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Cross-hedging strategies between CDS spreads and option volatility during crises

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A B S T R A C T

This paper presents a joint analysis of the term structure of credit default swap (CDS) spreads and the implied volatility surface for five European countries from 2007 to 2012, a sample period covering both the Global Financial Crisis (GFC) and the European debt crisis. We analyze to which extent effective cross-hedges can be performed between the credit and equity derivatives markets during these two crises. We find that during a global crisis a breakdown of the relationship between credit risk and equity volatility may occur, jeopardizing any cross-hedging strategy, which happened during the GFC. This stands in sharp contrast to the more localized European debt crisis, during which this fundamental relationship was preserved despite turbulent market conditions for both the CDS and volatility markets.

1. Introduction

Merton (1974) stresses the intrinsic relationship between credit spreads and equity volatility. A plethora of articles have studied this interrelation since, measuring credit spreads with yield spreads computed from bonds and equity volatility with mean squared returns. More recently, the rapid development of the credit default swap (CDS) market has provided convenient products to extract credit risk. Furthermore, the availability of implied volatility has led to a preferable alternative way to quantify equity volatility because option volatility is considered "forward looking". Therefore, over the

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last years many studies have focused on the interaction between credit default swap spreads and implied volatility. A first set of papers analyzes the relation between the 5-year CDS spread and the at-the-money (ATM) 1-month implied volatility; see Benkert (2004) and Forte and Pena (2009), for example. This kind of study was extended by considering other parts of the implied volatility surface (beyond the 1-month ATM volatility) and/or the term structure of CDS spreads (beyond the 5-year CDS spread). Cao et al. (2010) analyzed the 5-year CDS spread along with the at-the-money implied volatility and the implied volatility skew[2] (see also Cao et al., 2011). Cremers et al. (2008) analyzed the impact of both implied volatility (ATM) and the implied volatility skew on corporate bond credit spreads (long and short maturities) and found that these variables have strong explanatory power. Carr and Wu (2010) found a significant correlation between the level and the skew of the smile and the average (along the term structure axis) of the CDS spread on corporate data. Hui and Chung (2011) studied the 10-delta dollar-euro implied volatility in relation to the 5-year sovereign credit default swap spread. Han and Zhou (2011) found that the term structure of CDS spreads explains log stock returns, hence the slope of the CDS curve contains relevant information for the stock dynamics.

These works have naturally led to the development of joint models for the equity derivatives and credit default swap markets. Along this line, Carr and Wu (2007, 2010) proposed a joint model for the term structure of CDS spreads and options, whilst Carverhill and Luo (2011) analyzed the interaction between the factors of a model calibrated on collateralized debt obligations (CDOs) and the factors driving the implied volatility surface. Collin-Dufresne et al. (2012) proposed a joint analysis of index options and CDOs. Da Fonseca and Gottschalk (2013) jointly analyzed the entire implied volatility surface and the entire term structure of CDS spreads, using factor decompositions, and perform a cross-hedging analysis between the two markets.

The purpose of this work is to analyze – within the framework proposed by Da Fonseca and Gottschalk (2013) – how crises affect the intrinsic relationship that ties together the CDS and equity derivatives markets. Using a sample from May 2007 to September 2012 for major European index options (CAC40, FTSE100, DAX30, IBEX35, MIB40) and the term structure of CDS spreads computed for each country, we analyze the joint evolution of these two markets. We find that during the Global Financial Crisis (2007–2009) the relation between the European credit and volatility markets breaks down although the crisis affects both of them. The results are different beyond 2009, during the European debt crisis, when the relationship between the markets is preserved although the European countries are affected very differently by the crisis. As a result, we conclude that there can be a breakdown of the credit–volatility relationship during global crises, which jeopardizes the effectiveness of cross-hedges between credit and equity instruments. During the GFC, this problem could have been overcome by performing a hedge within the same type of market, but across different geographic locations.

The contribution of our paper is threefold. First, we show that the simple framework proposed in Da Fonseca and Gottschalk (2013) allows us to perform a reasonably effective cross-hedge between the CDS and equity derivatives markets. Second, we illustrate the fact that the relationship between the two markets can break down during a global crisis. In order to perform an effective hedge the cross-hedging position should be completed with a position on a similar product. Third, from a regulatory point of view our research underlines the claim for more stringent provisioning of hedgeable claims to cope with systemic risk.

The structure of the paper is as follows. In the first section, we describe the data and present descriptive statistics. In the second section, we perform factor decompositions for both the CDS curves and the implied volatility surfaces. The third section contains the empirical results: an analysis of contemporaneous interactions as well as cross-hedging strategies and intra-market linkages. The last section concludes the paper.

2. Data description

A credit default swap (CDS) is a credit derivative contract between two counterparties that essentially provides insurance against the default of an underlying entity. In a CDS, the protection buyer

[2] For a given time to maturity, the skewness of the smile can be defined either as the slope of the ATM smile or the difference between the in-the-money implied volatility and the out-of-the-money implied volatility.

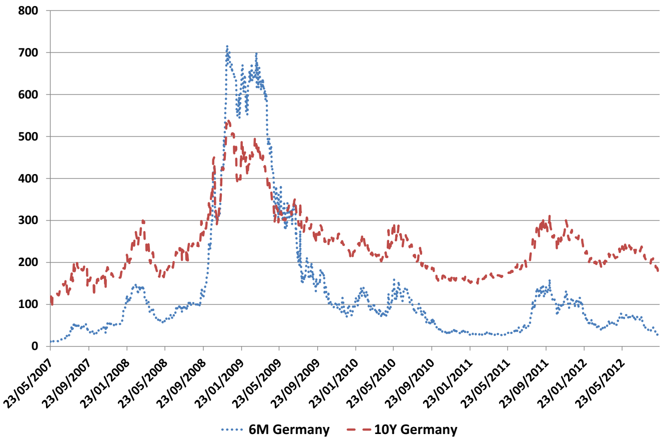

Fig. 1. CDS spreads (6-month and 10-year maturities) for Germany. Daily observations from 23/05/2007 to 17/09/2012.

makes periodic payments to the protection seller until the occurrence of a credit event or the maturity date of the contract, whichever is first. The premium paid by the buyer is denoted as an annualized spread in basis points and referred to as CDS spread. If a credit event (default) occurs on the underlying financial instrument, the buyer is compensated for the loss incurred as a result of the credit event, i.e. the difference between the par value of the bond and its market value after default.

