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Linking U.S. CDS Indexes with the U.S. Stock Market: A Multidimensional Analysis with the Market Price and Market Volatility Channels

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1. Introduction

The recent mortgage subprime crisis and the partly resulting global financial crisis shed light on the weaknesses and required enhancements of prevailing risk management practices (e.g. Basel 2 limitations and frailties). Among the most important enforcements, liquidity concerns, counterparty credit risk, the correlation between various risks (e.g. contagion risk) and model stress testing as well as related scenario analysis have been highlighted by the Basel Committee on Banking Supervision under the Basel 3 framework (Basel Committee on Banking Supervision, 2010). With regard to liquidity, various liquidity measures coupled sometimes with a stressed scenario analysis are proposed at both the level of financial assets and the bank level in in- and off-balance sheet prospects (Blundell-Wignall and Atkinson, 2010; Lumsdaine, 2011; Van Den End, 2011). On the correlation viewpoint, the risk of correlation between risks (e.g. impacts of liquidity risk on market risk and *vice versa*) refers to the linkages between asset classes, and linkages between banks/financial institutions among others (Embrechts *et al.*, 2002, 2003; Hull and White, 2006; Lumsdaine, 2011). On the stress testing and scenario viewpoints, the mitigation of potential model risk and measurement errors is targeted in risk assessment and risk forecast prospects (Basel Committee on Banking Supervision, 2010; Ferrari *et al.*, 2011).

Current research suggest that the credit market, as represented by credit default swaps or corporate bond spreads, is highly sensitive to the stock market trend and/or the corresponding market volatility as represented by equity volatility (Dupuis *et al.*, 2009; Gatfaoui, 2010; Scheicher, 2009; Vaz de Melo Mendes and Kolev, 2008). Under the Basel 3 setting, we focus concurrently on the correlation risk between credit default swap (CDS) spreads and referenced market risk components (Norden and Weber, 2009). Specifically, CDS spreads represent a credit risk proxy whereas market risk is envisioned with respect to two dimensions, namely a market price risk and a market volatility risk (Gatfaoui, 2010). The market price risk illustrates the impact of the global market trend (i.e. common general link within the stock market) whereas the market volatility risk represents the magnitude of global market moves (i.e. volatility feedback, liquidity concerns). In this lens, we study the asymmetric linkages between CDS spreads and both market price and market volatility risks, and we analyze the interaction between such linkages through a three-dimensional

copula methodology. In particular, we assess the impact of the stock market trend on the credit market trend while describing also how the magnitude of stock market moves impacts the magnitude of credit market moves. Hence, we address simultaneously two dependent questions, which illustrate the general market behavior. First, does the stock market trend drive the directional moves of the credit market? Second, does the magnitude of stock market moves influence the magnitude of credit market moves?

The previous multivariate setting targets a sound assessment of credit risk in the light of the stock market's influence with respect to the curse of dimensionality puzzle. The curse of dimensionality refers to the trade-off between the number of parameters, the problem's dimension and the sample size in order to ensure a sound model estimation process (i.e. convenient and acceptable risk representation). Indeed, the sample size constrains the number of model parameters with respect to the dimensionality of the problem under consideration (Bellman, 1961; Liebscher, 2005; Weiss, 2011). Specifically, the accuracy of the estimation procedure relies on an exponential link between the problem dimensionality and the corresponding required number of data. Moreover, the observed multivariate dependence structures exhibit a negative link between CDS spreads and market price risk (i.e. trend impact) on one side, and a positive link between CDS spreads and market volatility risk (i.e. magnitude effect) on the other side. Taking into account simultaneously the dependence of CDS spreads relative to both market price and market volatility channels, allows for a better assessment of the correlation risk between the credit market and the stock market. Indeed, finer risk scenarios can be raised with respect to the market trend (i.e. bad or good market signal) and its corresponding volatility impact (i.e. strength of the signal).

In this lens, this chapter is organized as follows. Section 2 introduces the data as well as related statistical properties and stylized features. In particular, the directional impact of the stock market trend on CDS spread changes is quantified while the influence of the stock market volatility on the magnitude of CDS spread moves is also measured. Then, section 3 introduces a three-dimensional copula study, which measures the impact of the stock market trend and volatility on CDS spreads. As an extension, a scenario analysis is provided in section 4 to study the sensitivity of CDS spreads relative to the two stock market channels. Specifically, we assess the corresponding tail dependence, namely the extent to which extreme variations in both stock market trend and volatility impact extreme variations in CDS spreads. Finally, section 5 draws some concluding remarks and proposes some future research insights.

2. Data and stylized features

We introduce the stock market and credit market data under consideration as well as their corresponding statistical patterns.

2.1 Data

We consider two categories of data; - 1) U.S. stock market indexes and 2) credit default swap data, which focus on both North America and emerging markets. Our daily data consists of closing quotes extracted from Reuters, and ranging at most from September 28th 2007 to March 24th 2010, namely 618 observations per data series. With regard to the first category of data, we consider the logarithmic returns of the Standard & Poor's 500

stock market index in basis points and the level of the CBOE implied volatility index. Specifically, those two indexes are considered to be a proxy of the two complementary dimensions of market risk, namely the market price risk and the market volatility risk (see Gatfaoui, 2010). With regard to the second category of data, the credit default swap data come from credit derivatives indexes, which are delivered by Markit Corporation. In particular, we consider the spreads of Markit credit default swap indexes, or equivalently, the spreads of credit derivatives indexes that we name Markit CDX spreads. Those CDX indexes are split into two groups among which one set of spreads focuses on reference entities domiciled in North America while the other one relates to reference entities domiciled in emerging markets (see Table 1). In particular, the CDXEM index focuses only on sovereign entities whereas the CDXED relates to both corporate and sovereign entities. Moreover, the crossover index accounts for potential rating divergences between Standard & Poor's and Moody's rating agencies with respect to the lowest investment grade and highest speculative grade ratings (i.e. divergences relative to the frontier between investment and speculative grade borrowers). Furthermore, the CDX spreads under consideration are expressed in basis point and consist of the mid-market quotes on individual issuers.[1] Incidentally, CDXEM spread data range from February 1st 2008 to March 24th 2010, namely 538 observations per data series.

CDS label	Detail about reference entities and indices*
CDXEM	Emerging Market
CDXED	Emerging Market Diversified
CDXHY	North America Investment Grade High Yield
CDXHB	North America Investment Grade High Yield and B-rated
CDXBB	North America Investment Grade High Yield and BB-rated
CDXIG	North America Investment Grade
CDXIV	North America Investment Grade High Volatility
CDXXO	North America Crossover
SP500	Standard & Poor's 500 stock index
VIX	CBOE Implied Volatility Index

* Emerging market entities consist of Africa, Asia, Eastern Europe, Latin America and Middle East.

