spreads mentioned above, we choose six explanatory variables. Following Han and Zhou (2011), we view a CDS contract as an out-of the money put option on a firm, and derive our variable predictions from the structural model. The main variables suggested by the structural model are equity volatility, leverage, and interest rate.

According to the Merton (1974) model, equity volatility of the reference entity can be used as a proxy for the volatility of the underlying firm asset. The volatility of a firm’s asset value affects its default probability. High values of volatility result in high CDS spreads because the value of risky debt decreases when volatility increases (see Pu et al., 2011, p. 66).

In this study, *Equityvola* is calculated via an exponentially weighted moving average (EWMA) model. Moving average models generate a time series of averages based on different fixed subsets of the data. The first element is obtained by taking the average of the initial fixed subset of the time series. Subsequently, the subset is shifted forward by excluding the first value and including the next value following the original subsample. Typically, moving average models are used to smooth short-term variations, and to expose the long-term behaviour of the data.

A simple moving average (SMA) model is the unweighted mean of the previous *n* values of a time series. It can be described by the following equation:

$$SMA_t = SMA_{t-1} - \frac{Y_{t-n}}{n} + \frac{Y_t}{n}$$

with

$$SMA = \frac{Y_t + Y_{t-1} + \cdots + Y_{t-(n-1)}}{n}$$

In contrast to this, a weighted moving average (WMA) model has multiplying factors which give different weights to the data within the subset. A WMA is given by the following equation:

$$WMA_t = \frac{nY_t + (n-1)Y_{t-1} + \cdots + 2Y_{(t-n+2)} + Y_{t-(n+1)}}{n + (n-1) + \cdots + 2 + 1}$$

An exponential weighted moving average is characterized by exponentially decreasing weighting factors:

$$EWMA_t = \lambda Y_{t-1} + (1-\lambda) EWMA_{t-1}$$

where $\lambda \in (0,1)$ denotes the degree of a weighting decrease and a higher α yields a faster discount of old observations. The initial $EWMA_1$ is undefined and may be set equal to an average of the first five observations. α is sensitive to the initial setting of $EWMA_1$ but the effect disappears for large λ.

We measure the volatility of the indices in this study by applying an EWMA model using a value of $\lambda = 0.94$ as suggested by JP Morgan (1996). Some studies find that EWMA models can be used to model conditional heteroscedasticity and related risk measures (see Akgiray, 1989, p.68; Balaban et al., 2006, p.185; Guermat and Harris, 2001, p.26).

Today, EWMA models are a standard technique in financial risk management, which can be seen from the fact that JP Morgan's RiskMetrics volatility forecasts are based on a EWMA model. *Equityvola* is estimated separately for each of the CDS indices. The *Equityvola* of the CDX.NA.IG is computed from the average of daily returns of the CDX.NA.IG components. Similarly, *Equityvola* of the CDX.NA.XO and the CDX.NA.HVOL are based on the average of daily returns of the CDX.NA.XO index or the CDX.NA.HVOL, respectively. The return data are obtained from Thomson Reuters Datastream.

The structural framework by Merton (1974) computes default as a function of the firm's leverage ratio. The leverage ratio reflects the capital structure of a firm. In the case the leverage ratio becomes one, the firm defaults. Thus, several studies analysed the impact of the leverage ratio on the credit risk of a firm and find a strong positive link (see Collins-Dufresne, Goldstein and Martin, 2001, p.2184; Blanco, Brennan and Marsh, 2005, p.2275; Avramore, Jostova and Philipov, 2007, p.100).

The variable *Leverage* is estimated via a two-step procedure. First, we follow Greatreux (2009), and compute leverage as book value of debt divided by the book value of debt plus the market value of equity for each component of the indices analysed in this study. In a second step, we compute the daily average of the component's leverage ratios, and define this ratio as the index leverage ratio at day *t*.

Thus, *Leverage* of index *i* is given by the following equation:

$$Leverage_{it} = (1/N) \sum_{f=1}^{N} \frac{BVD_{ft}}{(BVD_{ft} + MVE_{ft})}$$

where BVD_{ft} denotes the book value of debt of component f at day t. Similar, MVE_{ft} denotes the market value of equity at day t. The book values and market values are obtained from Thomson Reuters Datastream.

Interest is the third structural impact factor which is included in the analysis. The structural approach by Merton (1974) predicts that an increase in interest rates reduces the default risk. The intuition is that increasing interest periods often follow an economic recovery, which implies a decrease in company defaults. Thus, interest rates should have a negative impact on CDS spreads. Many empirical studies confirmed that the interest rate is a major determinant of CDS spreads (see Duffee, 1998, p.2240; Annaert et al., 2000, p.6; Düllmann et al.(2000), p.385; Leake (2003), p.23; Papageorgiou and Skinner (2006),p.421). Consequently, we examine the impact of changes in interest levels on the Z-factors by changes in the 6-month US Interbank Offered Rate. Daily data are obtained from Thomson Reuters Datastream.

The CDS spread term structure is influenced by macroeconomic factors (see Chen et al., 2007, p.133). Thus, a vector with macroeconomic variables is included in the analysis model: the slope of the yield curve and the GDP growth. Many studies find that the term structure of the risk-free asset affects the CDS spreads (see Collin-Dufresne, Goldstein and Martin, 2001, p.2186).These studies reason that an increase in the slope of the yield curve is related to improving overall economic health, whereas a decreasing slope indicates an economic recession. Therefore, the slope of the yield curve can be used as a proxy for the overall business climate. In this study, *Slope* is computed as the difference between the 20-year and the 2-year US treasury rates. Following the reasoning above, we expect a negative relation between the CDS spreads and *Slope*. The variable *Slope* is based on daily data which is obtained from Thomson Reuters Datastream.

The variable *GDP* also reflects different market environments. *GDP* is computed as the quarterly growth of the real gross domestic product. The GDP growth is a leading economic indicator frequently used in empirical literature. Many studies confirm a strong negative relation between the credit spread and the real GDP growth (see Koopman and Lucas, 2005, p. 316; see Hackbarth et al., 2006, p.548).

Some studies find that that unexplained residual of the structural models can be explained by the counterparty risk measured by the default correlation of stock returns (see Hull and White, 2001, p. 16; Morkoetter, 2012, p. 76). *Defcorr* is defined as the default correlation between the arithmetic mean of the equity returns of 14 major CDS dealers which give quotes for the firms included in the CDX.NA.IG index and the arithmetic mean of the equity returns of the components of the CDX.NA.IG, CDX.NA.XO, CDX.NA.HVOL, respectively. The 14 CDS dealers are used as a proxy for the major counterparties in the CDS market. According to the European Central Bank (ECB), a small number of large CDS dealers account for a significant portion of gross notional trading volume of the CDS market (see ECB, 2009, p. 4).

The default correlation of stock returns can be proxied by an ordinary correlation coefficient. However, this proxy might be biased, because a correlation coefficient is not able to capture the tail dependencies of stock returns.

Therefore, we compute the dependence structure between the stock returns of the 14 CDS dealers and the equity returns of index *i* by fitting a bivariate time-varying t-copula to the data.[3] The Student t copula is given by the following equation:

$$T_{\Sigma,v}(u_1, \dots, u_d) = t_{\Sigma,v}(t_v^{-1}(u_1), \dots t_v^{-1}(u_d))$$

where $t_{\Sigma,v}$ denotes the multivariate Student-t distribution with *v* degrees of freedom and the correlation matrix Σ. Low values of the parameter *v* indicate strong tail dependencies.