Our dataset uses credit default swaps on corporate bonds and comprises the evolution of the term structure of CDS spreads for five European countries: the United Kingdom, Germany, France, Italy, and Spain. We collect daily time series from Markit at maturities of 0.5, 1, 2, 3, 5, 7, and 10 years from May 23, 2007 to September 17, 2012. We take non-sovereign entities from all sectors; the CDSs are written on senior unsecured debt (RED tier code: SNRFOR) and denominated in Euro. For each country and each maturity we average the individual CDS spreads. As this time period spans both the Global Financial Crisis (GFC) and the European debt crisis, we split the full sample period into two subsamples for all our analyses. The first subsample (May 23, 2007–December 31, 2009) contains the US credit crunch and the GFC; the second subsample (January 1, 2010–September 17, 2012) is more tranquil for most countries, with the exception of Italy and Spain, where the turbulences of the European debt crisis are clearly visible in CDS levels.

Figs. 1–3 reflect the turmoil of the Global Financial Crisis from mid-2007 onwards, with CDS levels peaking at over 700 basis points in most countries around the default of Lehman Brothers (September 2008). During this period of hefty turbulence the term structure of CDS spreads becomes inverted. While CDS spreads come down in mid-2009 and the term structure returns to a normal positively sloped shape, the onset of the European debt crisis is visible in the European markets from mid-2010 onwards when CDS prices start to rise again. While we observe only slight increases in the price of credit protection for corporates in Germany, CDS levels in Italy and Spain show dramatic increases.[3]

In Table 1 we report summary statistics for CDS spreads in five European countries and the United States (for reference) for the full sample and two subsamples. While mean CDS levels normally increase with maturity, the shorter maturities display significantly higher volatility than the longer maturities.

The first subsample (May 2007–December 2009) displays significantly higher CDS spreads and elevated volatility for most countries due to the Global Financial Crisis. Moreover, the term structure is almost flat and at times even inverted, mainly because the very short-term end of the curve increased

[3] The figures for the UK (very similar to Germany), France (which displays a behavior between the German and Italian CDS curves) and also the US (for comparison purposes) are available upon request. For the US market, the North American benchmark CDS index CDX.NA.IG is used. For this index, for each maturity we average among the 125 entities that constitute the index. The curves show a behavior similar to the German market.

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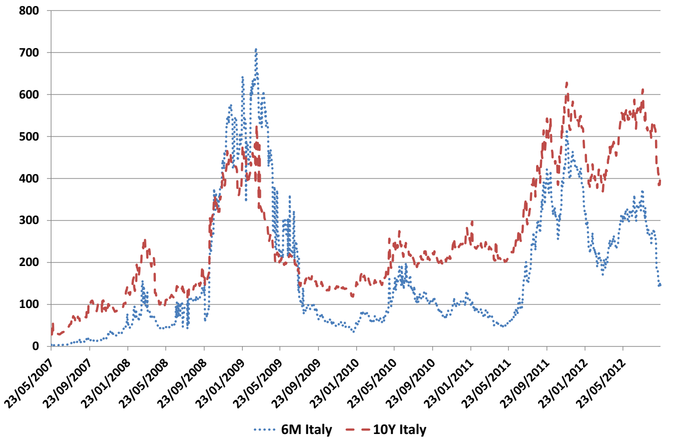

Fig. 2. CDS spreads (6-month and 10-year maturities) for Italy. Daily observations from 23/05/2007 to 17/09/2012.

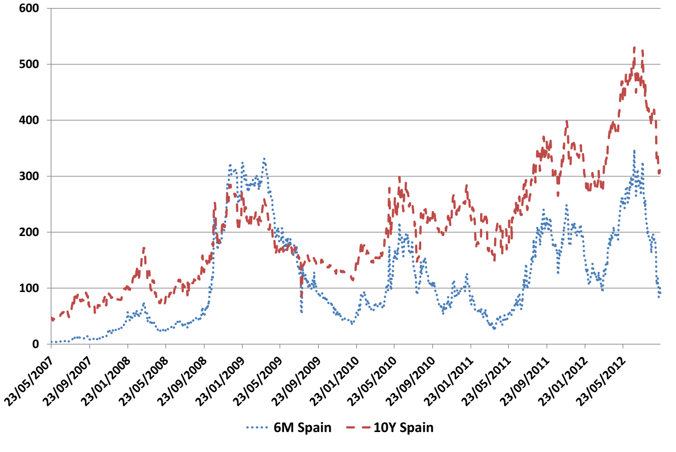

Fig. 3. CDS spreads (6-month and 10-year maturities) for Spain. Daily observations from 23/05/2007 to 17/09/2012.

significantly during that period. This stands in stark contrast to the second subsample (January 2010–September 2012). The steeper slope of the term structure is accompanied by lower CDS spread levels and drastically reduced volatility. Italy and Spain are the exceptions where CDS spreads reach higher levels during the second subsample, which includes the European debt crisis.

The implied volatility surfaces are constructed from European call and put options on the major European indices FTSE100, DAX30, CAC40, MIB40, and IBEX35. For the US market we take options on the S&P500. Daily prices of all available options are obtained from Datastream. Following market practice, we use only out-of-the-money (OTM) options for the construction of the implied volatility surfaces, see CBOE (2003).

3. Factor decompositions of CDS spreads and the implied volatility surface

3.1. The term structure of CDS spreads

For each European market, we compute the term structure of credit default swap spreads as described in the data section. Since the CDS curves have similar properties as the yield curve, we can

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Table 1
Descriptive statistics for all CDSs by country for the full sample and subsamples. Maturities range from 0.5 years to 10 years.