Table 1. Markit CDS indexes and stock market indices

2.2 Stylized features

We analyze the daily changes in CDX spreads, SP500 returns and VIX level. Incidentally, changes in CDX spreads reflect changes in credit markets and credit conditions. In particular, the direction of CDX spread moves (i.e. the sign of daily changes) illustrates the credit market status whereas the magnitude of CDX spread moves refers to the strength and health of the credit market. Indeed, increasing CDX spreads indicate a hazardous credit market so that lending becomes riskier (Fisher, 1959). Moreover, the larger the spread increase is, the riskier borrowing becomes and the higher the corresponding credit risk level is. In such a case, tougher credit conditions, which may

[1]The spreads are computed against corresponding LIBOR rates. The reader is invited to consult Markit Corporation's website at http://www.markit.com/en/ for further information.

illustrate a lack of funding liquidity or a deterioration in the corporate bond market liquidity among others (Brunnermeier, 2009; Das and Hanouna, 2009; Longstaff *et al.*, 2005), yield a weakened credit market because borrowing becomes more expensive in order to compensate for the increased risk of not refunding lenders (i.e. higher credit risk premium). Along with the referenced linkages between the credit and stock markets, we investigate the relationships between CDX spread changes and the variations in stock market conditions. Specifically, we focus on the link prevailing between CDX spreads changes on one side, and changes in both SP500 returns as well as VIX level. For this prospect, we first focus on the statistical properties of our time series (see Table 2). Changes in CDX spreads as well as market indexes exhibit mitigated skewness values and a positive excess kurtosis, underlining then their asymmetric and fat-tailed behavior over time. In particular, apart from CDXBB, CDXIV and CDXXO spreads, CDX spread changes exhibit a positive skewness, which underlines generally above average spread variations from one day to another. Moreover, we performed five different normality tests in order to cope with the asymmetric nature and the tail behavior of the considered financial times series.

All the statistics reject the Gaussian assumption at a five percent test level. Thus, CDX spread changes and variations in stock market indexes do not exhibit a Gaussian behavior. However, a complementary unit root test emphasizes the stationary behavior of the observed daily changes in both credit and market data as underlined by the Dickey-Fuller (DF) as well as the Z_τ and Z_ρ Phillips-Perron statistics for a unit lag (Dickey and Fuller, 1979; Fuller, 1996, Hamilton, 1994; MacKinnon, 1994; Newey and West, 1987; Phillips and Perron, 1988). Indeed, the stationary behavior is validated at both the one percent and the five percent test levels.[2]

Index	Mean	Std. Dev.	Excess kurtosis	Skewness	DF	Z_τ	Z_ρ	Normality tests*
CDXEM	0.0186	22.2388	33.2281	2.4708	-17.482	-17.546	-396.326	NO
CDXED	0.2042	22.1535	23.0788	2.2965	-23.693	-23.697	-590.169	NO
CDXHY	0.1426	27.8055	5.0361	0.0902	-20.399	-20.511	-513.335	NO
CDXHB	0.1361	25.1582	10.3125	0.3582	-20.090	-20.472	-537.111	NO
CDXBB	-0.0259	23.3170	26.5870	-0.0780	-27.804	-27.666	-724.143	NO
CDXIG	0.0681	6.1093	10.0182	0.0247	-21.775	-21.650	-504.261	NO
CDXIV	0.0340	11.4271	20.7487	-1.2384	-19.592	-19.658	-481.770	NO
CDXXO	0.0097	13.1560	15.5236	-0.6810	-31.220	-30.828	-796.120	NO
SP500	-0.0081	307.0674	4.5221	0.4861	-43.540	-753.123	-74.658	NO
VIX	0.0827	2.7742	8.9435	0.1618	-28.914	-624.136	-30.061	NO

* Jarque-Bera, Lilliefors, Cramer-Von-Mises, Watson, Anderson-Darling at a 5% level.

Table 2. Descriptive statistics of daily changes in CDX spreads and stock market factors

[2]The augmented Dickey-Fuller and Phillips-Perron unit root tests are performed without trend and constant terms, the Phillips-Perron test being robust to heteroskedasticity (e.g. serial correlation). The one- and five-percent critical levels are -2.5800 and -1.9500 for Dickey-Fuller test. Differently, the one- and five-percent critical levels correspond to -2.5800 and -1.9500 for Phillips-Perron Z_τ statistic whereas such critical levels consist of -13.8000 and -8.1000 for Phillips-Perron Z_ρ statistic.

Then, we control for an existing link based on the nonparametric Kendall and Spearman correlation coefficients (see Table 3). Indeed, the non-Gaussian behavior of our time series advocates the use of an appropriate correlation measure, which accounts for asymmetry and potential fat tails.

Spread	Kendall correlation with		Spearman correlation with	
	SP500	VIX	SP500	VIX
CDXEM	-0.2676	0.4200	-0.3634	0.5644
CDXED	-0.0916	0.2191	-0.1329	0.3114
CDXHY	-0.2423	0.4077	-0.3369	0.5627
CDXHB	-0.1382	0.3038	-0.1949	0.4246
CDXBB	-0.1409	0.2861	-0.1999	0.4042
CDXIG	-0.2887	0.4196	-0.4072	0.5779
CDXIV	-0.2107	0.3484	-0.2975	0.4887
CDXXO	-0.1772	0.2749	-0.2584	0.3912
SP500	1.0000	-0.4368	1.0000	-0.5533
VIX	-0.4368	1.0000	-0.5533	1.0000

Table 3. Kendall and Spearman correlations between CDX spread changes and changes in both SP500 and VIX

The obtained correlation estimates emphasize the significance of the correlation between the CDS market and the U.S. stock market. Indeed, all the correlation coefficients are significant at a five percent two-tailed Student t-test level. As expected, the link between CDS spreads and market price is negative whereas the link between CDS spreads and market volatility is positive. Moreover, the correlation between market prices and corresponding market volatility is negative. Such a pattern illustrates the well-known volatility feedback effect, which was formerly introduced by Black (1976). In particular, CDX spreads tend to increase when both stock market returns decrease and the corresponding stock market volatility augments. Conversely, CDX spreads tend to decrease when both SP500 returns increase and VIX level diminishes. Hence, a downward stock market trend and upward stock market volatility coincide both with upward CDS spreads. As a result, the statistical properties of stock- and credit market data support the investigation of a joint link between CDX spreads on one side, and both SP500 returns and VIX index on the other side (i.e. stock market price and volatility indexes). Such linkages are of high significance specifically when CDX spread moves are large (i.e. extreme variations and tail behaviors).

Importantly, the linkages prevailing between CDS spreads and the stock market volatility originate their full meaning from existing findings. In particular, market liquidity is strongly related to the corresponding market volatility (Brunnermeier and Pedersen, 2009) so that volatility encompasses liquidity features. Moreover, the interaction, or equivalently, the correlation between market risk and credit risk is well acknowledged nowadays (Brigo *et al.*, 2011; Hartmann, 2010; Liu *et al.*, 2006; Predescu *et al.*, 2009). Specifically, CDS spreads constitute a proxy of credit risk but also encompass a liquidity

premium, which evolves both on a cross-sectional basis and over time (Predescu *et al.*, 2009). Hence, studying the linkages between CDX spreads and stock market volatility makes fully sense in terms of the impact or transmission of liquidity shocks from the stock market to the credit market. Basically, such linkages illustrate how aggregate CDS spreads react to modifications in funding means among others. The previous linkages are therefore emphasized by the significant correlation coefficients between CDX spread changes and VIX index variations.

Focusing on the dependencies between CDX spreads and market indexes, we then investigate graphically the existence of such links. For this prospect, we plot the CDX spread changes against changes in SP500 index on one side, and changes in VIX implied volatility index on the other side (see Fig. 1 and Fig. 2). The two-dimensional plots exhibit clearly linkages between CDX spreads and both market price and market volatility. However, such bivariate linkages are asymmetric (Gatfaoui, 2010). Moreover, we notice clearly differences between the dependence structures of CDX spread changes with respect to SP500 changes, and the dependence structures of CDX spread changes with respect to VIX changes. Furthermore, Fig. 2 exhibits flatter relationships with respect to CDXED spread changes.

