Which market drives credit spreads in tranquil and crisis periods? An analysis of the contribution to price discovery of bonds, CDS, stocks and options

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Abstract

Credit spreads can be derived from the prices of securities traded in different markets. In this paper we investigate the price discovery process in single-name credit spreads obtained from bonds, credit default swaps, equities and equity options. Using a vector error correction model (VECM) of changes in credit spreads for a sample that includes the 2007-2009 financial crisis, we find that during periods of high volatility, price discovery takes place primarily in the option market, whilst the equity market leads the other markets during tranquil periods. By adding GARCH effects to the VECM specification, we also find strong evidence of volatility spillovers from the option market to the other markets in crisis periods. Finally, we show how GARCH models can be used to generate time-varying measures of price discovery.

JEL classification: G01; G12; G14; G20; D8

Keywords: credit spreads; price discovery; volatility spillovers; credit and equity derivatives; information flow

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1. Introduction

The financial crisis that began in 2007 was characterised by sharp changes in asset prices. Variations in credit spreads were an important contributing factor to asset price volatility. The increasing role of credit risk in securities prices in periods of market turmoil has led bank regulators to introduce new capital requirements that reflect the potential for credit risk related losses in traded instruments (Basel Committee on Banking Supervision, 2009). An extensive literature shows the impact of credit spreads on bond prices and recent research has started to single out and analyse a credit risk factor in stock prices (Vassolou and Xing, 2004). In the light of recent events, it is important for financial economists, traders and regulators to understand which markets more quickly incorporate credit risk related information and lead other markets in the price discovery process. Such knowledge may give an early warning on imminent and possible large shocks in asset prices. In addition, an understanding of the transmission mechanism of credit risk information across markets and its evolution over time may shed light on the relative efficiency of such markets and on how their functioning may change with changing market conditions. In this paper we investigate the discovery of the price of credit risk in the bond, CDS, stock and option markets before and during the 2007-2009 financial crisis.

The credit risk associated with a company may be measured in the credit market, via the credit spread of bonds issued by that company and the price of credit default swaps (CDS) written on those bonds. Indirectly, credit risk can also be quantified through implied credit spreads. For example, Kealhofer (2003a,b) and Vassalou and Xing (2004) show how information on credit risk can be extracted from equity prices. Hull et al. (2005), Stamicar and Finger (2006) and Cao et al. (2011), on the other hand, have more recently shown how to use the price of options written on a firm's stock to obtain implied credit spreads.

Several papers have looked at price discovery in the bond and CDS markets (e.g. Blanco et al., 2005 and Zhu, 2006) and bond, CDS and stock markets (Longstaff et al., 2003, Norden and Weber, 2009 and Forte and Peña, 2009). However, the role of the option market in the price discovery of credit risk has attracted less attention even though its relevance could be substantial. Indeed, recent research has found that the implied volatility of options written on stocks or stock futures can help explain credit spreads (Collin-Dufresne et al., 2001, Cremers et al., 2008, Berndt and Ostrovnaya, 2008, Cao et al., 2010 and Alexander and Kaeck, 2008). This is not surprising as banks and hedge funds routinely implement arbitrage trading strategies[1] that are based on the discrepancies between the credit spreads implied from equity options and the spreads of bonds and CDS contracts for individual firms.[2]

We add to the existing literature by (1) analysing, for the first time, all the markets that, according to previous studies, may contribute to the price discovery of credit risk, namely the bond, CDS, equity and option markets; (2) by performing our analysis over a sample period that includes the 2007-2009 financial crisis which allows us to investigate changes in price discovery between tranquil and crisis periods; (3) by investigating the presence and direction of volatility spillovers among the four markets; and (4) by introducing a time-varying price discovery measure based on a conditional volatility model. Our main finding is that the option market contributes the most to price discovery during periods of high volatility, followed by the bond and CDS markets. Although not dominant, the option market is also important during tranquil periods. On the other hand, it is the equity market that leads the other markets when volatility is low. The CDS market has an important but not a leading role in price discovery in both stable and turbulent periods. Moreover, our results are corroborated by robust evidence of volatility spillovers from the option market to the other markets for most of the companies analysed.