	Maturity	0.5	1	2	3	5	7	10
Panel A: Full sample (May 23, 2007–September 17, 2012)								
France	Mean	124.98	133.81	154.25	171.94	194.32	200.21	205.08
	Std. dev.	150.28	140.85	128.00	115.97	97.34	87.42	78.69
Germany	Mean	136.78	153.51	182.57	205.94	231.69	236.87	240.19
	Std. dev.	159.31	158.40	145.54	132.53	107.86	93.86	81.56
Italy	Mean	173.23	191.54	216.42	231.59	250.27	253.52	256.24
	Std. dev.	156.17	166.16	164.65	161.13	157.67	153.73	149.50
Spain	Mean	116.78	132.22	157.02	175.82	196.62	201.51	205.76
	Std. dev.	87.64	95.94	103.91	108.20	108.99	107.01	104.57
United Kingdom	Mean	135.88	144.29	161.54	177.03	198.39	204.15	208.88
	Std. dev.	163.96	155.28	137.76	123.74	102.01	91.43	81.65
United States	Mean	89.33	94.73	103.08	112.86	132.60	139.01	145.45
	Std. dev.	99.26	97.34	86.78	79.84	68.29	59.74	53.03
Panel B: First subsample (May 23, 2007–December 31, 2009)								
France	Mean	178.94	181.13	190.85	198.42	205.93	205.15	205.38
	Std. dev.	196.28	183.77	167.82	152.06	126.86	112.10	98.57
Germany	Mean	204.96	221.00	244.00	260.31	271.26	269.45	267.72
	Std. dev.	202.39	200.31	182.42	165.59	136.17	118.55	102.12
Italy	Mean	163.91	175.98	186.09	187.12	187.72	185.41	183.86
	Std. dev.	186.21	192.33	177.33	161.00	141.65	129.09	116.35
Spain	Mean	100.33	106.56	115.84	123.25	131.21	133.03	135.50
	Std. dev.	99.50	100.11	95.33	88.57	74.41	66.63	59.07
United Kingdom	Mean	201.20	204.97	213.68	221.53	230.00	230.43	231.05
	Std. dev.	213.34	202.40	180.08	162.64	136.24	122.72	109.74
United States	Mean	146.81	149.84	149.47	151.99	157.33	154.28	153.56
	Std. dev.	115.28	114.04	103.92	98.26	89.14	80.03	71.85
Panel C: Second subsample (January 1, 2010–September 17, 2012)								
France	Mean	72.33	87.64	118.54	146.12	182.98	195.38	204.79
	Std. dev.	37.97	44.16	48.24	51.74	52.65	52.91	52.57
Germany	Mean	70.26	87.66	122.63	152.89	193.08	205.09	213.34
	Std. dev.	35.25	40.82	46.09	47.60	43.44	40.69	38.91
Italy	Mean	182.32	206.72	246.01	274.98	311.29	319.96	326.85
	Std. dev.	119.26	134.26	145.40	149.08	148.40	146.68	144.47
Spain	Mean	132.84	157.26	197.20	227.11	260.43	268.33	274.30
	Std. dev.	70.73	84.54	95.96	100.80	99.11	96.21	93.20
United Kingdom	Mean	72.15	85.09	110.67	133.60	167.54	178.50	187.25
	Std. dev.	22.51	24.34	25.18	25.33	23.12	22.35	21.97
United States	Mean	33.33	41.04	57.88	74.73	108.50	124.13	137.54
	Std. dev.	12.40	14.06	14.57	15.37	17.15	18.99	20.01

CDS spreads are expressed in basis points.
Means and standard deviations are based on daily data.

apply a well-established factor decomposition. Let us denote by $\{\ln CDS(t,\tau_i); i = 1 \ldots N_1\}$ the time series of CDS spreads (in logarithms) for the available maturities. Using $\Delta x_t(\tau_i) = \ln CDS(t,\tau_i) - \ln CDS(t-1,\tau_i)$, we can perform a principal component analysis decomposition as in Litterman and Scheinkman (1991). We obtain similar results for all countries (see Da Fonseca and Gottschalk, 2013, for an example of eigenvector shapes and eigenvalues).[4] All CDS curves lead to the same decompositions, a result similar to that obtained for yield curve studies. The first eigenvector is always positive and corresponds to a shift of the CDS spread curve. Its associated eigenvalue dominates as it represents a large fraction of the global variance (85% on average among the five European countries). The second eigenvector implies a change of the slope because the short-term part is positive, whereas the long-term part is negative. The second eigenvalue accounts for 10% of the global variance on average. The third eigenvector has a U-shaped form and is related to a change of the convexity of the term structure. Similar to yield curve

[4] The numerical results and figures are available upon request.

factor decompositions, the third eigenvalue only represents a very small fraction of the global variance (around 3%). The overall results resemble what is obtained for yield curves in the sense that we get the usual level, slope and curvature factor decomposition. It is not necessary to go beyond the first three factors as their sum amounts to 98% of market variance.

3.2. The implied volatility surface

To build an implied volatility surface on which we can apply a factor decomposition, we follow the approach used in Da Fonseca and Gottschalk (2013).[5] We denote by $c_{bs}(t, s_t, K, T, \sigma)$ the Black–Scholes formula for a European option (either call or put) at time t, with maturity T, strike price K, spot price s_t and volatility σ of the underlying asset. The implied volatility for an option whose market price is $c(t, s_t, K, T)$ is denoted by $\sigma_t^{\mathrm{bs}}(T, K)$ and is the solution of the equation

$$c_{\mathrm{bs}}\left(t, s_t, K, T, \sigma_t^{\mathrm{bs}}(T, K)\right) = c(t, s_t, K, T). \tag{1}$$

As the Black–Scholes formula is monotonic with respect to volatility, this equation has a unique solution, and the function $\{\sigma_t^{\mathrm{bs}}(K, T); (K, T)\}$ is called the implied volatility surface. We can parametrize this function in terms of time to maturity and moneyness ($m = K/s_t$), so we define the function: $I_t(m, \tau) = \sigma_t^{\mathrm{bs}}(ms_t, t + \tau)$. As this surface is usually non-flat and exhibits a U-shaped form for all times to maturity with less convexity for long-term options, it is often referred to as the smile.[6] This smile fluctuates over time.