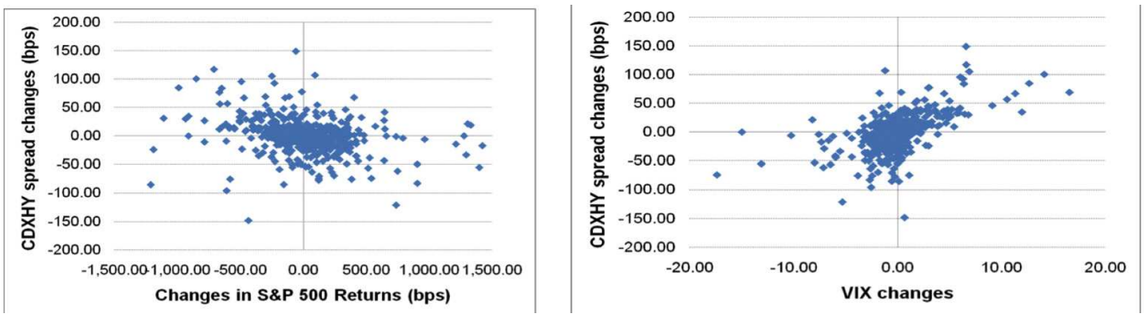


Fig. 1. Dependence structures of CDXHY spreads with both SP500 and VIX indexes

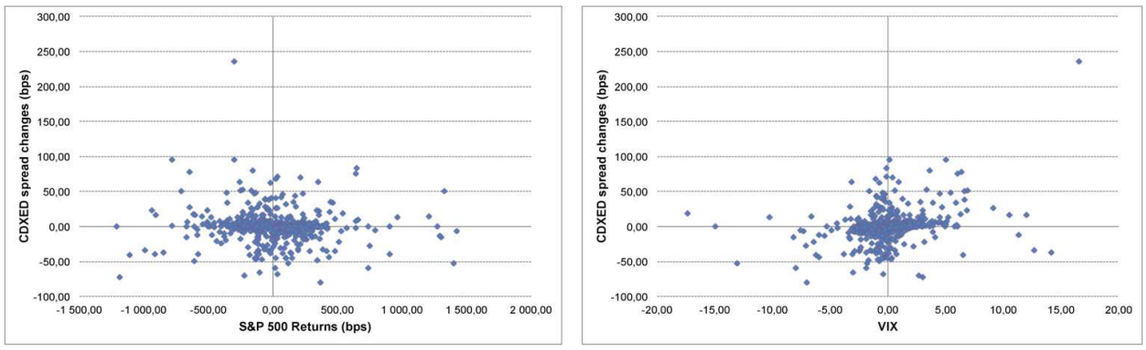


Fig. 2. Dependence structures of CDXED spreads with both SP500 and VIX indexes

As a complementary investigation, Fig. 3 aggregates the previous two-dimensional linkages while considering the three-dimensional dynamics of CDX spread, SP500 return and VIX level daily changes. Seemingly, the three-dimensional relationships reveal to be elliptical. Again, Fig. 3 exhibits flatter relationships with respect to CDXED spread variations.

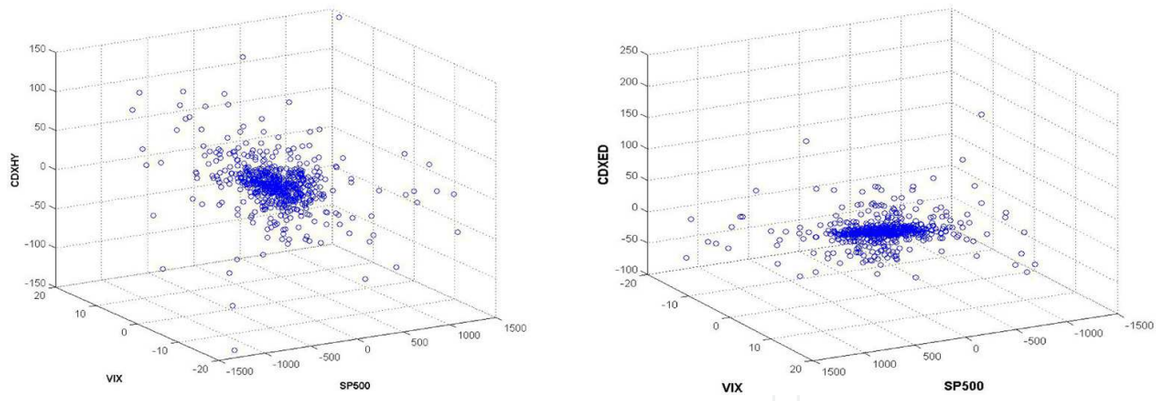


Fig. 3. Dependence structures of CDXHY and CDXED spreads with respect to both SP500 and VIX indexes

As a result, there exist negative linkages between CDX spread changes and SP500 return changes, and positive linkages between CDX spread changes and VIX changes. Such two-dimensional linkages reveal to be asymmetric and the two types of dependence structures of CDX spread changes relative to SP500 return changes and VIX changes respectively exhibit noticeable differences. However, according to Fig. 3, the three-dimensional joint behavior is rather elliptical, and exhibits some symmetric pattern from a tail prospect.

Such empirical findings are important for two main reasons. First, they confirm the well-known negative link between price and volatility, which was formerly referenced in the equity market (Black, 1976). Second, they underline competing effects with respect to the impact of equity prices, on the one hand, and equity volatility, on the other hand, on CDX spreads. With regard to the first reason, the negative link reflects an intuitive and straightforward situation. Indeed, equity volatility tends to increase during market disturbances and bear market times while prices are decreasing or low. Conversely, equity volatility tends to decrease during calm market periods and bull market trends while prices are generally increasing. One explanation for such an asymmetric volatility relies on the investors' behaviors. Basically, investors want all to get rid of their bad stocks when prices are decreasing, which generates a higher market activity and therefore a higher volatility of stock prices. Since many investors want to sell the same stocks at the same times, such common behaviors generate large price declines so that prices fluctuate importantly over time. That's also why volatility is often related to liquidity (Brunnermeier and Pedersen, 2009), namely the propensity of a stock (or an asset) to be transformed into cash. With regard to the second reason, the credit market is closely linked with the equity market (Brigo *et al.*, 2011; Fisher, 1959; Hartmann, 2010; Liu *et al.*, 2006; Predescu *et al.*, 2009). Therefore, two distinct linkages between the credit market and the equity market need to be considered. The first linkage is the negative impact of equity prices on CDX spreads whereas the second linkage is the positive impact of equity volatility on CDX spreads. As a result, the evolution of CDX spreads over time results from a tradeoff between the two previous market channels. In particular, an increase in CDX spreads is associated to both a decreasing market trend and an increasing market volatility. Hence, the first price channel gives information about the directional impact of the stock market on CDX spreads whereas the second market volatility channel indicates the magnitude of such an impact on CDX spread changes.