In the bivariate case, Genest and Rémillard (2009) show that the dependence parameter *rho* of the Student-t copula can be calculated as a function of Kendall's Tau τ.

$$rho = \sin(\frac{\pi\tau}{2})$$

where τ denotes Kendall's sample τ which is given by the following equation:

$$\tau = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j>i} A_{ij}$$

A_{ij} denotes the indicator variables for the estimation of τ from a random sample of *n* pairs (*Xi,Yi), i = 1,..., n*.$_{ij}$is given by:

$$A_{ij} = sgn\left(X_i - X_j\right)(Y_i - Y_j)$$

To obtain daily values of *rho* and to investigate the nature of dependence through time, a rolling time frame approach of 126 days is applied (see Giacomini et al., 2009, p. 236; Grégoire et al., 2008, p. 67). High values for *rho* indicate high default correlations and, therefore, a high systematic counterparty risk for the firms which are comprised in the CDX.NA.IG, CDX.NA.XO, CDX.NA.HVOL, irrespectively. Thus, the credit spread of index *i* is expected to increase when *Defcorr* increases.

Daily equity return data are obtained from Thomson Reuters Datastream, and the copula dependence parameters are estimated via MatLab. However, Table 2 shows that the explanation variables are highly correlated. Thus, regression models based on a combination of these variables would be biased due to multicollinearity (see Farrar and Glauber, 1967, p.92). Typically, coefficients affected by multicollinearity are unstable in such a way that

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[3] see Jondeau and Rockinger (2006), p. 840. We performed the same estimations with the Clayton and the Gumbel copula and found that the reported results were not altered by the change of the copula. Results are available upon request.

already a small change in the regression model yields large changes in the predictor coefficients (see Farrar and Glauber, 1967, p.93).

Table 2: Correlation Matrix

CDX.NA.IG						
	Equityvola	Leverage	Defcorr	Interest	GDP	Slope
Equityvola	1					
Leverage	0.8289	1				
Defcorr	0.4616	0.496	1			
Interest	0.9666	0.8923	0.4409	1		
GDP	-0.8895	-0.9139	-0.5786	-0.942	1	
Slope	-0.7683	-0.5621	-0.5235	-0.731	0.7036	1
CDX.NA.HVOL						
	Equityvola	Leverage	Defcorr	Interest	GDP	Slope
Equityvola	1					
Leverage	0.8678	1				
Defcorr	0.6861	0.6481	1			
Interest	0.9675	0.9108	0.6924	1		
GDP	-0.9224	-0.9077	-0.7572	-0.942	1	
Slope	-0.7372	-0.6222	-0.652	-0.731	0.7036	1
CDX.NA.XO						
	Equityvola	Leverage	Defcorr	Interest	GDP	Slope
Equityvola	1					
Leverage	0.8318	1				
Defcorr	0.6108	0.4858	1			
Interest	0.9621	0.8809	0.6163	1		
GDP	-0.9047	-0.7858	-0.6947	-0.942	1	
Slope	-0.7575	-0.7051	-0.6581	-0.731	0.7036	1

Notes: Table2 reports the pair wise correlations between the explanatory variables used in this study. All variables are based on daily data.

Thus, a PCA procedure is used to convert the set of highly correlated variables into a few linearly uncorrelated common factors or principal components. PCA goes back to Pearson (1901), and is closely related to factor analysis, but incorporates less specific assumptions about the underlying structure, and solves eigenvectors of a slightly different matrix. Thus, it is a data exploratory tool which is used in many fields of applications. Therefore, PCA is also named empirical orthogonal functions, eigenfunction decomposition, empirical component analysis or quasiharmonic modes (see Lorenz, 1956, p.14). As mentioned above, PCA can be regarded as a special case of the factor analysis.

It yields dimension reduction via orthogonal transformation, and can be done by eigenvalue decomposition of data covariance or correlation matrix of mean-centred data. The transformation procedure is defined in such a way that the common factors are compiled in a descending order with respect to the portion of explanation regarding the variability in the data. Thus, the first principal component accounts for most of the variation in the data. Usually, the results of PCA are discussed in terms of component scores and loadings. Component scores are the transformed variables which correspond to a particular data point, and loadings are the weight by which each input variables should be multiplied to get the component score.

The principal components can be calculated by the following multi-step procedure. First, the random vector of time series $X_{t,n}$ is mean centred:

$$\bar{X}_{t,n} = X_{tn} - E(X_{t,n})$$

where $E(X_{t,n})$ denotes the empirical mean of the data. Second, the covariance or correlations matrix is calculated. In our study, we use a PCA based on eigenvalue decomposition of the correlations matrix:

$$C = \begin{pmatrix} corr_{1,1} & \cdots & corr_{1,n} \\ \vdots & \ddots & \vdots \\ corr_{n,1} & \cdots & corr_{n,n} \end{pmatrix}$$

Subsequently, the eigenvalues and eigenvectors (= principal components) of this matrix can be computed. We estimate the eigenvalues and eigenvectors by using the statistical software STATA. The eigenvalues eig and eigenvectors PC which correspond to the correlations matrix **C** are given by the following equation:

$$V^{-1}CV = D$$

where $V = (PC_1, \dots, PC_n)$ denotes the matrix of eigenvectors which diagonalizes the correlations matrix C and $D = (eig_1, \dots, eig_n)$ equals the diagonal matrix of eigenvalues of C.

Third, the principal components are ordered with respect to their explanatory power. This is achieved by ordering the corresponding eigenvalues eig in such a way that:

$$eig_1 > eig_2 > \cdots > eig_n$$

In this study, only the first eigenvector is kept for further analysis.

The first principal component for each index variable set is regressed on the first *Z*-factor of the corresponding DSFM model. Therefore, the regression model is given by the following equation:

$$\hat{Z}_{i,1,t} = c + PC_{i,1,t} + \varepsilon_t$$

where $PC_{i,1,t}$ denotes the first principal component of a set of variables corresponding to index *i* at day *t* and $\hat{Z}_{i,1,t}$ equals the first *Z*-factor of index *i* at day *t*.

5. RESULTS

5.1 DSFM Results

The following figures show the estimated factor functions and time series of a DSFM model specification with two *Z*-factors (*L*= 2) for the three CDS indices analysed in this study. The data ranges from December 8, 2008 to September 30, 2010.

The left panel of Figure 2 reports the factor functions, and the right panel shows the time series for the CDX.NA.IG. The first basis function m_0 is clearly U-shaped, whereas the second and third functions are relatively flat and slightly downward sloping with increasing maturity.

The U-shaped function possibly reflects the liquidity of the individual maturities. Mid-term CDS contracts and especially 5-year CDS are the most frequently traded CDS contracts (see Pan and Singleton, 2008, p.2349; Da Fonseca and Gottschalk, 2013, p.495). Some studies find that liquidity reduces CDS spreads. The function m_0 exhibits a clear drop for maturities between 5 and 7 years, and a minimum at 6.5 years to maturity. Thus, the first basis function reflects the tradability of the CDS contracts.

The second function m_1 is slightly increasing for short maturities, exhibits a maximum at 5 years, and is decreasing for long maturities. The corresponding time-series Z_1 is always positive, and decreases from approximately 600 to values around 300. This corresponds to the very high CDS spreads during the peak of the recent financial crisis. Since June 2009, CDS spreads revealed normal levels, and the term structure exhibits its ordinary upward sloping shape. Thus, the downward sloping function Z_1 can possibly be interpreted as a shift in the whole term structure with increasing maturity during this period.