For a given day t we observe a set of implied volatility values $\{I_t(m_i,\tau_i); i=1\ldots N_t\}$ in the market, defined on a grid of pairs $\{(m_i,\tau_i); i = 1\ldots N_t\}$ that will change over time because as the underlying stock moves, the available moneynesses will change due to the option's fixed strike. Similarly, as time passes the options get closer to their maturities, so the available times to maturity will change over time. Following the methodology used in Da Fonseca and Gottschalk (2013), we build a time series of implied volatility surfaces denoted $\{I_t(\overline{m}_j, \overline{\tau}_j); j = 1\ldots N\}$ on a fixed grid of points $\{(\overline{m}_j, \overline{\tau}_j); j = 1\ldots N\}$. As for the CDS spread curves, we focus on daily variations of the logarithm of implied volatility. Thus, using $\Delta X_t(\overline{m}_j, \overline{\tau}_j) = \ln I_t(\overline{m}_j, \overline{\tau}_j) - \ln I_{t-1}(\overline{m}_j, \overline{\tau}_j)$ we can perform a factor decomposition and denote by $\{e_k(\overline{m}_j, \overline{\tau}_j); j = 1\ldots N\}$ and λ^k the kth eigensurface and eigenvalue, respectively. Note that we have $\sum_{j=1}^{N} e_{k_1}(\overline{m}_j, \overline{\tau}_j) e_{k_2}(\overline{m}_j, \overline{\tau}_j) = \delta_{k_1 k_2}$, with $\delta_{k_1 k_2}$ the Kronecker function. Having these key quantities available, we can analyze the shape of the factors underlying the dynamics of the smile of our data.

All options sets lead to same-shaped factors as well as the same eigenvalue decomposition, which are similar to those obtained in Da Fonseca and Gottschalk (2013).[7] We briefly recall the main findings. Since the first eigensurface is always positive, it is associated with a translation or shift of the smile. As the first eigenvalue accounts for 75% of the global variance on average, we conclude that a one-factor model, based on this eigensurface, provides a reasonably good model for the dynamics of the smile. For a more accurate model we need to go beyond this first factor. The second eigensurface is, for all times to maturity, positive for moneyness lower than one and negative otherwise. A shock along this mode implies that out-of-the-money (OTM) put options, whose volatility is given by the smile with moneyness lower than one, will become more expensive. OTM call options, whose volatility is given by the smile with moneyness greater than one, will become less expensive. As a consequence, this eigensurface is associated with a bear market movement. The corresponding eigenvalue represents 17% of the total variance on average. This factor affects the skew of the smile. Lastly, the third eigensurface is associated with a bull market movement. A shock along this eigensurface implies a decrease of long-term implied volatility for all times to maturity, a strong increase of short-term OTM call prices and a

[5] For the factor decomposition of the smile the methodology was proposed in Skiadopoulos et al. (1999) and Cont and Da Fonseca (2002). For related works on factor decompositions of the implied volatility surface see Fengler et al. (2003), Fengler et al. (2007), Chalamandaris and Tsekrekos (2010, 2013).

[6] More precisely, on the equity/index derivatives market we observe a smirk for each time to maturity.

[7] The figures and numerical results are available upon request.

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Table 2
Correlation between log stock returns $\Delta \ln s_t = \ln s_t - \ln s_{t-1}$ and the factors $\Delta VOL_{k,t}$ and $\Delta CDS_{k,t}$ for $k = 1,2,3$ in two subsamples.

	ΔVOL_1	ΔVOL_2	ΔVOL_3	ΔCDS_1	ΔCDS_2	ΔCDS_3
Panel A: 23/05/2007–31/12/2009						
Germany	−0.65	−0.33	0.35	−0.30	−0.04	−0.06
Italy	−0.58	−0.26	0.24	−0.25	0.05	0.09
Spain	−0.67	0.15	0.26	−0.32	0.11	−0.02
Panel B: 01/01/2010–17/09/2012						
Germany	−0.60	−0.37	0.25	−0.65	−0.25	−0.50
Italy	−0.61	−0.36	0.38	−0.69	−0.22	−0.26
Spain	−0.62	0.17	0.11	−0.59	0.01	−0.42

lesser increase of short-term OTM put prices. Its eigenvalue is equal to around 5% of the total variance. As the first three eigenvalues account for 97% of the total variance, it is not necessary to go beyond these three factors.

We can now decompose the dynamics of the smile into these factors. We define the three scalar processes

$$\Delta VOL_{k,t} = \sum_{j=1}^{N} \Delta X_t(\overline{m}_j, \overline{\tau}_j) e_k(\overline{m}_j, \overline{\tau}_j); \quad k = 1,2,3, \tag{2}$$

which are the projection of the implied volatility change on the eigensurfaces, hence each one quantifies to which extent the smile "moves" along the direction given by the corresponding factor. Therefore, $\Delta VOL_{1,t}$ is associated with a shift of the smile, $\Delta VOL_{2,t}$ with a change of the skew (slope) of the smile, and $\Delta VOL_{3,t}$ with a change of the convexity of the smile. Note that we could have used other functions to decompose the dynamics of the implied volatility surface. The principal component analysis relates the functions used to the covariance structure of the process. The factor decomposition allows us to reduce the dynamics of the smile, which is a surface, into three scalar time series that encompass most of the statistical properties.