The decomposition of the two stock market channels helps identify more precisely the market risk and therefore its link with credit risk. Specifically, we target to assess the risk that CDX spreads cross upward a specific high threshold given that the stock market price and volatility channels also cross some corresponding downward and upward thresholds respectively. Recall that growing CDX spreads indicate a riskier lending activity and therefore a risk of not being refunded for lenders. The higher CDX spreads become or the more they grow, the riskier the credit risk is. In general, risk assessment and risk management techniques focus on the probability of occurrence of bad scenarios and the impact of such scenarios (e.g. credit losses and their consequences). In our case, a bad scenario is so that CDX spreads increase while the stock market trend is downward and the stock market volatility increases. The strength of each scenario depends on the chosen thresholds for credit and equity market data. Thus, the market price and volatility channels have a huge significance for risk management practitioners because a more accurate link between credit risk and market risk can be drawn.

As an example, we consider the changes in CDX spreads and corresponding changes in VIX and SP500 returns. We rank by ascending order those CDX spread changes and we also take the value, which indicates the beginning of the 10% largest CDX spread increases among the sample (i.e. the 10% biggest positive changes). Such a threshold value highlights the beginning of the 10% highest CDX spread sample, which is also called an upper tail. The upper tail stresses critical high values for the CDX spreads under consideration, and therefore describes high credit risk scenarios (e.g. extreme CDX spread values). Then, we count the number of cases when the sign of CDX spread changes coincides with the sign of the changes in both SP500 returns and VIX level (i.e. same directional moves). Such a counting process is achieved for the whole sample of CDX spreads and the corresponding 10% upper tail. The coincidence study between the changes across the whole sample illustrates the average correlation risk between credit risk and market risk factors whereas the coincidence study across the upper tail sample underlines some extreme correlation risk. We report in Table 4 the percentage of sign coincidence between CDX spread changes and changes in both SP500 returns and VIX level. Setting the 50% threshold as a discriminant value, CDX spreads evolve in the opposite direction of SP500 returns and in the same direction as VIX level across the whole sample and on an average basis. With respect to the upper tail sample of CDX spreads, high CDX spread changes generally evolve in the same way as the whole sample, and such behavior is even enforced. Indeed, the percentage of similar directional moves between high CDX spreads and SP500 returns diminishes whereas the percentage of matching directional moves between high CDX spreads and VIX level increases. Thus, we start considering some critical spread variations in relation with the corresponding changes in the two referenced stock market channels, namely SP500 returns and VIX level.

Therefore, managers can easily focus on three specific questions. First, can a critical threshold in stock market prices be linked to a critical threshold in CDX spreads? Second, can a critical threshold in stock market volatility be linked to a critical threshold in CDX spreads? Finally, can critical thresholds in both stock market price and stock market volatility be linked to a critical threshold in CDX spreads? Such management issues can be difficult to answer unless we understand the linkages between the credit and stock markets. Moreover, a better understanding also yields the use of more appropriate techniques for risk assessment prospects. Indeed, Fig. 1 and Fig. 2 exhibit clearly the non-linear nature of the previous linkages else we would clearly notice straight lines on those

figures. Furthermore, the two stock market channels require considering a three-dimensional setting in order to assess the link between credit risk and market risk. As an extension, Fig. 3 also advocates the non-linear nature of the linkages between the two stock market channels and CDX spreads.

Index	Global coincidence		Upper tail coincidence*	
Spread	SP500	VIX	SP500	VIX
CDXEM	31.9287	63.3712	8.9552	34.3284
CDXED	39.0600	58.1848	38.7097	56.4516
CDXHY	35.6564	70.5024	25.8065	88.7097
CDXHB	41.0049	64.9919	30.6452	74.1935
CDXBB	41.3290	65.9643	33.8710	69.3548
CDXIG	35.4943	70.6645	17.7419	85.4839
CDXIV	38.8979	67.7472	22.5806	77.4194
CDXXO	41.1669	64.5057	17.7419	79.0323

* It is the sample of the 10% highest CDX spread increases.

Table 4. Percentage of sign coincidence between CDX spread changes and changes in both SP500 and VIX

3. A multivariate copula application

The previous stylized facts advocate the use of an appropriate statistical tool to handle simultaneously the dependence structure between the CDS market and the two components of market risk, namely market price and market volatility risks. For this purpose, we introduce the three-dimension copulas under consideration, the corresponding data fitting process and the selection criterion of the best copula model.

3.1 Copulas

Copulas are a useful tool to model multivariate dependence structures (Cherubini *et al.*, 2004; Durrleman *et al.*, 2000; Embrechts *et al.*, 2003; Genest *et al.*, 1995; Joe, 1997; McNeil *et al.*, 2005; Nelsen, 1999; Patton, 2009; Sklar, 1959, 1973). They present the advantage of not necessarily having to determine the distribution function of each of the variable under consideration. Hence, it is possible to specify the global dependence structure without knowing the margins (i.e. univariate distribution functions) of each variable under consideration. As a consequence, the corresponding model risk is minimized. As an example, Fig. 4 plots the empirical copula function, which describes the bivariate dependence structure of CDXHY spread changes with respect to SP500 changes on one side, and VIX changes on the other side (Deheuvels, 1979, 1980). The observed empirical behavior can easily be linked to the theoretical behavior of some well-known copula representations (Cherubini *et al.*, 2004; Joe, 1997; Nelsen, 1999).

Along with the previous framework, we focus on the three-dimensional representations of the dependence structures of CDX spread changes and the changes in the two market risk channels. Specifically, Sklar's theorem (1959) introduces a three-dimensional copula function as follows:

Theorem: Let F be a joint distribution function with margins F_X, F_Y and F_Z. Then there exists a copula C such that for all x, y, z in the real number set,

$$F(x,y,z) = \text{Prob}(X \le x, Y \le y, Z \le z) = C\left(F_X(x), F_Y(y), F_Z(z)\right) \quad (1)$$

If F_X, F_Y and F_Z are continuous, then C is unique; otherwise, C is uniquely determined on $\text{Ran}F_X \times \text{Ran}F_Y \times \text{Ran}F_Z$. Conversely, if C is a copula and F_X, F_Y and F_Z are distribution functions, then the function F defined by relation (1) is a joint distribution function with margins F_X, F_Y and F_Z.

Notice that the copula function can be rewritten as $C(u_1, u_2, u_3)$ where $U_1=F_X(X)$, $U_2=F_Y(Y)$ and $U_3=F_Z(Z)$ as well as $u_1=F_X(x)$, $u_2=F_Y(y)$ and $u_3=F_Z(z)$ take values in the [0,1] real subset. We label ΔCDX, $\Delta SP500$ and ΔVIX the daily changes in CDX spreads, SP500 returns and VIX level respectively. In particular, daily changes are computed as follows for any time *i* within the sample period under consideration:

$$\Delta CDX_i = X_i = CDX_i - CDX_{i-1} \quad (2)$$

$$\Delta SP500_i = Y_i = SP500_i - SP500_{i-1} \quad (3)$$

$$\Delta VIX_i = Z_i = VIX_i - VIX_{i-1} \quad (4)$$

Under such a setting, we face the well-known curse of dimensionality, which represents the trade-off between the dimension of our setting (i.e. a three-dimension setting), the number of parameters for each considered copula representation, and finally the number of available data points. Given that statistics often advocate parsimonious models, we'll focus on a specific set of Archimedean and Elliptical copulas (see Table 5). In particular, the Frank and Gaussian copulas exhibit no tail dependence, namely no link between the variables' extreme values. However, the Student T copula exhibits a symmetric left- and right-tail dependence. Differently, the remaining copulas exhibit asymmetric tail dependences. In particular, the Clayton copula exhibits lower tail dependence whereas the Gumbel copula exhibits upper tail dependence. Hence, we are able to capture various tail behaviors within financial markets.