Our findings should be of interest to various market participants. Policymakers, concerned about the stability of the whole financial system, should benefit from a better understanding of how equities, bonds, options and credit derivatives are interlinked during periods of high and low volatility. Also, understanding which of those markets contributes the most to price discovery and volatility spillovers becomes crucial to provide timely responses to systemic crises. Speculators, hedgers and arbitrageurs are also clearly interested in receiving the earliest possible signals to identify credit risk reversals.

The remainder of the paper is organised as follows: Section 2 reviews the related literature on credit risk price discovery. Sections 3 and 4 describe the data and our methodology. In Section 5 and 6 we discuss the main results and robustness tests. Section 7 concludes.

2. Literature review

Only recently researchers have started to look at price discovery in credit spreads. Zhu (2004) analyses CDS and bond spreads with Vector Error Correction Model (VECM) and finds that CDSs lead price

[1] See JPMorgan (2006).
[2] These strategies do not ensure riskless profits as the traditional meaning of arbitrage implies, hence they are referred to as "risky arbitrage".

discovery in the US market. However, the bond market is found to have a leading role in Europe and Asia. A similar study is that of Blanco et al. (2005) who look at the relationship between the bond and CDS markets in Europe and the US. They conclude that the CDS market is responsible, on average, for about 80 percent of price discovery over their sample period. A more recent study from Bai and Collin-Dufresne (2011) finds that price discovery in the CDS market decreased during the financial crisis of 2008 in favour of the bond market for a sample of US companies.

Acharya and Johnson (2007) study the information flow between CDS and equity markets and find evidence of insider trading in the CDS market They argue that insider trading could be a reason for the leading role of the CDS market against the equity market. However, this informational advantage is found only in the presence of negative credit news.

Longstaff et al. (2003) are the first to analyse the lead-lag relations between bonds, CDSs as well as stocks. They find that the CDS and equity markets lead the bond market most of the time. Similarly, Norden and Weber (2009) analyse the lead-lag relationship between changes in CDS spreads, bond spreads and stock returns using a VAR model. They find that the stock market is more likely to lead the other two markets and the CDS market appears to lead the bond market. However, when a VECM specification is used for CDS and bond spread changes, a leading role of the CDS market is found only for the US companies in their sample, whereas both markets contribute the same amount to price discovery in the case of the European companies. The first study to analyse the three markets (CDS, bonds and equities) in a VECM framework is that of Forte and Peña (2009). They perform a price discovery analysis that is intuitively more appealing than in previous contributions as they compare homogeneous measures of credit risk in terms of observed or implied credit spreads obtained from the three markets. Their main finding is consistent with Norden and Weber (2009) in the sense that the stock market leads the price discovery process, followed by the CDS market.

The literature on volatility spillovers between credit markets for individual companies is thin. Baba and Inada (2009) find evidence of volatility spillovers from the CDS to the bond market by analysing four Japanese banks' subordinated CDS and bond spreads. Meng et al. (2009) extend the analysis to the equity market and find evidence of spillovers from equities to bonds and vice versa. On the other hand, the CDS market sends less volatility to the other two markets than it receives. They conclude that all three markets are important and none of them is more efficient than the others.

Early insights into the relevance of the information in the option market, in particular of option implied volatilities, as determining factors of credit spreads, are given in the seminal paper of Collin-Dufresne et al. (2001). The study finds that changes in the slope of the "smirk" of implied volatilities of options on

S&P500 futures is a statistically significant explanatory variable for the changes in bond credit spreads. Cao et al. (2010) find that the option-implied volatility of individual companies is important to explain single-name CDS spreads and becomes statistically more significant for companies characterised by high volatility in CDS spreads, low credit rating and large option trading volume. Similar results are found by Cremers et al. (2008), who confirm the importance of option-implied volatilities in explaining levels of bond credit spreads. They also find that the volatility skew of individual companies is significant, in line with the results of Collin-Dufresne et al. (2001). Another interesting study is that of Alexander and Kaeck (2008), who use Markov switching regressions to explain changes in European CDS indices in different regimes. Their main conclusion is that option-implied volatilities represent the main determinant of changes in CDS spreads in a volatile regime, whereas in stable conditions equity market returns have a predominant role. However, although they examine low volatility and high volatility periods, their sample does not include the peak of the crisis in 2008-2009.