In order to gain further understanding of the factors, it is fruitful to compute the correlation between $\Delta VOL_{k,t}$ and the log stock returns $\Delta \ln s_t = \ln s_t - \ln s_{t-1}$ for all factors. In Table 2 we report the results, which are consistent with intuition. The correlation between log stock returns and the first factor is negative because, if stock prices decrease, the overall surface will move upwards due to the leverage effect. The second correlation coefficient is negative because, if stock prices decrease, it is a bear market configuration, which implies a steepening of the smile, hence an increase along the second factor. Lastly, if stock prices increase, it is a bull market configuration, which implies an increase along the third factor, hence a positive correlation coefficient.

4. Cross-market linkages

4.1. Contemporaneous interactions

First, we turn our attention to contemporaneous effects by computing the correlations between the different variables and report the results in Table 3 for Germany, Italy and Spain (with similar conclusions for the other countries[8]).

Whenever significant, the cross-market correlations are similar for all countries across the sample. The signs remain largely the same although we observe some minor changes. We note that during the GFC the second credit factor, ΔCDS_2, is most often uncorrelated with the volatility factors. To a lesser extent this remark applies to the third credit factor, ΔCDS_3, which is significant in one-third of the cases when we aggregate all countries. These two facts should be compared with the results for the second subsample, covering the European debt crisis, where the regressions for these two factors lead to a

[8] The additional tables are available upon request.

Table 3
Cross-market factor correlations in the two subsamples.

	23/05/2007–31/12/2009			01/01/2010–17/09/2012		
	ΔCDS_1	ΔCDS_2	ΔCDS_3	ΔCDS_1	ΔCDS_2	ΔCDS_3
Panel A: Germany						
ΔVOL_1	0.21***	0.02	0.06*	0.42***	0.16***	0.35***
ΔVOL_2	0.11***	−0.00	0.09**	0.26***	0.08**	0.19***
ΔVOL_3	−0.11***	0.01	−0.03	−0.12***	0.01	−0.05
Panel B: Italy						
ΔVOL_1	0.16***	0.01	−0.03	0.38***	0.10***	0.18***
ΔVOL_2	0.03	−0.00	−0.01	0.26***	0.06*	0.11***
ΔVOL_3	−0.07**	0.03	0.04	−0.25***	−0.10***	−0.12***
Panel C: Spain						
ΔVOL_1	0.25***	0.05	0.07*	0.38***	0.01	0.31***
ΔVOL_2	0.01	0.03	0.07*	−0.09**	−0.05	−0.03
ΔVOL_3	−0.11***	0.08**	0.02	−0.03	−0.01	−0.02

The symbol *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

greater number of statistically significant coefficients. One possible explanation could be that during the GFC CDS spreads were moving in one direction, upwards in that case, which would imply that the CDS curve was mainly driven by one factor.[9] This is corroborated by the small values (in absolute terms) for the correlation between the ΔCDS_2 and ΔCDS_3 factors and the stock returns given in Table 2.

During the GFC we can restrict our analysis to the first credit factor. However, the interpretation of correlations is also valid for the second subsample. We observe a positive correlation between ΔCDS_1 and ΔVOL_1, which implies that an increase of the smile is associated with an increase of the CDS spread. If we take into account the negative correlation between stock returns and volatility as well as the negative correlation between stock returns and the first CDS factor, we end up with a consistent dynamics of the stock price, the level of volatility, and the level of the CDS spread. The correlation between ΔCDS_1 and ΔVOL_2 is positive,[10] whereas the correlation between ΔCDS_1 and ΔVOL_3 is negative for all countries and subsamples. An increase of the CDS level implies more default risk. This is associated with a bear stock market configuration, which in turn implies a steeper skew, hence a positive correlation sign for ΔVOL_2 because of the interpretation developed in the factor decomposition of the smile. The third volatility factor is associated with a bull market configuration so that an increase of the level of the CDS curve should produce the opposite effect on the stock price, hence a negative sign for the correlation between ΔCDS_1 and ΔVOL_3.

To facilitate the analysis of the results it might be useful to consider the cross-market correlations given in Table 3 in conjunction with the correlation of log stock returns with the derivatives markets reported in Table 2. The factor ΔVOL_1 is positively correlated with either ΔCDS_2[11] or ΔCDS_3 because to an increase of this factor corresponds a decrease of the stock price with two consequences: it will increase the likelihood of a default according to Merton (1974), and it will increase the second factor and third factor due to the negative correlation between stock returns and these factors. Consequently, we must have a positive correlation. The positive correlation between ΔCDS_2 and ΔVOL_2 can also be understood through the stock market. An increase of ΔVOL_2 implies a decrease of the stock price, which in turn implies an increase along ΔCDS_2. Lastly, an increase of ΔCDS_2 leads to a decrease of the stock price, which due to positive correlation with ΔVOL_3 implies a decrease of this volatility factor, hence a negative correlation between the second CDS factor and the third volatility factor. The correlation of stock returns with the credit factors and volatility factors helps understand the sign of the correlations between the factors.

During the European debt crisis, the regression coefficients for ΔCDS_2 and ΔCDS_3 on the volatility factors are more often significant and the correlation of these factors with stock returns is stronger (in

9 Eichengreen et al. (2012) highlight the importance of common factors in bank CDS spreads during the Subprime Crisis.
10 An exception is Spain during the second subsample.
11 An exception is the negative correlation (not reported here) between ΔVOL_1 and ΔCDS_2 for France during the GFC.

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absolute terms). Lastly, the coefficients that are not consistent with the interpretation given above are the correlation between ΔVOL_1 and ΔCDS_2 for France during the GFC, the correlation between ΔVOL_2 and stock returns for Spain (both subsamples) and the correlation between ΔCDS_2 and stock returns for Spain during the GFC.

The important ingredient that allows to understand the relations between the credit factors and volatility factors is the correlation between these factors and the stock returns. Because of the leverage effect between stock price and volatility, as explained in Black (1976), and the tight relation between stock price and credit risk, as shown by Merton (1974), the interactions between credit and volatility factors can be analyzed through their relation with the stock price.