The third function m_2 is characterized by a monotone decrease and a change from positive to negative at 6 years. In contrast to $Z_{1,}$ the second time-series Z_2 yields values between –43.73 and +54.91. The first values of Z_2 are positive, whereas Z_2 yields negative or near-zero values from June 2009 (t=202) onwards. Da Fonseca and Gottschalk (2013) show that the term structure for investment grade companies is typically upward sloping. However, in a struggling market environment, CDS term structure tends to be downward sloping. As our sample period covers the recent financial crisis, a major part of this time series is characterized by an inverted, i.e. downward sloping term structure.

Following Da Fonseca and Gottschalk (2013), we interpret the first factor as the level or shift of the CDS term structure, and the second factor as a change of the slope.

We do not decompose the CDS term structure into further factors, as these two factors already explain approximately 95% of the term structure variations.

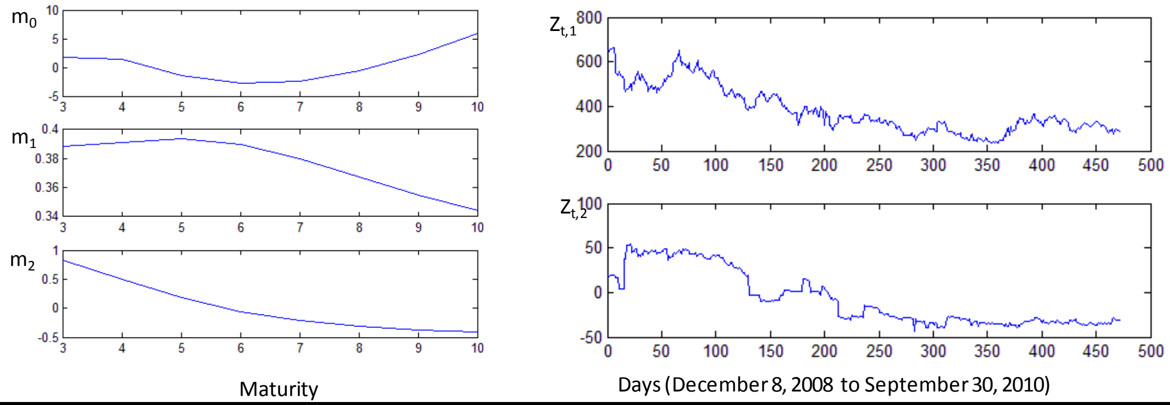
We obtain quite similar results for the CDX.NA.HVOL data set. Given the higher risk due to the higher volatility of the equity values compared to those of the CDX.NA.IG, the CDS spreads are expected to range on a higher level than those of the CDX.NA.IG. This hypothesis is confirmed by the high values of Z_1, which range between 510.55 and 1878.97 indicating a significantly higher risk level than the Z_1 values of the CDX.NA.IG.

Similar, the time series Z_1 for CDX.NA.XO starts at 1933.44 reflecting the extremely high credit risk level of high-risk firms during the recent financial crisis, and decreases to lower levels of approximately 494.72. The corresponding basis function m_1 decreases monotony indicating a downward shift of the CDS term structure for high-risk firms.

The shapes of the functions m_2 and the time series Z_2 of the CDX.NA.HVOL and the CDX.NA.XO do not differ significantly from those of the CDX.NA.IG. As mentioned above, the findings for the term structure of non-investment grade CDS are quite ambiguous. Our findings are in line with Sarig and Warga (1989), Fons (1994) and Lando and Mortensen (2005) who report a downward sloping term structure for non-investment grade firms. However, it is crucial to notice that the first half of the sample period reflects a struggling market environment. Thus, our findings also indicate that the CDS term structure of high-risk firms is inverted during financial crisis.

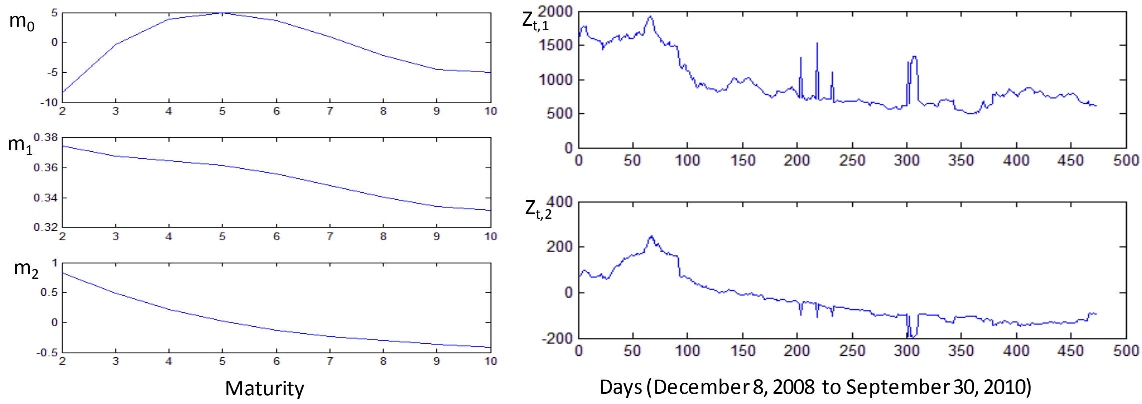
Interestingly, the first basis function m_0 of the CDX.NA.XO is convex, whereas the first basis functions m_0 of the CDX.NA.IG and the CDX.NA.HVOL are concave. This might reflect the restricted tradability of the mid-term CDS market for high-risk firms. Speculative investors either buy short-term CDS or long-term CDS but are not interested in medium-term CDS.

Figure 2: DSFM Factors of the CDX.NA.IG



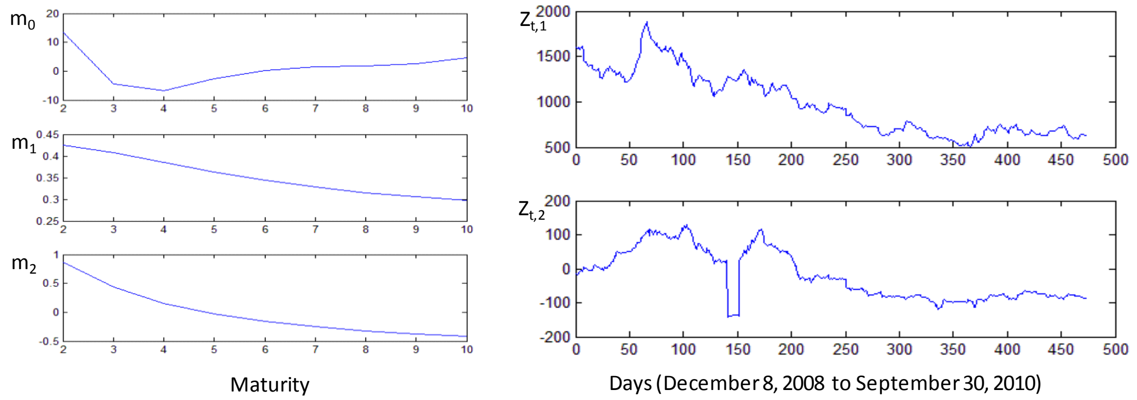
Notes: Figure 2, Panel A shows the estimated factor functions m_0, m_1 and m_2 and panel B reports the time series $Z_{t,1}$ and $Z_{t,2}$ for the CDX.NA.IG based on data from December 8, 2008 to September 30, 2010. Maturity is measured in years.