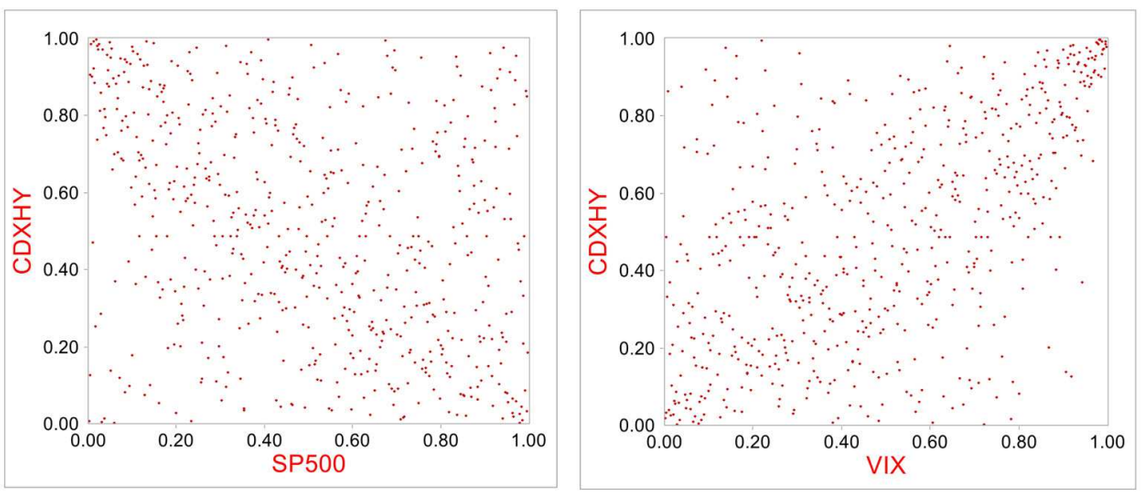


Fig. 4. Empirical bivariate copula functions of CDXHY spread changes

Copula	Attribute	Parameters
Clayton Frank Gumbel	Archimedean	Correlation θ
Gaussian	Elliptical	Correlation matrix
Student T		Degree of freedom ν, Correlation matrix

Table 5. Three-dimension copulas and characteristics

Each of the three dimensions of our multivariate copula framework relates respectively to CDX spread changes (i.e. first dimension, or equivalently first variable), SP500 return changes (i.e. second dimension), and finally VIX changes (i.e. third dimension) from one day to another. This way, the relationship between CDX spreads and the two market dimensions are simultaneously accounted for. As an example, Fig. 4 exhibits the corresponding U_1 values for CDXHY spread changes on the vertical axis whereas it displays the corresponding U_2 and U_3 values of SP500 return and VIX level changes on the horizontal axis respectively.

For any positive correlation parameter θ and u_1, u_2, u_3 in [0,1], the *Clayton* copula writes:

$$C(u_1,u_2,u_3;\theta)=\frac{1}{\left(u_1^{-\theta}+u_2^{-\theta}+u_3^{-\theta}-2\right)^{1/\theta}} \tag{5}$$

For any correlation matrix ρ and u_1, u_2, u_3 in [0,1], the *Gaussian* copula writes:

$$C(u_1,u_2,u_3;\rho)=\frac{1}{|\rho|^{1/2}}\exp\left\{-\frac{1}{2}\xi^t\left(\rho^{-1}-\mathbf{1}\right)\xi\right\} \tag{6}$$

where ρ and ρ^{-1} are a three-dimension matrix and its inverse respectively, $|\rho|$ is the determinant of the correlation matrix, ξ is the vector of the inverse standard univariate Gaussian cumulative distribution function applied to each element u_1, u_2, u_3, and finally ξ^t is the transposed vector of ξ. We also introduce a three-dimension vector **1** of unit numbers.

The Archimedean and elliptical copulas under consideration satisfy specific assumptions as follows. For any positive correlation parameter θ and u_1, u_2, u_3 in [0,1], the *Frank* copula writes:

$$C(u_1,u_2,u_3;\theta)=-\frac{1}{\theta}\ln\left\{1-\frac{\left(e^{-\theta u_1}-1\right)\left(e^{-\theta u_2}-1\right)\left(e^{-\theta u_3}-1\right)}{\left(e^{-\theta}-1\right)^2}\right\} \tag{7}$$

For any positive correlation parameter θ and u_1, u_2, u_3 in [0,1], the *Gumbel* copula writes:

$$C(u_1,u_2,u_3;\theta)=\exp\left(-\left\{\left(-\ln u_1\right)^\theta+\left(-\ln u_2\right)^\theta+\left(-\ln u_3\right)^\theta\right\}^{1/\theta}\right) \tag{8}$$

For any correlation matrix ρ, degree of freedom ν and u_1, u_2, u_3 in [0,1], the *Student T* copula writes:

$$C\left(u_1,u_2,u_3;\rho,\nu\right)=\frac{1}{\left|\rho\right|^{1/2}}\frac{\Gamma\left(\frac{\nu+3}{2}\right)\left\{\Gamma\left(\frac{\nu}{2}\right)\right\}^3\left(1+\frac{1}{\nu}\xi^t\rho^{-1}\xi\right)^{-\frac{\nu+3}{2}}}{\left\{\Gamma\left(\frac{\nu+3}{2}\right)\right\}^3\Gamma\left(\frac{\nu}{2}\right)\prod_{n=1}^{3}\left(1+\frac{\xi_n^2}{\nu}\right)^{-\frac{\nu+1}{2}}} \tag{9}$$

where ρ and ρ^{-1} are a three-dimension matrix and its inverse respectively, $|\rho|$ is the determinant of the correlation matrix, Γ is the Gamma function, ξ is the vector (ξ_1, ξ_2, ξ_3) of the inverse univariate Student[3] cumulative distribution function applied to each element u_1, u_2, u_3, and finally ξ^t is the transposed vector of ξ. Charpentier *et al.* (2006) advocate a minimum number of two hundreds observations when the copula dimension is below or equal to three. According to those authors the length of our time series, or equivalently, the chosen sample size reduces thus the curse of dimensionality problem.

3.2 Estimation and selection

According to (Weiss 2011), the maximum likelihood method yields less biased and more stable parameter estimates for parametric copulas. Hence, we first estimate the copula parameters while running a Maximum Likelihood Estimation methodology (MLE). Specifically, we apply a semi-parametric MLE process, which is also known as canonical MLE. The semi-parametric MLE procedure relies on two stages so that the copula is specified while the univariate margins of the considered variables are not specified. The first stage computes the nonparametric cumulative distribution function (i.e. univariate margin) of each variable whereas the second stage maximizes the log-likelihood of the copula under consideration as a function of the corresponding copula parameters (Choros *et al.*, 2010; Genest *et al.*, 1995; Yan, 2006). However, we correct for possible parameters' uncertainty while applying a parametric bootstrapping technique in order to conform to the related MLE asymptotics (i.e. bootstrap MLE; Chen and Fan, 2006; Chernick, 1999; Davison and Hinkley, 2006; Efron, 1979; Simon, 1997; Varian, 2005).[4] The parametric bootstrap, which is also a resampling method, allows for assigning an accuracy measure to parameter estimates. Indeed, parameter uncertainty usually yields the under- or overestimation of model parameters when samples are not large enough. Correcting for uncertainty and sticking to MLE assumptions allow therefore for getting more accurate estimates and thus sounder risk assessment. Then, our selection process of the most appropriate copula representation relies on the information criterion principle (i.e. selection tool). In particular, we consider the Akaike, Schwarz and Hannan-Quinn information criteria. Those information criteria encompass two components, which are the forecast error committed by the model and number of estimated unconstrained parameters (Akaike, 1974; Lütkepohl, 2006; Hannan and Quinn, 1979; Schwarz, 1978). The model selection rule requires minimizing the information criterion. By doing so, the selection process targets an accurate and parsimonious model, which reduces the potential errors and estimation problems.