4.2. *Cross-hedging between credit and volatility factors*

Having gained a better understanding of the relationships between the different factors, we now focus on a regression analysis of the first factor (i.e. the main factor). More precisely, we regress the first volatility factor on a set of explanatory variables chosen among the credit factors. As a given factor is worthy of consideration only if lower-order factors are taken into account, the sets of variables will be nested. (A lower-order factor is a factor with a small eigenvalue.) Since we have three credit factors, we perform three regressions. Also, we reverse the analysis by regressing the first credit factor on a set of volatility factors. These regressions are of practical interest as they allow us to devise cross-hedging strategies. The regressions are

$$\Delta CDS_{1,t} = a + \sum_{k=1}^{N} b_k \Delta VOL_{k,t} + \varepsilon_t^{N,1} \tag{3}$$

$$\Delta VOL_{1,t} = \alpha + \sum_{k=1}^{N} \beta_k \Delta CDS_{k,t} + \varepsilon_t^{N,2}, \tag{4}$$

with N successively equal to {1,2,3}. The regression coefficients of these equations can be seen as hedging ratios. Of special importance is the adjusted R^2 of these regressions as it measures the effectiveness of the hedge.

Our point of view differs slightly from the literature studying the interaction between the CDS and volatility markets in the sense that most papers focus on the determinants of CDS spreads. As such, most if not all the regressions performed use other financial and macroeconomic variables along with volatility (defined in a broad sense) and the volatility skew. In this work we focus on the interaction between the CDS and volatility markets: All the variables belong to these two markets, so the comparison of our results with the existing literature requires caution. Our approach is of interest for trading activities involving credit and volatility derivatives as the ratio computed in the regressions above can be used for the risk management of such portfolios of derivatives. Our work is more in line with derivatives-oriented papers focusing exclusively on the credit–volatility relation, see, e.g., Carr and Wu (2007, 2010, 2011) and Carverhill and Luo (2011). The first two papers present consistent pricing frameworks for the two markets but are very challenging to implement. The third one proposes an equity derivative, the DOOM put, that mimics the CDS payoff. The last paper calibrates a three-factor intensity model on CDO quotes and analyzes the interaction of these factors with factors driving the implied volatility surface. Our approach jointly analyzes the entire implied volatility surface and the entire term structure of CDS spreads and is very simple to implement. As we have two subsamples, the first with the GFC and the second with the European sovereign debt crisis, we present the results separately.

4.2.1. *Credit–volatility disconnection during the GFC*

We first analyze the GFC period and report in Table 4 (left-hand side) the regressions for Germany, Italy, and Spain for the period 23/05/2007–31/12/2009.[12] All regressions lead to small R^2, no matter

[12] The other markets lead to similar conclusions, and results are available upon request.

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Table 4
Cross-market factor regressions for Germany, Italy, and Spain in two subsamples.

Dependent variable	Independent variables	23/05/2007–31/12/2009 (1)	(2)	(3)	01/01/2010–17/09/2012 (1)	(2)	(3)
Panel A: Germany							
ΔCDS_1	ΔVOL_1	0.06***	0.06***	0.06***	0.10***	0.10***	0.11***
	ΔVOL_2		0.08***	0.08***		0.20***	0.19***
	ΔVOL_3			−0.16***			−0.18***
	Adj. R^2	0.05	0.06	0.07	0.18	0.27	0.30
ΔVOL_1	ΔCDS_1	0.80***	0.81***	0.79***	1.87***	2.11***	1.74***
	ΔCDS_2		−0.22	−0.20		−0.94**	−0.78*
	ΔCDS_3			0.80			2.12**
	Adj. R^2	0.05	0.05	0.05	0.18	0.18	0.19
Panel B: Italy							
ΔCDS_1	ΔVOL_1	0.05***	0.05***	0.04***	0.07***	0.07***	0.06***
	ΔVOL_2		0.02	0.04*		0.09***	0.10***
	ΔVOL_3			−0.06*			−0.11***
	Adj. R^2	0.02	0.02	0.03	0.15	0.21	0.26
ΔVOL_1	ΔCDS_1	0.49***	0.54***	0.64***	2.23***	2.42***	2.30***
	ΔCDS_2		−0.19	−0.21		−1.29**	−1.37**
	ΔCDS_3			−0.79**			3.59**
	Adj. R^2	0.02	0.02	0.03	0.15	0.15	0.16
Panel C: Spain							
ΔCDS_1	ΔVOL_1	0.07***	0.07***	0.07***	0.11***	0.11***	0.11***
	ΔVOL_2		0.03	0.03		−0.02	−0.02
	ΔVOL_3			−0.11**			0.11**
	Adj. R^2	0.06	0.06	0.07	0.14	0.14	0.15
ΔVOL_1	ΔCDS_1	0.89***	0.88***	0.88***	1.36***	1.39***	1.00***
	ΔCDS_2		−0.38	−0.38		0.83*	−0.80
	ΔCDS_3			−0.07			3.94***
	Adj. R^2	0.06	0.06	0.06	0.14	0.15	0.17

Regression intercepts have been suppressed in order to conserve space.
The symbol *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

whether we consider the credit risk factor as dependent variable and the volatility factors as explanatory variables or the volatility factor as dependent variable and the credit risk factors as explanatory variables. To put our results in perspective with the literature, many studies find volatility, usually given by the ATM 1-month implied volatility, to be a rather good explanatory variable of credit risk, given by the 5-year CDS spread. For example, in Ericsson et al. (2009), Table 4, the regression of the change in the 5-year CDS spread on the change of equity volatility (computed as mean squared log returns), leads to an R^2 of 12%. Most other studies analyze the level of the 5-year CDS spread and find volatility (either historical or implied) to be a significant explanatory variable with the regression R^2 rather high.[13] Therefore, from our results we conclude that there is a disconnection between the credit market and the option market during the GFC. Obviously, the GFC started in the US and spread to Europe, so it seems interesting to analyze what happened to the US market. Regressions performed for the US lead to a very small R^2, confirming the disconnection between the credit and volatility markets.