Figure 3: DSFM Factors of the CDX.NA.XO



Notes: Figure 3, panel A shows the estimated factor functions m_0, m_1 and m_2 and panel B reports the time series $Z_{t,1}$ and $Z_{t,2}$ for the CDX.NA.XO based on data from December 8, 2008 to September 30, 2010. Maturity is measured in years.

Figure 4: DSFM Factors of the CDX.NA.HVOL



Notes: Figure 4, panel A shows the estimated factor functions m_0, m_1 and m_2 and panel B reports the time series $Z_{t,1}$ and $Z_{t,2}$ for the CDX.NA.HVOL based on data from December 8, 2008 to September 30, 2010. Maturity is measured in years.

5.2 Sub Period DSFM Results

In order to analyse the effect of different market environments on the CDS term structure, we divided the sample into two sub periods. The first sub period ranges from December 8, 2008 to September 30, 2009 and, therefore, covers the market turmoil during the recent financial crisis. It is characterized by a downward sloping term structure of both, low and high-risk CDS. The second period ranges from October 1, 2009 to September 30, 2010 and mirrors a more relaxed market environment. Consequently, the term structures of investment grade and high-risk CDS is upward sloping.

Figures 5, 6, and 7 report the *m*-functions of the CDX.NA.IG, CDX.NA.XO, and the CDX.NA.HVOL, respectively. The left panel refers to the first sub period and the right panel shows the *m*-functions for the second sub period. In the first period, m_0 is convex for all indices, whereas m_0 is u-shaped in the second period. Given that m_0 represents the tradability of the CDS, our findings indicate that the CDS market became illiquid in general during the financial crisis. Further, speculative investors dominated the market and, thus, unusual maturities became more liquid than 5yr CDS. In the second period, m_0 shows the expected u-shape for all indices indicating that 5yr CDS are the most liquid contracts.

The second functions m_1 of all indices exhibits a monotone decrease in the first period, but in the second period m_1 are increasing for longer maturities.[4] The corresponding first *Z*-factors are equal to the values, which are reported for the entire sample. The Z_1 values of the first period are positive and range always above those of the second period indicating the increased default risk across all companies during the recent financial crisis.[5]

Irrespective of index and period, the third functions m_2 are decreasing and, therefore, are similar to those of the entire sample. However, the results of the corresponding Z_2- time series differ from those of the entire sample.[6] As mentioned above, the first period is characterized by a downward sloping term structure, whereas the term structure of the second period is upward sloping. Therefore, it is not surprising that Z_2 is positive on average in the first period and negative in the second period. Multiplied by positive m_2 values for short maturities and negative values for long maturities this leads to higher CDS-spreads for long maturities in the second period indicating a downward sloping term structure in first period and an increasing term structure in the second period.

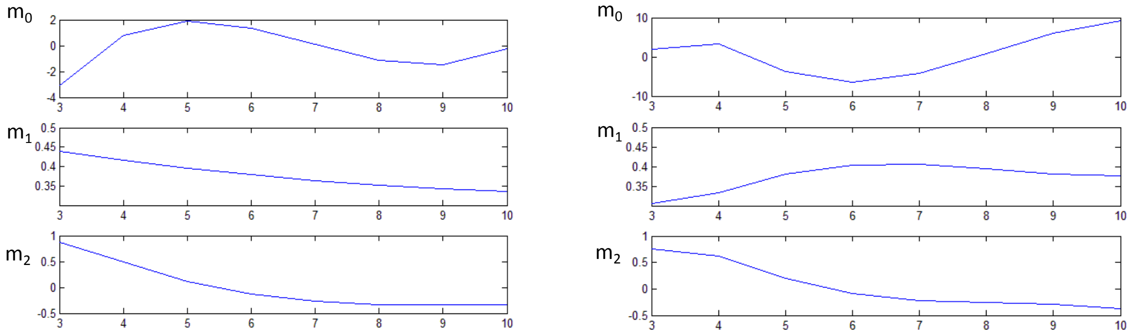
[4] This shape also indicates the positive slope of the term structure in the second period.

[5] The Z_1-time series of the entire sample are reported in Figure 2 to 4.

[6] Not reported. Estimations are available on request.

On the bottom line, the subsample results are in line with our findings for the entire sample indicating that the first Z-factor reflects shifts of the CDS term structure, whereas the second Z-factor mirrors the slope of the term structure.

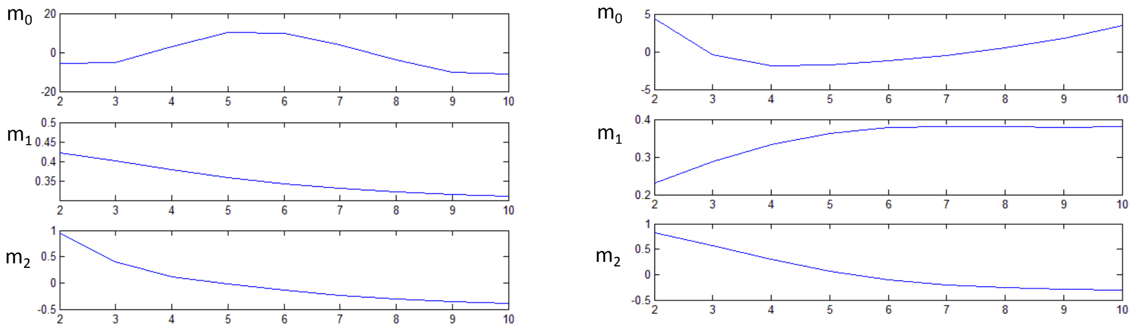
Figure 5: Sub Period m-Functions of the CDX.NA.IG



First period (December 8, 2008 to September 30, 2009) Second period (October 1, 2009 to September 30, 2010)

Notes: Figure 5, left panel shows the estimated factor functions m0 ,m1 and m2 of the CDX.NA.IG for the first period (December 8, 2008 to September 30, 2009) and the right panel reports the factor functions of the CDX.NA.IG based on data from October 1, 2009 to September 30, 2010. Maturity is measured in years.

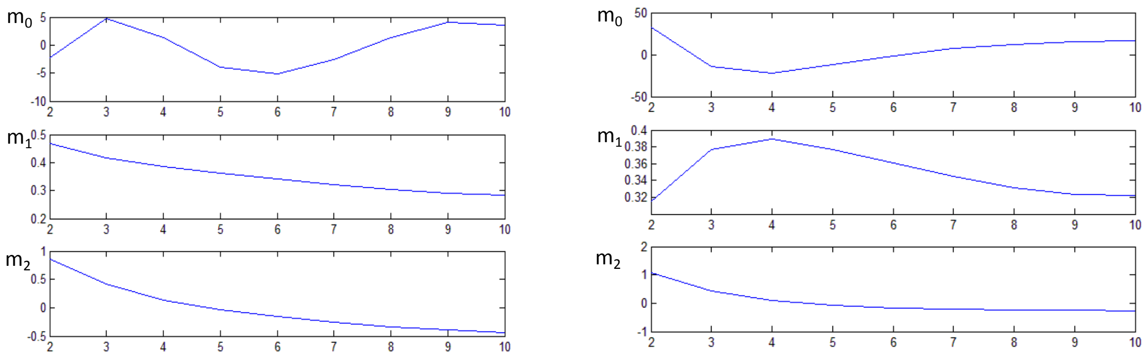
Figure 6: Sub Period m-Functions of the CDX.NA.XO



First period (December 8, 2008 to September 30, 2009) Second period (October 1, 2009 to September 30, 2010)

Notes: Figure 6, left panel shows the estimated factor functions m0 ,m1 and m2 of the CDX.NA.XO for the first period (December 8, 2008 to September 30, 2009) and the right panel reports the factor functions of the CDX.NA.XO based on data from October 1, 2009 to September 30, 2010. Maturity is measured in years.