Lastly, Berndt and Ostrovnaya (2008) study how negative news is built into option prices, CDS spreads and stock prices. Based on Acharya and Johnson (2007) they employ a model which allows CDS and option market participants to have insider information and trade on this information in advance, before the public disclosure of future negative events. Overall, they conclude that the flow of information in the CDS and option market works both ways. But, prior to some adverse market news, such as accounting scandals, they find that the option market carries superior information. Interestingly, Cao et al. (2010) with a similar methodology find that option implied volatility innovations are more capable to predict future CDS spread changes than the other way around. However, both Berndt and Ostrovnaya (2008) and Cao et al. (2010) do not convert the information from different markets into common and comparable credit risk measures, that is, credit spreads. Hence, they cannot take into account the long run equilibrium relationship that may exist among the spreads implied from the different markets. Furthermore, in their analysis they do not consider the bond market which may be an important source of information in the price discovery process.

3. Data

In our analysis we use the daily observations of CDS mid-quotes, bond yields, equity prices and option implied volatilities for a sample of 12 European non-financial companies from January 2006 until July

2009[3]. Following Longstaff et al. (2003), starting from a much larger sample we retain only those companies for which at least 100 observations per year (55 observations in 2009 as our sample ends in July 2009) are simultaneously available, on the same dates, for all of the above securities. Having a high number of companies to analyse has always been a problem in the price discovery literature, mainly due to missing data. Our study is the first that considers four markets at the same time, which means that additional missing values further shorten the sample of dates available for the analysis and hence restrict the number of companies with sufficient observations across all the four markets. As a result, one should expect our sample to be somewhat more restricted than in previous studies.[4]

A. CDS and Bond Data

CDS bid and ask quotes for various maturities are obtained from GFI, a market leader in OTC credit derivatives trading. End-of-day quotes are compiled by GFI at 6pm London Time. The dataset covers the period from January 2006 to July 2009. We restrict our analysis to senior unsecured CDSs with 5 year maturity as they are the most liquid. For the same companies and time period, we derive credit spreads from their outstanding corporate bonds. Following previous studies, we construct synthetic 5-year credit spreads for each company using yields for two bonds with the following characteristics: they are denominated in Euros[5] and are senior unsecured; they have "generic" Bloomberg mid-market prices which are average quotes from at last five brokers or dealers; they are not floating-rate and do not have embedded options or any special features; one bond has a maturity below 5 years while the other has a maturity above 5 years.[6] Bond yields are downloaded from Bloomberg. From the same source we also obtain 5-year swap rates for Euros[7] which we use as a proxy for the risk free rate as in previous studies (see Hull et al., 2005 and Houweling and Vorst, 2005). The reference time for the European bond data provided by Bloomberg is 7.20 pm London time.

B. Equity and Option Data

[3] The series of spreads for some companies do not cover the whole sample period. In particular, time series for Renault are available from May 10, 2006. For Telenor and Vodafone, credit spreads series are available until February 3, 2009 and May 26, 2009, respectively.

[4] Given our additional constraints, our sample of 12 companies does not compare unfavourably with the sample size in previous studies: 17 in Forte and Peña (2009), 18 in Blanco et al. (2005) and 16 in Zhu (2006).

[5] In the case of Marks&Spencer, we only find bonds denominated in GBP, and we use these in our analysis.

[6] For most of the companies, we calculate 5-year spreads via linear interpolation. However, for two companies (Lvmh and Upm) and for only a small part of the sample, we could not find bonds with maturity above 5 years so we had to resort to linear extrapolation.

[7] In the case of Marks&Spencer we use 5-year swap rates in GBP in order to obtain the 5-year credit spreads.