This is problematic because from a theoretical point of view credit risk and volatility are closely related. This is one of the main messages of Merton (1974) and the subsequent extensions, Black and Cox (1976) and Huang and Huang (2012).[14] Because of this relation equity options can be used (and are

[13] Maybe more in line with our results is Table 5 of Zhang et al. (2009), where 5-year CDS spread changes for US corporates are explained only marginally by either the (changes of the) VIX or the (changes of the) historical volatility, as the R^2 obtained by these authors is around 4%.

[14] All these models belong to the category of the so-called structural credit risk models. Within this framework Che and Kapadia (2012) focus on hedging credit risk with the equity market. As previously mentioned, our modeling point of view fits better into the credit risk intensity framework of Duffie and Singleton (1999) which, when jointly analyzed with equity volatility, leads to the works of Carr and Wu (2007, 2010).

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in fact used in practice) to hedge credit risk. However, our results underline the fact that the hedge is likely to perform poorly and that a short credit risk trader might suffer heavy losses. Even though credit risk and equity volatility both increased during the GFC, there was a breakdown of the intrinsic relationship between these markets. However, the relation should have prevailed even during these troubled times.

Our result is potentially worrying for the following reason. From a risk management point of view, the connection between credit and equity markets is the basis for all cross-hedging strategies. This is particularly true at a portfolio or aggregate level, and our results illustrate the fact that it might be impossible to manage risk. One could argue that the entities in the credit market and those in the equity index market are not the same, thereby explaining the failure of this connection. However, we work at the highest possible level, the index level. Note that the regression coefficients are significant, hence a correlation between the factors exists, but the R^2 which indicate the effectiveness of the hedge are small. It is certainly of interest to perform a similar analysis of CDS spreads and the implied volatility at company level because this is where the connection between the two markets should be the strongest.

Note also that our approach is based on the implied volatility surface and CDS spreads, i.e. it is model-free. If we wanted to use a consistent model, we would need to perform a joint calibration, which is numerically tedious, and we would need to have enough factors for both markets. A “good” model would be a model able to fit both markets accurately, on a daily basis. In other words, the model should be able to reproduce the dynamics of the implied volatility surface and the term structure of CDS spreads. Therefore, the use of a consistent model is unlikely to change our conclusions.

4.2.2. Credit–volatility connection during the European debt crisis

We now focus on the second subsample and report in Table 4 (right-hand side) the regression results for the European markets for the period 01/01/2010–17/09/2012. All regressions now lead to higher R^2, meaning that the CDS–volatility relation is reasonably good in the second subsample. When we look at how the first credit risk component can be hedged using the volatility factors, we observe that with only the first volatility factor we can achieve an average (among European countries) R^2 of 13.4%, more than three times the result obtained in the first subsample. Important is the fact that during this period the Italian and Spanish CDS markets entered into the sovereign debt crisis and, therefore, experienced a significant increase of their CDS spreads as shown by Figs. 2 and 3 as well as the descriptive statistics reported in Table 1. Consequently, even when the CDS and volatility markets are volatile, they can still be connected. This aspect is crucial from a hedging point of view as underlined before. From these tables we can also ascertain the impact of lower volatility factors. Adding two volatility factors leads to an average R^2 of 22.6%. If we take into account the fact that we work with changes in the dependent variable, this is a very good result. The third factor, whose eigenvalue is very small, increases the R^2 by 3.4%. The second factor significantly improves the quality of the regressions for Germany (and also for the UK), increasing the R^2 by 10%. Its impact for Italy is small (as for France), improving the R^2 by 5%, whilst for Spain adding factors beyond the first one does not improve the R^2 at all. However, the R^2 is still significantly higher than what we obtain during the GFC.

For the US market, for this second subsample we can draw the following conclusions. Contrarily to the European market the first volatility factor leads to an R^2 of 4%, which is quite low. Interestingly, the second volatility factor increases the R^2 by 19%, which is a huge improvement. Lastly, the third factor adds 12% to the R^2, in contrast to the European results. This case also underlines the importance of lower-order factors despite their small eigenvalue in the spectral decomposition. Furthermore, it has a profound impact on the choice of the number of factors because our results suggest that, if we wanted to work with a consistent model, we would need a three-factor model.

We now analyze the regressions of the volatility factor on the credit factors and start with the European countries. In this case the situation is rather different. The second and third credit factors do not improve the regressions for any of the countries as the R^2 remain virtually unchanged after the addition of these factors. The first credit factor allows us to obtain a low R^2 of 9% for France, but an average R^2 of 14.5% for the other countries. This is clearly an improvement compared with the earlier subsample. What is also important to note is that Italy and Spain experienced the turmoil of the sovereign debt crisis during that period – and still, the connection between the credit and volatility

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markets was intact. For the US, the results are similar in the sense that adding factors does not improve the R^2 and, in contrast with the European markets, the first volatility factor leads to an R^2 as low as 4%.

In conclusion, the hedge of the credit factor using volatility factors can be effective and lower-order factors improve the quality of the hedge (as represented by the adjusted R^2) significantly. This latter aspect has important consequences on the specification of a consistent model that we will discuss later. The hedge of the volatility factor using credit factors cannot be improved beyond the first credit factor but the results are reasonably good. Two important conclusions emerge from these results. The GFC led to a breakdown of the relationship between the credit market and the volatility market, jeopardizing any attempt to perform credit–volatility cross-hedges during that period. However, this relation can be effective during a crisis as the Italian and Spanish markets show during the second subsample covering the sovereign debt crisis.[15]

The results also underline the importance of including higher modes although the associated eigenvalues might be small. Improved explanatory power is found in regressions of both the first CDS factor on volatility factors and the first volatility factor on CDS factors, although our results suggest that the CDS market can be hedged more effectively with the volatility market than vice versa. The R^2 increase by anything between twofold and 11-fold when comparing the second to the first subsample. This is interesting insofar as the findings apply to all countries across the board, no matter whether they were severely affected by the European debt crisis (like Italy and Spain) or barely affected (like Germany and the UK). We conclude that depending on the nature of the crisis the CDS–volatility relation can vanish.