Figure 7: Sub Period m-Functions of the CDX.NA.HVOL



First period (December 8, 2008 to September 30, 2009) Second period (October 1, 2009 to September 30, 2010)

Notes: Figure 7, left panel shows the estimated factor functions m0 ,m1 and m2 of the CDX.NA.HVOL for the first period (December 8, 2008 to September 30, 2009) and the right panel reports the factor functions of the CDX.NA.HVOL based on data from October 1, 2009 to September 30, 2010. Maturity is measured in years.

5.3 Regression Results

In the previous section we have shown that the CDS term structure variations can be decomposed into two major factors, representing the level and slope of the CDS term structure. In this section we examine the factors, which affect the level and slope of the CDS term structure.

As mentioned above, several studies showed that (5-year) CDS spread variations can be explained by the impact factors of the structural model invented by Merton (1974). The residual variations are likely to be explained by the counterparty risk in the CDS market (see Pu et al., 2011, p. 69).

Based on the study by Han and Zhou (2011), we derived some predictions for the impact of the structural variables and the counterparty risk on the whole CDS term structure. To verify these predications we run univariate regressions for each variable. Dependent variables are CDS spreads at maturities of 2, 3, 4, 5, 6, 7, 8, 9 and 10 years comprised by the CDX.NA.IG, the CDX.NA.XO and the CDX.NA.HVOL. Table 3 shows the adjusted R^2 for each regression model. The main finding is that all variables are significant at the 1% level and, therefore, have high adjusted R^2 indicating a strong explanatory power for all maturities. Thus, these variables can be used as impact factors of the CDS term structure.

Furthermore, our findings show that the explanatory power of *Equityvola* increases from short to medium term maturities, which is in line with our prediction and Han and Zhou (2011), who find that equity volatility has an increasing impact on longer maturities of the CDS term structure between 1yr and 5yr CDS. However, we also find that the explanatory power of equity volatility decreases for very long maturities.

In addition, we find that the impact of *Leverage* slightly decreases for longer maturities instead of increasing as predicted by the option pricing theory. Similar, the explanatory power of *GDP* decreases when maturity increases.

The explanatory power of *Defcorr* reaches a maximum for 6yr CDS spreads and decreases for long-term CDS spreads. The shape of the explanation function of *Defcorr* is similar to the one of *Equityvola*; this might be due to the fact that both variables are based on short-term stock return variations.

The effect of the interest rate is expected to be stronger for longer maturities, because the firm value grows more under a high interest rate. In contradiction to this prediction, our findings show, that the impact of the interest rate decreases for long maturities.

Due to the fact that a shock increases the long-term rate more than the short-term rate, we expected *Slope* to affect the CDS term structure more for long maturities. Our findings are in line with the prediction, and show an increase of the explanatory power as the maturity increases.

Further, our findings show that the impact of the variables on the CDS spread variations is independent from the credit risk of the underlying firms. Only the impact *Defcorr* seems to be stronger for high-risk firms than for low-risk firms.

Subsequent to the univariate analysis, we perform two PCAs to examine the combined explanatory power of the variables introduced above on the two major determinants of the CDS term structure. The first PCA is based on Equityvola, *Leverage*, and *Interest* as suggested by the structural model. The input variables of the second PCA are *Slope* and *GDP*. The correlations matrix above shows that the CDS determinant variables are highly correlated. Thus, they are likely to have common factors.

Table 4 Panel A shows the weights or score coefficients of the first and second PCA. One can see from the table that the input variables are nearly equally weighted and, thus, the input variables equally reflect the common factors.

Table 4, Panel B shows the eigenvalues and explanation proportions of the first principal component for each CDS index. The results indicate that the first common factor explains approximately 93% or 85% of the total variations, respectively. Thus, the explanatory power of the first principal component is sufficiently high and we can exclude the other common factors.

Using the PCA procedure, we reduced the number of impact variables on the CDS term structure to a single common factor. Table 4 Panel C shows that the time series Z_1 can be explained by the first principal component of PCA 1. The high adjusted R^2 between 85% and 95.5% indicate the strong explanatory power of this single factor for all CDS indices. Further, the results show that first principal components are highly significant for the three CDS indices. Thus, the level factors variations of CDS term structures are driven by the same determinants, irrespective of the level of credit risk of the underlying firms. Our findings differ from Han and Zhou (2011), who find that the variables suggested by the structural model explanation proportions of the CDS term structure of high-risk firms are larger than those of low-risk firms.

Some studies argue that the residual variations can be explained by the counterparty risk in the CDS market. Thus, we regress a systematic counterparty risk proxy on the regression residual of the level factor of the DSFM model.

Table 4, Panel E reports the regression results of *Defcorr* on Z_1 estimated by the DSFM approach. We find that *Defcorr* is significant at the 1% level. Thus, systematic counterparty risk significantly impacts the level of the CDS term structure.

Table 4, Panel D shows the regression results for the second time series Z_2 and the first principal components of the second PCA. Again, all coefficients are significant at the 1% level. However, the explanatory power of the second principal component is not as high as the adjusted R^2 for the first principal components. The first principal component‘s coefficient of the second PCA is negative. Thus, an increase in the first common factor of *Slope* and *GDP* leads to decrease of the slope of the CDS term structure.

It can be concluded that the first factor Z_1 of the CDS term structure reflects the level of the term structure, and can be explained by the first common factor of a mixture of structural variables, and a counterparty risk proxy. Subsequently, we find that the second factor Z_2 mirrors the slope of the term structure, and can be explained by the first common factor of the slope of the yield curve and the GDP growth. Given the fact that in the DSFM approach the basic functions, and the evolution of the times series Z_1 and Z_2 are estimated in a non-parametric way from the data, these results are somewhat surprising.

Table 3: Univariate Regressions

	sign	2y	3y	4y	5y	6y	7y	8y	9y	10y
CDX.NA.IG										
Equityvola	pos.		86.62%	87.07%	88.01%	87.88%	86.75%	85.84%	84.62%	83.06%
Leverage	pos.		89.60%	90.29%	89.19%	86.99%	83.91%	81.05%	77.72%	74.37%
Interest	pos.		91.88%	92.12%	91.85%	90.18%	87.16%	84.70%	84.70%	82.14%
Defcorr	pos.		25.94%	27.91%	28.86%	29.24%	28.92%	27.37%	25.39%	23.50%
GDP	neg.		90.32%	91.06%	89.18%	85.55%	80.79%	76.66%	72.37%	68.51%
Slope	neg.		44.84%	46.41%	47.56%	47.99%	47.33%	47.46%	47.94%	48.45%
CDX.NA.XO		2y	3y	4y	5y	6y	7y	8y	9y	10y
Equityvola	pos.	79.23%	79.38%	77.60%	74.47%	72.03%	68.94%	65.59%	62.33%	59.23%
Leverage	pos.	84.58%	84.89%	84.44%	84.17%	83.06%	81.09%	78.87%	76.61%	74.34%
Interest	pos.	86.38%	86.36%	84.05%	80.28%	77.40%	73.54%	69.57%	65.80%	62.27%
Defcorr	pos.	36.40%	40.15%	41.29%	40.18%	40.05%	38.94%	37.52%	36.00%	34.57%
GDP	neg.	79.96%	79.83%	76.75%	71.09%	66.87%	62.12%	57.49%	53.17%	49.28%
Slope	neg.	50.20%	52.78%	53.59%	53.57%	54.87%	54.89%	54.19%	53.27%	52.27%
CDX.NA.HVOL		2y	3y	4y	5y	6y	7y	8y	9y	10y
Equityvola	pos.	74.50%	76.29%	77.46%	78.30%	78.48%	77.94%	76.84%	75.48%	74.01%
Leverage	pos.	80.07%	82.83%	84.87%	86.66%	87.33%	87.27%	86.97%	86.49%	85.82%
Interest	pos.	75.08%	77.34%	78.98%	80.51%	81.14%	80.82%	79.99%	78.97%	77.79%
Defcorr	pos.	52.28%	52.89%	52.79%	52.48%	52.62%	52.45%	51.71%	50.81%	49.86%
GDP	neg.	84.35%	86.49%	87.53%	87.86%	87.69%	87.19%	86.13%	84.81%	83.37%
Slope	neg.	30.02%	30.40%	32.09%	34.14%	35.78%	36.66%	36.98%	37.14%	37.15%