We employ the CreditGrades structural model to estimate the 5-year equity implied spreads. The model is widely used by both researchers and practitioners. Recent studies that have employed this model are Duarte et al. (2007) and Yu (2006). A summary of its main features is presented in Appendix A. In order to implement CreditGrades, we need the following inputs for each company: daily series of stock prices and market capitalizations; accounting data including short-term and long-term liabilities, minority interest, preferred shares; the mean global recovery rate $\bar{L}$ and its standard deviation λ; the recovery rate of the firm's senior unsecured debt, R; the annualized equity volatility σ_S and the 5-year risk-free interest rate r.

Stock prices, market capitalisations, accounting data and 5-year swap rates are downloaded from Bloomberg. The reference time for stock prices and market capitalisation varies according to the market close of the European exchange in which a company is listed.[8] For $\bar{L}$ and λ we take the estimated values of 0.5 and 0.3, respectively, reported in the CreditGrades Technical Document (2002), which are based on historical data of about 300 non-financial companies. The recovery rate R is estimated as the Moody's average historical recovery rate on senior unsecured debt over the period 1982-2009 (see Moody's 2011) and is equal to 0.326. To compute bond spreads, we use the 5-year swap rates for Euros as a proxy for the risk-free rate. To estimate the equity volatility σ_S we follow the CreditGrades Technical Document (2002). However, while CreditGrades employs a 1,000-day moving average of past equity stock returns, we resort to a 40-day moving average to improve the volatility's responsiveness to changing market conditions. This is consistent with the shorter time span (2 months) used in the literature to obtain option implied volatilities for the estimation of option implied spreads, which is discussed next.

We employ two different models to estimate the 5-year option implied spreads. Firstly, we use an extended version of the CreditGrades model as described in Stamicar and Finger (2006). To implement the model we only need daily implied volatilities for 2-month equity ATM (at-the-money) put options which we obtain from Bloomberg. Secondly, we also implement a reduced form type model, based on the seminal work of Merton (1976) and developed in Hull et al. (2005). Its inputs are the 2-month ATM and 25-delta OTM (out-the-money) equity option implied volatilities for each firm in our dataset, the moneyness κ of the options and the recovery rate, R. Daily implied volatilities are taken from Bloomberg. The corresponding moneyness κ of the two options can be derived by inverting the formula for an option's delta and solving for κ. The results reported in the paper are based on the extended

[8] The market close in London time for the main exchanges represented in our sample is 4.30 pm (London Stock Exchange), 7 pm (Frankfurt Stock Exchange), 4:30 pm (Euronext Paris Stock Exchange) and 6.20 pm (Oslo Stock Exchange).

CreditGrades model. We use a reduced form type model to check the robustness of our results. The reference time for the option market is the same as for the equity market and it depends on the closing time of the exchange in which a specific company is traded. By comparing the reference time of the pricing data across the four markets it appears that the bond market may have a marginal informational advantage as its closing quotes are the last to be collected each day.

Descriptive statistics of the four series of credit spreads are shown in Table 1. Average spreads across the four markets vary with the CDS market recording the lowest spread (101 basis points) followed by the bond market (123 bp) option market (161 bp) and equity market (194 bp). Upon closer inspection, the abnormally high spreads from the equity market appear to be due to the two car companies in our sample, Volkswagen and Renault. Stamicar and Finger (2006) report abnormally high equity implied spreads for the car companies in their sample due to the difficulty of modelling the true level of their liabilities. Accounting data cannot be taken at face value in these cases as they are affected by large amounts of secured debt issued by the firms' financial subsidiaries. The option market implied spread is similarly affected by leverage.

We expect the level of spreads obtained from the bond and CDS markets not to be perfectly aligned with those implied from the equity and option markets. Both equity and option implied spreads are estimated with CreditGrades which is based on the Merton (1974) model. The discrepancy of these spreads relative to the bond and CDS markets should be expected given the well-known inaccuracy of the Merton model at capturing the level of market spreads (see Jones et al. (1984), Eom et al. (2004), Huang and Huang (2003), Ericsson et al. (2007)). However, our focus is on the changes in the credit spreads rather than the levels. These are the real determinants of the prices discovery of a given market and these are the focus of our analysis. Then, our implicit assumption is that the Merton model can capture changes in credit spreads accurately which is confirmed by the leading role in price discovery of equity and option implied spreads in tranquil and crisis periods respectively as evidenced by our results[9].