[3]This is a Student distribution with ν degree(s) of freedom.

[4]Recall that asymptotic principles rely on the infinite sample assumption.

The negative Kendall correlation between CDX spreads and SP500 return changes is incompatible with the Clayton copula representation. Moreover, the obtained parameter estimates for Frank copula are also incompatible with the corresponding theoretical specification. As a result, we display only the chosen information criteria for the remaining copulas, which consist of the Gumbel, Gaussian and Clayton copulas (see Tables 6, 7 and 8). Amongst the range of representations under consideration, the best copula or the optimal three-dimension copula estimation is that one which minimizes at least one (when not all) of the information criteria previously mentioned, namely Akaike, Schwarz and Hannan-Quinn information criteria. According to Tables 6 to 8, the optimal copula representation consists of the Student T copula for all CDX spreads under consideration, which implies a symmetric tail dependence of CDX spreads with respect to market risk channels.

Spread	Information criterion		
	Akaike	Schwarz	Hannan-Quinn
CDXEM	2.00747665	6.28599811	3.67664928
CDXED	2.00650408	6.42486904	3.72035251
CDXHY	2.00650411	6.42486907	3.72035253
CDXHB	2.00650411	6.42486907	3.72035254
CDXBB	2.00650407	6.42486903	3.72035250
CDXIG	2.00650409	6.42486905	3.72035252
CDXIV	2.00650410	6.42486906	3.72035253
CDXXO	2.00650415	6.42486911	3.72035258

Table 6. Information criterisa for Gumbel copula estimation

Spread	Information criterion		
	Akaike	Schwarz	Hannan-Quinn
CDXEM	-496.82	-484.01	-491.84
CDXED	-409.29	-396.05	-404.16
CDXHY	-592.34	-579.11	-587.22
CDXHB	-472.05	-458.82	-466.93
CDXBB	-444.55	-431.31	-439.43
CDXIG	-616.53	-603.30	-611.41
CDXIV	-517.10	-503.86	-511.98
CDXXO	-429.38	-416.15	-424.26

Table 7. Information criteria for the Gaussian copula estimation

Spread	Information criterion		
	Akaike	Schwarz	Hannan-Quinn
CDXEM	-709.90	-692.83	-703.27
CDXED	-505.90	-488.27	-505.90
CDXHY	-704.44	-686.81	-704.44
CDXHB	-578.60	-560.97	-578.60
CDXBB	-517.75	-500.11	-517.75
CDXIG	-735.21	-717.57	-735.21
CDXIV	-604.00	-586.37	-604.00
CDXXO	-486.81	-469.17	-486.81

Table 8. Information criteria for the Student T copula estimation

Further, Table 9 displays the corresponding Student T parameter estimates, namely the elements of the correlation matrix ρ and the corresponding number ν of degrees of freedom.

Spread	Correlation with		Correlation between	Degree of
	SP500	VIX	SP500 and VIX	freedom
CDXEM	-0.1185	0.3448	-0.6216	3
CDXED	0.0116	0.2182	-0.6072	4
CDXHY	-0.2580	0.5142	-0.6223	4
CDXHB	-0.1185	0.3448	-0.6216	3
CDXBB	-0.0589	0.2280	-0.5775	4
CDXIG	-0.3466	0.5648	-0.6061	3
CDXIV	-0.2893	0.4166	-0.5967	3
CDXXO	-0.1655	0.2379	-0.6068	5

Table 9. Parameter estimates of the three-dimension Student T copula

Apart from CDXED spreads, results conform to empirical facts so that:

- the correlation between the changes in CDX spreads and SP500 returns is negative,
- the correlation between the changes in CDX spreads and VIX levels is positive,
- the correlation between the changes in SP500 returns and VIX levels is negative.

The positive correlation between the changes in CDXED spreads and SP500 returns may result from the curse of dimensionality concern as well other data- and market-specific features of the emerging market diversified CDX index. However, we have only around 100 data points less as compared to the other CDX spread time series. Moreover, emerging corporate and sovereign credit markets require a specific attention and study (e.g. pricing issues, default events and correlations, quotation disruptions),[5] which is beyond the scope of the current research. Finally, the obtained correlation matrix elements are slightly different from the previous Kendall correlation estimates. Indeed, the average differences between the copula-based correlation and the Kendall counterparts are 0.0267 and 0.0237 with respect to SP500 returns and VIX level (i.e. average correlation differences between CDX spreads and referenced stock market benchmarks). In the same way, the average absolute differences between those two types of correlation estimates are 0.0648 and 0.0665 with respect to SP500 returns and VIX level.

Finally, the obtained results seem to conform to the theoretical behavior of the Student copula representation. As a rough guide, Fig. 5 plots the theoretical copula representation based on the simulation of pseudo-random numbers while using the estimated CDXHY copula parameters.[6] Strikingly, the similarity between the theoretical and empirical copula representations is obvious and noticeable.

[5] On the 18th July 2011, the CDXED spread series is still discontinued (see the Credit Index Rules published as of April 15, 2011 at http://www.markit.com/en/products/data/indices /credit-and-loan-indices/cdx/ cdx.page#).

[6] We simulated 1000 points of the theoretical dependence structure.

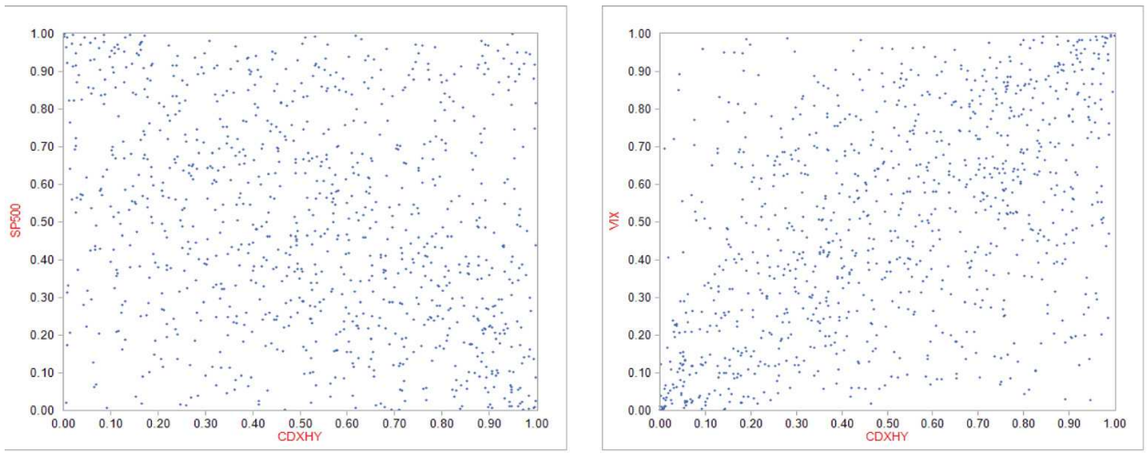


Fig. 5. Theoretical bivariate copula functions of CDXHY spread changes

4. Scenario analysis

We set up a stress testing methodology while considering two specific types of scenarios, namely a good scenario and a bad scenario.