Notes: Table 3 reports the adj. R^2 of the variables for each index between December 8, 2008 and September 30, 2010. Maturities range from 2 to 10 or 3 to 10 years. All statistics are based on daily data. Execept Interest, all variables have the predicted signs and the coefficients are significant at the 1% level.

Table 4: PCA and Regression Results

Panel A: Weights (Scoring coefficients) for the first principal component of PCA 1 and 2						
	CDX.NA.IG		CDX.NA.XO		CDX.NA.HVOL	
	PCA1	PCA2	PCA1	PCA2	PCA1	PCA2
Equityvola	0,579		0,580		0,579	
Leverage	0,562		0,562		0,566	
Interest	0,591		0,590		0,587	
GDP		0,707		0,707		0,707
Slope		0,707		0,707		0,707

Panel B: Eigenvalues & explanation power for the first common factor of PCA 1 and 2			
		Eigenvalue	Proportion
CDX.NA.IG	PCA 1	2,793	0,931
	PCA 2	1,704	0,852
CDX.NA.XO	PCA 1	2,784	0,928
	PCA 2	1,704	0,852
CDX.NA.HVOL	PCA 1	2,831	0,944
	PCA 2	1,704	0,852

Panel C: Regression results Z_1 and first principal component of PCA 1			
	CDX.NA.IG	CDX.NA.XO	CDX.NA.HVOL
Comp1_IG	60,6889 ***		
Comp1_XO		206,4618 ***	
Comp1_HVOL			189,2131 ***
Obs.	473	474	474
Adj. R^2	95,50%	85,55%	85,91%
F	10024,51	2800,79 ***	2883,88 ***

Panel D: Regression results Z_2 and first principal component of PCA 2			
	CDX.NA.IG	CDX.NA.XO	CDX.NA.HVOL
Comp1_IG	-1,03 ***		
Comp1_XO		-64,53 ***	
Comp1_HVOL			-35,20 ***
Obs.	473	474	474
Adj. R^2	68,07%	67,28%	40,03%
F	1007,45 ***	973,51 ***	316,68 ***

Panel E: Regression results residuals Z_1 and Defcorr			
	CDX.NA.IG	CDX.NA.XO	CDX.NA.HVOL
Defcorr	5,77 ***	4,70 ***	5,00 ***
Obs.	473	474	474
Adj. R^2	6,39%	4,28%	4,82%
F	33,25 ***	22,13 ***	24,95 ***

Notes: Table 4 reports the results for the OLS of the principal components on the Z factors estimated by the DSFM model. Panel A shows the weights of the first principal component of PCA 1 and PCA 2 for each CDX index. Input variables for the first PCA are the variables Equityvola, Leverage and Interest as suggested by the structural model. The second PCA is based on the variables GDP and Slope. Panel B reports the eigenvalues of the PCAs for each CDX index. Panel C and D showthe regression results. Dependent variables are the first and the second Z factor of the DSFM model. Panel E shows the regression results of the variable Defcorr and the residuals of the first Z-factor.

5.4 Regression Results Sub Periods

The first sub period ranges from December 8, 2008 to September 30, 2009 and, therefore, covers the market turmoil due to the recent financial crisis. It is characterized by a downward sloping term structure for low and high-risk CDS. Table 5 reports the regression results for the first sub period. Table 5, Panel A shows the weights or score coefficients of the first and second PCA. Similar to the results for the entire sample, the input variables are nearly equally weighted indicating an equal reflection of the common factors.

Again, we only retain the first common factor because the explanatory power of sufficiently high. Table 5, Panel B reports the explanatory proportions of the first principal component for PCA 1 and 2. The results do not differ significantly from the findings for the entire sample.

In a next step, we regress the first common factor on the first Z-factor of each CDX index. Compared to the entire sample results, we find that the explanatory power of the first principal component is slightly reduced but R^2 still ranges between 89.9% and 71.5% (see table 5, panel C).

The results are in line with the finding for the entire sample indicating that the level factors variations of CDS term structures are driven by the same determinants, irrespective of the level of credit risk of the underlying firms. However, the results for the counterparty risk proxy differ from those of the entire sample. Table 5, panel E shows that the variable *Defcorr* is insignificant for the CDX.NA.HVOL index. Thus, systematic counterparty risk does not impact the level of the term structure of high-volatility CDS in a stressed market environment. However, *Defcorr* explains 18.61% of the regression residual of the first Z-factor indicating a strong impact on the term structure for high-risk CDS.

Table 5, Panel D shows the regression results for the second time series Z_2 and the first principal components of the second PCA. In contrast to the results for entire sample, the coefficients have heterogeneous signs. The coefficient for the CDX.NA.IG is positive, whereas it is negative for the CDX.NA.XO. Thus, an increase in the first common factor of *Slope* and *GDP* leads to an increase of the slope of the investment grade CDS term structure but to a decrease of the slope of high-risk CDS term structures.

For all indices the explanatory power of the common factor of *Slope* and *GDP* is significantly reduced in the first period.

Table 6 reports the regression results for the second sub period. Table 6, Panel A shows the input variables in the second period are also nearly equally weighted indicating an equal reflection of the common factors.

In comparison to the first period, the explanatory power of the first common factors of PCA 1 and 2 is reduced and explains only up to 66.38% or 74.40% of the input variables' variations, respectively (see table 6, panel B).

Similar, the explanatory power of the OLS of the first common factor of PCA 1 on the first Z-factor of each CDX index is reduced. The structural variables explain only 12.99% of the Z_1-factor variations of the CDX.NA.XO (see table 6, panel C). However, the first common factor accounts for more than 70% of the Z_1- factor variations of the CDX.NA.IG. Thus, for this sub period, the level of credit risk matters for the explanatory power of the structural variables.

This impact of systematic counterparty risk is significant for the second period, as well. The variable *Defcorr* is highly significant and the adjusted R^2 ranges between 9% and 15% (see table 6, panel E). It can be concluded that systematic counterparty risk also impacts the CDS term structure in a relaxed market environment.

Table 5, Panel D shows the regression results for the second time series Z_2 and the first principal components of the second PCA. In contrast to the results for first period, the coefficients have negative signs. Therefore, the results for Z_2 are in line with those for the entire sample. However, the explanatory power of the common factor of *Slope* and *GDP* is significantly reduced for all indices.