In the analysis that follows we split our sample into a pre-crisis sub-sample, which starts in January 2006 and ends in July 2007, and a crisis sub-sample that begins in August 2007 and lasts until the end of the observation period in July 2009. We set August 1st, 2007 as the starting time of the crisis because the cost of insurance against default for several companies doubled in that month.

[9] Moreover, it has been found that the CDS-bond basis for a given company to be significantly different from zero during the crisis an indication that CDS and bond markets were also pricing credit risk differently.

4. Methodology

To determine which market is the "first to move", i.e. which market anticipates the credit spread changes observed in or implied from the other markets, we employ a VECM specification. The first step of our analysis is to check for the presence of unit roots in the four series of spreads for each company. If the series are I(1), the second step is to analyse whether CDS, bond, equity and option markets are linked by a long run equilibrium relation. The general model to describe changes in credit spreads for the four markets is given below:[10]

$$\Delta CDS_t = \alpha_1 + \lambda_{11}CE_1 + \lambda_{12}CE_2 + \lambda_{13}CE_3 + \sum_{j=1}^{p}\beta_{1j}\Delta CDS_{t-j} + \sum_{j=1}^{p}\delta_{1j}\Delta BCS_{t-j} + \sum_{j=1}^{p}\gamma_{1j}\Delta EIS_{t-j} + \sum_{j=1}^{p}\varphi_{1j}\Delta OIS_{t-j} + \varepsilon_{1t} \tag{1}$$

$$\Delta BCS_t = \alpha_2 + \lambda_{21}CE_1 + \lambda_{22}CE_2 + \lambda_{23}CE_3 + \sum_{j=1}^{p}\beta_{2j}\Delta CDS_{t-j} + \sum_{j=1}^{p}\delta_{2j}\Delta BCS_{t-j} + \sum_{j=1}^{p}\gamma_{2j}\Delta EIS_{t-j} + \sum_{j=1}^{p}\varphi_{2j}\Delta OIS_{t-j} + \varepsilon_{2t} \tag{2}$$

$$\Delta EIS_t = \alpha_3 + \lambda_{31}CE_1 + \lambda_{32}CE_2 + \lambda_{33}CE_3 + \sum_{j=1}^{p}\beta_{3j}\Delta CDS_{t-j} + \sum_{j=1}^{p}\delta_{3j}\Delta BCS_{t-j} + \sum_{j=1}^{p}\gamma_{3j}\Delta EIS_{t-j} + \sum_{j=1}^{p}\varphi_{3j}\Delta OIS_{t-j} + \varepsilon_{3t} \tag{3}$$

$$\Delta OIS_t = \alpha_4 + \lambda_{41}CE_1 + \lambda_{42}CE_2 + \lambda_{43}CE_3 + \sum_{j=1}^{p}\beta_{4j}\Delta CDS_{t-j} + \sum_{j=1}^{p}\delta_{4j}\Delta BCS_{t-j} + \sum_{j=1}^{p}\gamma_{4j}\Delta EIS_{t-j} + \sum_{j=1}^{p}\varphi_{4j}\Delta OIS_{t-j} + \varepsilon_{4t}, \tag{4}$$

where ε_{1t}, ε_{2t}, ε_{3t}, ε_{4t} are i.i.d. error terms. The CE_i terms are cointegration equations defined as:

$$CE_1 = CDS_{t-1} - \phi_{11} - \phi_{21}OIS_{t-1} \tag{5}$$

[10] In line with most previous studies we specify the VECM by using the original series of spreads. An alternative would be to use the logarithm of credit spreads like in Forte and Peña (2009).

$$CE_2 = BCS_{t-1} - \phi_{12} - \phi_{22} OIS_{t-1} \tag{6}$$

$$CE_3 = EIS_{t-1} - \phi_{13} - \phi_{23} OIS_{t-1}, \tag{7}$$

where *CDS*, *BCS*, *EIS* and *OIS* indicate CDS mid-quotes, bond credit spreads, equity implied spreads and option implied spreads, respectively.