4.1 Scenarios and conditional probabilities

We consider two extreme scenarios among which an extremely bad situation and a very good situation for the credit market. The bad situation refers to a deterioration of the credit market through the widening of CDS spreads while the good situation refers to an improvement of the credit market through a tightening of credit spreads.

The stress testing analysis is driven by the relationships between CDX spreads on one side, and both SP500 returns and VIX level on the other side. Remember that CDX spreads widen when either SP500 returns decrease (i.e. negative correlation) or VIX level increases (i.e. positive correlation). Conversely, CDX spreads diminish when either SP500 returns augment or VIX level declines. As a result a three-dimensional bad scenario is such that CDX spreads expand when both SP500 returns drop and VIX level rises. Conversely, a good scenario is such that CDX spreads tighten when both SP500 returns enhance and VIX level falls. Therefore, we perform a stress testing study (i.e., scenario analysis) based on the *Student T* optimal copula C^*, and compute the probability of occurrence of the bad situations (i.e. scenario 1) and the good situations (i.e. scenario 2). In particular, we assess the probability that CDX spreads increase (*decrease*) due to both a decrease (an *increase*) in SP500 returns and an increase (a *decrease*) in VIX level. Hence, we propose a three-dimensional tail-dependence analysis. With regard to the first scenario (scenario 1), the probability of occurrence of bad states is computed as follows:

$$\text{Prob}\left(U_1 > 1-\text{u}_\alpha \middle| U_2 \le \text{u}_\alpha, U_3 > 1-\text{u}_\alpha\right) = 1 + \frac{C^*\left(1-\text{u}_\alpha, \text{u}_\alpha, 1-\text{u}_\alpha;\theta\right) - C^*\left(1-\text{u}_\alpha, \text{u}_\alpha, 1;\theta\right)}{\text{u}_\alpha - C^*\left(1, \text{u}_\alpha, 1-\text{u}_\alpha;\theta\right)} = \alpha \qquad (10)$$

where α is the critical risk level under consideration (e.g., 5%, 10%), and u_α is the related quantile level. Recall also that we state $U_1=F_X(X)$, $U_2=F_Y(Y)$ and $U_3=F_Z(Z)$ with $X=\Delta CDX$,

Y=ΔSP500 and *Z=ΔVIX*. Specifically, the probability of facing scenario 1 is a quantile-quantile dependence measure. Indeed, it measures to which extent the occurrence of both an extreme SP500 return decrease and an extreme increase in VIX level impacts the occurrence of an extreme CDX spread increase. Therefore, the higher the probability level α, the more correlated the 'bad' extremes are, or equivalently, the stronger the tail dependence is (Coles *et al.*, 1999). Moreover, a decreasing u_α value corresponds to an increasing value of (1- u_α), which highlights a worsening of the credit market through larger CDX spread increases. In practice, a very bad scenario is represented by a wide and positive CDX spread variation coupled with both a huge decrease in SP500 return (i.e., return variation with high magnitude and negative value) and a large positive variation in VIX level. Symmetrically, the probability of occurrence of good states as represented by scenario 2 is computed as follows:

$$\text{Prob}\left(U_1 \le \text{u}_\alpha \middle| U_2 > 1-\text{u}_\alpha, U_3 \le \text{u}_\alpha\right) = \frac{C^*\left(\text{u}_\alpha, 1, \text{u}_\alpha; \theta\right) - C^*\left(\text{u}_\alpha, 1-\text{u}_\alpha, \text{u}_\alpha; \theta\right)}{\text{u}_\alpha - C^*\left(1, 1-\text{u}_\alpha, \text{u}_\alpha; \theta\right)} = \alpha \tag{11}$$

Therefore, the higher the probability level α, the more correlated the 'good' extremes are. On a practical viewpoint, a very good scenario is represented by a wide and negative CDX spread variation coupled with both a huge increase in SP500 return (i.e., return variation with high magnitude and positive value) and a large negative variation in VIX level (e.g., lower volatility regime). Indeed, the credit risk level is as low as u_α is small.

4.2 Estimation

Whatever the scenario under consideration, we fix a value for the critical risk level α and then solve for u_α in the conditional probabilities displayed in the previous section. For this purpose, we estimate the corresponding quantile u_α while solving numerically for a nonlinear optimization problem. We request a tolerance level of 10^{-5} for the gradient of the estimated coefficients. Basically, we consider successively two distinct stress levels, namely a 10 and 5 percent critical risk levels. Each obtained quantile u_α corresponds to a specific joint variation of CDX spreads, SP500 returns and VIX level.

Stating α = 5% and 10%, we consider the worst case (*scenario 1*), and the very good situation (*scenario 2*). We report the corresponding values for the dependence structure between CDX spreads and both SP500 and VIX in Tables 10 and 11. As a result, we are able to characterize critical thresholds for the variations in CDX spreads, SP500 returns and VIX level, which correspond to the relevant stress scenario. Notice that a positive value indicates an increase in the market data under consideration whereas a negative value illustrates a decrease from one day to another. For example, there is a 5 percent probability level that CDXEM spreads increase by 12.9600 basis points given that SP500 returns decrease by 306.0669 basis points and VIX index grows by 2.6000 between February 1st 2008 and March 24th 2010. Symmetrically, there is a 5 percent probability level that CXEM spreads drop by 24.4100 basis points given that SP500 returns increase by 402.1336 basis points and VIX index declines by 2.9300 over the sample time. Moreover, noticeable differences between the 5 and 10 percent risk thresholds can be listed.

With respect to scenario 1, CDX spreads and VIX level exhibit a larger increase under the 5 percent threshold whereas SP500 returns display a bigger decrease as compared to the 10 percent threshold. With respect to scenario 2, CDX spreads and VIX level exhibit a greater decline under the 5 percent threshold whereas SP500 returns display a higher increase as compared to the 10 percent threshold. Hence, results confirm the strength of the 5 percent probability setting as compared to the 10 percent probability threshold (i.e., tougher credit risk situation under the 5 percent probability level).