Table 5: PCA and Regression Results First Period

Panel A: Weights (Scoring coefficients) for the first principal component of PCA 1 and 2

	CDX.NA.IG		**CDX.NA.XO**		**CDX.NA.HVOL**	
	PCA1	PCA2	PCA1	PCA2	PCA1	PCA2
Equityvola	0,590		0,573		0,578	
Leverage	0,529		0,564		0,549	
Interest	0,611		0,594		0,604	
GDP		0,707		0,707		0,707
Slope		0,707		0,707		0,707

Panel B: Eigenvalues & explanation power for the first common factor of PCA 1 and 2

		Eigenvalue	Proportion
CDX.NA.IG	PCA 1	2,576	85,86%
	PCA 2	1,753	87,67%
CDX.NA.XO	PCA 1	2,763	92,11%
	PCA 2	1,753	87,67%
CDX.NA.HVOL	PCA 1	2,659	88,62%
	PCA 2	1,753	87,67%

Panel C: Regression results Z_1 and first principal component of PCA 1

	CDX.NA.IG		**CDX.NA.XO**		**CDX.NA.HVOL**	
Comp1_IG	50,30	***				
Comp1_XO			209,24	***		
Comp1_HVOL					103,20	***
Obs.	213		213		213	
Adj. R^2	89,83%		83,23%		71,50%	
F	1872,64	***	1053,12	***	532,83	***

Panel D: Regression results Z_2 and first principal component of PCA 2

	CDX.NA.IG		**CDX.NA.XO**		**CDX.NA.HVOL**	
Comp1_IG	8,38	***				
Comp1_XO			-28,84	***		
Comp1_HVOL					3,63	
Obs.	213		213		213	
Adj. R^2	33,74%		37,65%		0,27%	
F	108,93	***	129,03	***	1,57	

Panel E: Regression results residuals Z_1 and Defcorr

	CDX.NA.IG		**CDX.NA.XO**		**CDX.NA.HVOL**	
Defcorr	377,16	***	3393,62	***	-734,63	
Obs.	213		213		213	
Adj. R^2	4,32%		18,61%		0,78%	
F	10,57	***	49,48	***	2,66	

Notes: Table 5 reports the OLS-results of the principal components on the Z-factors for the first sub period. Panel A shows the weights of the first principal component of PCA 1 and PCA 2 for each CDX index.Input variables of the first PCA are Equityvola, Leverage and Interest as suggested by the structural model. The second PCA is based on the variables GDP and Slope. Panel B reports the eigenvalues of the PCAs for each CDX index. Panel C and D showthe regression results. Dependent variables are the first and the second Z-factor of the DSFM model. Panel E shows the regression results of the variable Defcorr and the residuals of the first Z-factor.

Table 6: PCA and Regression Results Second Period

Panel A: Weights (Scoring coefficients) for the first principal component of PCA 1 and 2

	CDX.NA.IG		**CDX.NA.XO**		**CDX.NA.HVOL**	
	PCA1	PCA2	PCA1	PCA2	PCA1	PCA2
Equityvola	0,682		0,698		0,697	
Leverage	0,376		0,117		0,348	
Interest	0,627		0,707		0,627	
GDP		0,707		0,707		0,707
Slope		0,707		0,707		0,707

Panel B: Eigenvalues & explanation power for the first common factor of PCA 1 and 2

		Eigenvalue	Proportion
CDX.NA.IG	PCA 1	1,991	66,38%
	PCA 2	1,488	74,40%
CDX.NA.XO	PCA 1	1,792	59,73%
	PCA 2	1,488	74,40%
CDX.NA.HVOL	PCA 1	1,973	63,21%
	PCA 2	1,488	74,40%

Panel C: Regression results Z_1 and first principal component of PCA 1

	CDX.NA.IG	**CDX.NA.XO**	**CDX.NA.HVOL**
Comp1_IG	20,45 ***		
Comp1_XO		40,56 ***	
Comp1_HVOL			37,46 ***
Obs.	261	261	261
Adj. R^2	71,72%	12,99%	20,56%
F	660,23 ***	39,8 ***	68,31 ***

Panel D: Regression results Z_2 and first principal component of PCA 2

	CDX.NA.IG	**CDX.NA.XO**	**CDX.NA.HVOL**
Comp1_IG	-2,50 ***		
Comp1_XO		-8,13 ***	
Comp1_HVOL			-13,18 ***
Obs.	261	261	261
Adj. R^2	17,56%	15,15%	25,92%
F	56,4 ****	47,41 ***	91,97 ***

Panel E: Regression results residuals Z_1 and Defcorr

	CDX.NA.IG	**CDX.NA.XO**	**CDX.NA.HVOL**
Defcorr	181,68 ***	1296,38 ***	435,80 *
Obs.	261	261	261
Adj. R^2	15,45%	9,65%	1,06%
F	48,52 ***	28,78 ***	3,79 *

Notes: Table 6 reports the OLS-results of the principal components on the Z-factors for the second sub period. Panel A shows the weights of the first principal component of PCA 1 and PCA 2 for each CDX index.Input variables of the first PCA are Equityvola, Leverage and Interest as suggested by the structural model. The second PCA is based on the variables GDP and Slope. Panel B reports the eigenvalues of the PCAs for each CDX index. Panel C and D showthe regression results. Dependent variables are the first and the second Z factor of the DSFM model. Panel E shows the regression results of the variable Defcorr and the residuals of the first Z-factor.

6. CONCLUSIONS

In this paper we examined the dynamics of the CDS term structure by applying a DSFM model. We find that a model with two factors, respectively three basis functions, amounts to a sufficiently high percentage of the total variation in the CDS term structure. The first factor reflects the shift of the term structure, and is driven by the first common factor of a mixture of the variables suggested by the structural model including a proxy for the systematic counterparty risk. More precisely, the first common factor of equity volatility, leverage, and interest explains 85-95% of the total variation in the first DSFM-factor. Further we find that the regression residual of the first Z-factor is significantly determined by systematic counterparty risk.

The second factor mirrors the slope of the CDS term structure and can be explained by the first principal component of the variables slope of the yield curve, and GDP growth.

Thus, our findings provide evidence that the variables of the structural model, including a systematic counterparty risk proxy, explain a significant proportion of the CDS term structure's shifts. In contradiction to Han and Zhou (2011), we find that the impact of the structural variables does not differ significantly between high-risk and low-risk firms. Instead, we find that the shape first basis function of the DSFM model for struggling market environments is significantly distinct from the one in a relaxed market. For struggling markets, the first basis function is convex, whereas for healthy markets the first basis function is concave. We suggest that the difference in shapes can be explained by the investor's preferences and trading strategies. Typically, the risk-averse investors invest 5yr CDS, whereas speculative investors prefer either long-term or short-term CDS. During the recent financial crisis the CDS market was nearly illiquid and dominated by speculative investors. Thus, 5yr CDS were the most illiquid ones. However, when the market calmed, 5yr CDS became again the most liquid contracts. Consequently, the first basis function is convex. Thus, we find that the first basis function, respectively the time-invariant factor, can be associated with the tradability of the CDS.

Finally, we find evidence that in a healthy market environment the CDS term structure for both investment-grade and high risk CDS is upward sloping. However, when the market environment weakens, the CDS term structure can be inverted.

REFERENCES

Akgiray, V.; (1989) "Conditional Heteroskedasticity in Time Series of Stock Returns: Evidence and Forecasts", Journal of Business, Vol. 62, 55–80.

Annaert, J.; De Ceuster, M; De Jonghe, F. (2000) "Modelling European Credit Spreads", Research Report, Deloitte & Touche

Augustin, P. (2012) "The Term Structure of CDS Spreads and Sovereign Credit Risk", Working Paper, 1-60. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2172382

Avramov, D.; Jostova, G.; Philipov A. (2007) "Understanding Changes in Corporate Credit Spreads," Financial Analysts Journal, Vol. 63, 96-105.