4.2.3. Analysis of intra-market linkages

During the GFC there was a breakdown of the relationship between the credit and the volatility markets both in the US and Europe. As this was a global crisis, we wonder to which extent the European credit and volatility markets were connected to the US markets. To quantify this relation we restrict ourselves to the first credit and volatility factors and perform regressions of these factors on the first US credit and volatility factors separately during the GFC.[16] From a mathematical point of view for the credit factors we perform the regressions

$$\Delta \mathrm{CDS}^{\mathrm{Eur}}_{1,t} = a + b_1 \Delta \mathrm{VOL}^{\mathrm{US}}_{1,t} + \varepsilon^{\mathrm{cv}}_t \tag{5}$$

$$\Delta \mathrm{CDS}^{\mathrm{Eur}}_{1,t} = \alpha + \beta_1 \Delta \mathrm{CDS}^{\mathrm{US}}_{1,t} + \varepsilon^{\mathrm{cc}}_t . \tag{6}$$

These allow us to determine if the European credit factors can be hedged using either the US volatility factor (5) or the US credit factor (6). Similarly, for the volatility factors we carry out the regressions

$$\Delta \mathrm{VOL}^{\mathrm{Eur}}_{1,t} = a + b_1 \Delta \mathrm{VOL}^{\mathrm{US}}_{1,t} + \varepsilon^{\mathrm{vv}}_t \tag{7}$$

$$\Delta \mathrm{VOL}^{\mathrm{Eur}}_{1,t} = \alpha + \beta_1 \Delta \mathrm{CDS}^{\mathrm{US}}_{1,t} + \varepsilon^{\mathrm{vc}}_t . \tag{8}$$

The results for these regressions are reported in Table 5. For the European credit factors regressed on the US volatility factor and for the European volatility factors regressed on the US credit factor we obtain similar results. Namely, the adjusted R^2 is very small (less than 2%), thus implying a poor credit–

[15] Nevertheless, the results for Germany and the UK suggest that this connection is stronger during non-volatile periods. This is problematic in the sense that the purpose of a CDS contract is precisely to hedge against a default event, when a stock enters a period of trouble.

[16] In this part we drop the qualifier “first” when we refer to the first factors.

volatility market linkage. This is not a surprise as we cannot expect these relationships to be stronger than the relationship between the credit market and the volatility market within the same country, which is known to be weak for this subsample (see the previous sections of this paper). More interesting is the intra-market analysis, that is the relation between the US and European credit market (volatility market). The regressions of the European credit factors on the US credit factor result in high R^2 (on average 19.6%). Similarly, for the volatility market we obtain an average R^2 of 22%. Compared with the cross-hedge R^2 of the previous subsection the improvement is significant. The implication of this is that, during the GFC, the hedge of a European CDS (volatility) position could have been more effective using the US CDS (volatility) market than using the European volatility (CDS) market. The same applies to a US CDS position, which could have been hedged using the European CDS markets.

5. Conclusion

In this work we propose a joint analysis of the term structure of credit default swap spreads and the implied volatility surface for different European countries. Using the methodology developed in Da Fonseca and Gottschalk (2013), we develop a factor decomposition for both markets which allows us to study them globally, i.e. the entire term structure of credit default swap spreads and the entire implied volatility surface. We implement our methodology on a database of options and the term structure of CDS spreads for five European countries in a sample covering both the Global Financial Crisis and the European sovereign debt crisis (2007–2012). A correlation analysis between contemporaneous factors along with stock returns confirms the ability of our methodology to perform viable factor decompositions for the implied volatility surface and the CDS curve. These allow us to handle the joint statistical properties of the two markets.

To quantify how crises affect the relationship between the credit and volatility markets we perform a regression analysis which underlines the cross-hedging opportunities between the two markets. We find that during the European debt crisis the connection between the credit and volatility markets is rather good albeit some of the countries (Spain and Italy) experienced severe turmoil in this period. During the GFC there is a clear breakdown of the relationship between the two markets for all countries. Robustness checks with US data confirm these results. Consistently with Da Fonseca and Gottschalk (2013) we find that the relation is not reciprocal, i.e. credit factors can be hedged more effectively using volatility factors than vice versa. Moreover, factors with small eigenvalues can be very important from a cross-hedging point of view; this has far-reaching consequences from a risk management perspective as the number of factors chosen for a model should not depend only on the eigenvalue decomposition.

Our work suggests some extensions. We analyze the credit market through credit default swap contracts but collateralized debt obligations (CDOs) could be used instead, see Carverhill and Luo

Table 5

Cross-market and cross-country factor regressions for Germany, Italy, and Spain in the first subsample (23/05/2007–31/12/2009). In Panel A, each country's first CDS factor is regressed on the United States' first CDS and volatility factor. In Panel B, each country's first volatility factor is regressed on the United States' first CDS and volatility factor.

	Germany		Italy		Spain	
	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: dependent variable ΔCDS_1						
ΔCDS_1^{US}	0.24***		0.30***		0.36***	
ΔVOL_1^{US}		0.01		0.01		0.01
Adj. R^2	0.14	0.00	0.11	0.00	0.25	0.00
Panel B: dependent variable ΔVOL_1						
ΔCDS_1^{US}	0.24***		0.38***		0.40***	
ΔVOL_1^{US}		0.49***		0.31***		0.38***
Adj. R^2	0.01	0.29	0.02	0.07	0.02	0.14

Regression intercepts have been suppressed in order to conserve space.
The symbol *** denotes statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

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(2011). As these products are similar to options, they might lead to more effective cross-hedges. The correlations between the factors found in our study impose some strong constraints for the development of a model in the spirit of Carr and Wu (2010). Lastly and maybe more importantly, when we put the results of Da Fonseca and Gottschalk (2013) in perspective with the results of this study, it seems of interest to analyze to which extent the connection between the credit and volatility markets is preserved at the firm level. We leave these open and challenging issues for future research.

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