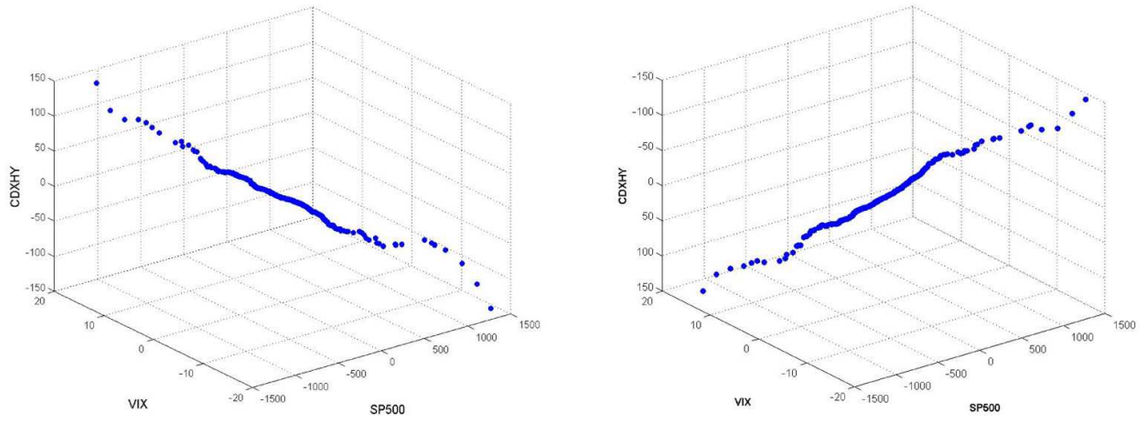
	Scenario 1			Scenario 2		
Index	**$\Delta CDX > x_\alpha$**	**$\Delta SP500 < y_\alpha$**	**$\Delta VIX > z_\alpha$**	**$\Delta CDX < x_\alpha$**	**$\Delta SP500 > y_\alpha$**	**$\Delta VIX < z_\alpha$**
CDXEM	12.9600	-306.0669	2.6000	-24.4100	402.1336	-2.9300
CDXED	17.2100	-309.5813	2.6100	-19.2000	300.4147	-2.1700
CDXHY	18.8900	-230.5572	1.7400	-15.7100	193.1290	-1.2800
CDXHB	24.1600	-298.1570	2.3200	-17.8400	241.8523	-1.6300
CDXBB	19.2399	-298.5321	2.3400	-14.0300	238.2396	-1.5400
CDXIG	6.0600	-306.0669	2.6000	-5.0100	256.4785	-1.8500
CDXIV	11.6300	-306.0669	2.6000	-7.7500	243.1394	-1.6400
CDXXO	12.0000	-309.5813	2.6100	-8.4100	240.9530	-1.6100

Table 10. CDX spread and market risk changes under a α=5% risk level

	Scenario 1			Scenario 2		
Index	**$\Delta CDX > x_\alpha$**	**$\Delta SP500 < y_\alpha$**	**$\Delta VIX > z_\alpha$**	**$\Delta CDX < x_\alpha$**	**$\Delta SP500 > y_\alpha$**	**$\Delta VIX < z_\alpha$**
CDXEM	8.5500	-230.9755	1.7400	-11.0100	256.4785	-1.8500
CDXED	8.7300	-230.5573	1.7400	-7.8100	205.3360	-1.3200
CDXHY	18.2300	-228.2211	1.7300	-10.9200	149.1986	-1.0400
CDXHB	16.7200	-225.9790	1.6400	-15.4500	216.3420	-1.4400
CDXBB	15.2400	-233.2346	1.7800	-13.6700	230.4725	-1.5300
CDXIG	4.5900	-229.2211	1.7300	-4.7100	240.9530	-1.6100
CDXIV	9.6900	-253.6435	1.9200	-7.6400	241.8523	-1.6900
CDXXO	10.0000	-230.9755	1.7500	-8.3400	238.5514	-1.5700

Table 11. CDX spread and market risk changes under a α=10% risk level

As a rough guide, we also plot the corresponding empirical CDX spread and market risk changes as a function of quantile u_α for CDXHY and CDXED indexes. Fig. 6 reports the scenarios 1 and 2 for CDXHY whereas Fig. 7 displays only scenario 1 for CDXED. In Fig. 6 under scenario 1, the top left corner corresponds to the highest CDX spread increase (i.e., lowest possible value of u_α), which matches both the biggest decrease in SP500 return and the largest increase in VIX level. Conversely, the bottom right corner of scenario 1 panel represents the largest CDX spread decrease (i.e., highest possible value of u_α), which matches both the biggest increase in SP500 return and the largest decrease in VIX level. Naturally, scenario 2 exhibits a symmetric behavior since it represents the mirror evolution of scenario 1. Strikingly, Fig. 7 displays some tail discontinuity with respect to the upper left corner as opposed to the bottom right corner. Such an outlier may generate estimation problems. Hence, such a pattern requires further investigation, which is left for future research.



Scenario 1 Scenario 2

Fig. 6. CDXHY spread and market risk changes for various α levels under scenarios 1 and 2

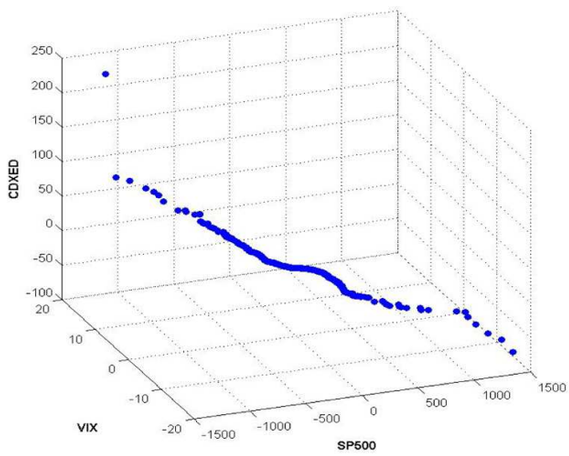


Fig. 7. CDXED spread and market risk changes for various α levels under scenario 1

5. Concluding remarks and future work

In this paper, we focused on the dependence structures between CDX spread changes on the one hand, and changes in both SP500 returns and VIX index, on the other hand. We empirically exhibited the asymmetric nature of each bivariate dependence structure, namely the dependence structures between CDX spreads and SP500 returns and between the CDX spreads and VIX index. We also emphasized the differences between those two types of bivariate dependence structures, which we handled simultaneously within a three-dimension copula analysis. Balancing the curse of dimensionality with a parsimonious modeling framework, we selected three Archimedean copulas and two classic elliptical copulas in order to test for various tail dependencies.

The estimation process and the selective information criterion statistics exhibited the Student T dependence structure as an optimal three-dimension copula representation. Therefore, we have to cope with symmetric tail dependencies between CDX spreads and the two stock market risk channels above-mentioned. Additionally, we are able to realize a

more accurate and global credit risk scenario analysis in the light of both the stock market trend and stock market volatility levels. As an example, we quantified a 10 and 5 percent tail dependence levels in order to illustrate a stress testing analysis under two types of stock market stress. Such a scenario analysis helps identify thresholds for the variations in both stock market price and volatility, which impact variations in CDX spreads. In other words, we are able to characterize the impact of the stock market risk channels on the evolution of CDS spreads. Consequently, the three-dimension copula framework is a useful tool for risk monitoring/management and risk reporting prospects under Basel 3. In particular, the scenario analysis is of high significance for portfolio insurance when credit lines are involved in the investment portfolio under consideration. Indeed, such a framework is useful for value-at-risk or even stressed value-at-risk implementations as well as related scenario analysis (Embrechts and Höing, 2006). Further research should therefore focus on the dynamic implementation of the three-dimensional copula framework in a forecasting perspective.

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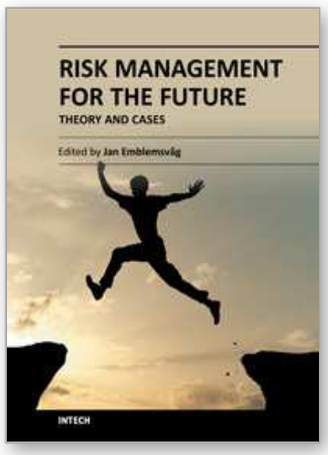
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A large part of academic literature, business literature as well as practices in real life are resting on the assumption that uncertainty and risk does not exist. We all know that this is not true, yet, a whole variety of methods, tools and practices are not attuned to the fact that the future is uncertain and that risks are all around us. However, despite risk management entering the agenda some decades ago, it has introduced risks on its own as illustrated by the financial crisis. Here is a book that goes beyond risk management as it is today and tries to discuss what needs to be improved further. The book also offers some cases.

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