Balaban, E.; Bayar, A.; Faff, R. (2006) "Forecasting Stock Market Volatility further International Evidence", The European Journal of Finance, Vol. 122, 171-188.

Benkert, C. (2004) "Explaining credit default swap premia", Journal of Futures Markets, Vol. 24, 71–92.

Blanco, R.; Brennan, S.; Marsh, J. (2005) "An empirical analysis of the dynamic behaviour between investment grade bonds and credit default swaps," Journal of Finance, Vol. 60, 2255-2281.

Borak, S.; Weron, R.; (2008) "A semiparametric factor model for electricity forward curve dynamics," Journal of Energy Markets, Vol. 1, No. 3, 3-16.

Chen, L.; Lesmond, D. A.; Wei J. (2007) "Corporate Yield Spreads and Bond Liquidity", Journal of Finance, Vol. 62, No.1, 119-149.

Chen, R.; Cheng, X.; Wu, L. (2012) "Dynamic Interactions between Interest-Rate and Credit Risk: Theory and Evidence on the Credit Default Swap Term Structure", Review of Finance, Vol. 17, 403-441.

Collin-Dufresne, P.; Goldstein, R. S.; Martin S.J. (2001) "The Determinants of Credit Spread Changes", Journal of Finance, Vol. 56, No. 5, 2177- 2207.

Cossin, D.; Hricko, T. (2001) "Exploring for the Determinants of Credit Risk in Credit Default Swap Transaction Data", Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=273454

Da Fonseca, J.; Gottschalk, K. (2013) "A Joint Analysis of the Term Structure of Credit Default Swap Spreads and the Implied Volatility Surface", Journal of Futures Markets, Vol. 33, Issue 6, 494-517.

Duffee, G. R. (1998) "The Relation between Treasury Yields and Corporate Bond Yield Spreads", Journal of Finance, Vol. 53, No.6, 2225-2241.

Düllmann, K.; Uhrig-Homburg, M.; Windfuhr, M. (2000) "Risk structure of interest rates: an empirical analysis for Deutschmark-denominated bonds", European Financial Management, Vol. 6, No. 3, 367-388.

ECB (2009) „Credit Default Swaps and Counterparty Risk“, European Central Bank, http://www.ecb.int/pub/pdf/other/creditdefaultswapsandcounterpartyrisk2009en.pdf

Farrar, D. E.; Glauber, R. (1967) “Multicollinearity in regression analysis: the problem revisited“, Review of Economics & Statistics, Vol. 49, No. 1, 92-107.

Fons, J.S. (1994) “Using Default Rates to Model the Term Structure of Credit Risk", Financial Analysts Journal, Vol. 50, No. 5, 25-32.

Forte, S.; Pena, J. I. (2009) “Credit spreads: An empirical analysis on the informational content of stocks, bonds, and CDS”, Journal of Banking and Finance, Vol. 33, 2013– 2025.

Giacomini, E.; Härdle, W.; Spokoiny, V. (2009) “Inhomogeneous dependence modelling with time-varying copulae”, Journal of Business and Economic Statistics, Vol. 27, Issue 2, 224-234.

Greatreux, C. (2009) “Credit Default Swap Market Determinants”, Journal of Fixed Income, Winter 2009, 18-32.

Grégoire, V.; Genest, C.; Gendron, M. (2008) “Using copulas to model price dependence in energy markets”, Energy Risk Vol. 5, Issue 5, 58-64.

Guermat, C.; Harris, R. (2001) “Robust conditional variance estimation and value-at-risk”, Journal of Risk, Vol. 4, 25-41.

Hackbarth, D.; Miao, J.; Morellec, E. (2006) “Capital Structure, Credit risk and Macroeconomic Conditions“, Journal of Financial Economics, Vol. 82, No.3, 519-550.

Han, B.; Zhou, Y. (2011) “Understanding the Term Structure of Credit Default Swap Spreads”, Working Paper, 1- 43. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2148076

Han, B.; Zhou, Y. (2011b) “Term Structure of Credit Default Swap Spreads and Cross-Section of Stock Returns”, McCombs Research Paper Series, No. FIN-01-11

Helwege, J.; Turner, C.M.(1999) “The Slope of the Credit Yield Curve for Speculative - Grade Issuers”, Journal of Finance, Vol. 54, No. 5, 1869-1884.

Huang, J. ; Zhang, X. (2008) “The Slope of Credit Spread Curves”, Journal of Fixed Income, Vol. 18,56-71.

Hull, J.; White, A. (2001) “Valuing Credit Default Swaps II: Modelling Default Correlations“, Journal of Derivatives, Vol. 8, Issue 3, 12-21.

Jondeau, E.; Rockinger, M. (2006) “The copula-garch model of conditional dependencies: An international stock market application”, Journal of International Money and Finance, Vol. 25, 827–853.

JP Morgan (1996) “Riskmetrics TM Technical Document”, fourth edition, New York.

Koopman, S. J.; Lucas, A. (2005) “Business and Default Cycles for Credit Risk,” Journal of Applied Econometrics, Vol. 20, No.2, 311-323.

Lando, D.; Mortensen, A. (2005) “Revisiting the Slope of the Credit Spread Curve”, Journal of Investment Management, Vol. 3, 1-27.

Leake, J. (2003) “Credit spreads on sterling corporate bonds and the term structure of UK interest rates“, Bank of England, Working Paper

Lorenz, E. (1956) “Empirical Orthogonal Functions and Statistical Weather Prediction”, Cambridge: MIT, Department of Meteorology, Statistical Forecasting Project, Scientific Report No 1, 1-49.

Merton, R.C. (1974) “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates“, Journal of Finance, Vol. 29, No.2, 449-470.

Morkoetter, S.; Pleus, J.; Westerfeld, S. (2012) “The Impact of Counterparty Risk on Credit Default Swap Pricing Dynamics”, Journal of Credit Risk, Vol. 8, Issue 1, 63-88.

Pan, J.; Singleton, K. (2008) “Default and Recovery Implicit in the Term Structure of Sovereign *CDS* Spreads“, Journal of Finance, Vol. 64, No.5, 2345-2383.

Papageorgiou, N.; Skinner, F. S. (2006) “Credit Spreads and the Zero-Coupon Treasury Spot Curve“, Journal of Financial Research, Vol. 29, No.3, 421-439.

Park, B.; Borak, S.; Härdle, W.; Mammen, E. (2009) “Time series modelling with semiparametric factor dynamics,” Journal of the American Statistical Association, Vol. 104, 284-298.

Pu, X.; Wang, J.; Wu, C. (2011) “Are Liquidity and Counterparty Risk Priced in the Credit Default Swap Market?“, The Journal of Fixed Income, 59-79.

Ramsay, J.; Silverman, B. (1997) “Functional Data Analysis”, Springer Verlag

Sarig, O.; Warga, A. (1989) “Some Empirical Estimates of the Risk Structure of Interest Rates”, Journal of Finance, Vol.44, No. 5, 1351–1360.

Trueck, S.; Härdle, W.; Weron, R. (2012) “The relation between Spot and Futures CO_2 Emission Allowances Prices in EU-ETS,” Working Paper, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2137346

Zhang, B. Y.; Zhao, H.; Zhu, H. (2009) “Explaining credit default swap spreads with the equity volatility and jump risks of individual firms”, Review of Financial Studies, Vol. 22, 5099–5131.