This general representation applies to the companies for which the maximum number of cointegrating equations (three) is found. We call this *Model I*. However, a restricted version of this general representation will apply if the number of cointegrating equations is less than three. In particular, if only two cointegrating equations are found, a restricted model, *Model II,* is employed. For companies with only one cointegrating equation, we define a further restricted model called *Model III*.

To determine the contribution to price discovery of the various markets, one can focus on the statistical significance and sign of the error correction coefficients λ's. For instance, if the option market leads the discovery of the price of credit risk, the λ_{ii}'s in equations (1) to (3), under *Model I,* will be negative and statistically significant as all the other three markets will adjust when they deviate from the option market. On the other hand, if the option market is the least important in the price discovery process all the λ's in equation (4) will be positive and statistically significant as the option market adjusts when it deviates from the other markets. If all λ_{ii}'s in equations (1) to (3) and all the λ's in equation (4) are significant and with the signs indicated above, then price discovery takes place, to some degree, in all markets. In general, to determine which market has a leading role in price discovery two indicators are used in the literature, the information share (IS) indicator developed by Hasbrouck (1995) and the GG indicator of Gonzalo and Granger (1995).

While the GG measure includes only the error correction coefficients λs, in the IS measure the error correction coefficients are weighed by the variances and covariances of the error terms in the VECM. It can be shown that these are linked to the variance of a latent common factor, that is the efficient market price of credit risk, implied by the long term cointegration relationship. Then, the information share of a market can be interpreted as the proportion of the variance of the common factor explained by that market. The higher the proportion, the closer the market to the efficient price, and the more dominant its role in price discovery.

We further extend our study of the information flow across markets by analysing volatility spillovers. This is done through a 4-variate GARCH model which can be represented as follows:

$$\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{9}$$

where $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \varepsilon_{4t})'$ is the vector of disturbances from the VECM estimated with *Model I* through equations (1)-(7), and Ω_{t-1} is the information set at time *t*-1. The vector ε_t is assumed to be normally distributed. Following Baba and Inada (2009), we use a two-step procedure where the first step involves estimating the VECM and the second step is the application of the multivariate GARCH model to the VECM residuals. Our analysis is based on the BEKK specification of the GARCH model as presented by Engle and Kroner (1995):

$$H_t = C'C + A'(\varepsilon_{t-1}\varepsilon_{t-1}^{'})A + B'H_{t-1}B \tag{10}$$

where $H_t = \begin{pmatrix} h_{11,t} & \cdots & h_{14,t} \\ \vdots & \ddots & \vdots \\ h_{41,t} & \cdots & h_{44,t} \end{pmatrix}, C = \begin{pmatrix} c_{11} & \cdots & c_{14} \\ \vdots & \ddots & \vdots \\ 0 & \cdots & c_{44} \end{pmatrix}, A = \begin{pmatrix} a_{11} & \cdots & a_{14} \\ \vdots & \ddots & \vdots \\ a_{41} & \cdots & a_{44} \end{pmatrix},\ B = \begin{pmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ b_{41} & \cdots & b_{44} \end{pmatrix}.$

In addition to an investigation of volatility spillovers, the above model lends itself well to a further application. As IS is defined as a function of the volatility of the error terms in the VECM, we can produce a time dependent (daily) IS by replacing the unconditional error volatilities with the conditional volatilities obtained with (10). As a result, we can derive dynamic price discovery measures which have not been explored before and offer the opportunity to represent, in a clear and intuitive way, the time varying behaviour of the information flow among markets.

5. Results

Our procedure to allocate companies to specific models starts with a unit root test on the series of credit spreads obtained from the four markets. We find that most of them are non-stationary at the 5 percent level of significance. However, stationarity is found for Vivendi (for its equity and option implied spreads), Volkswagen (for its equity and option implied spreads) and Casino Guichard (for its option implied spreads). The results of the Johansen cointegration test for each of the 12 companies are shown in Table 2.[11] We find evidence of three cointegrating relationships for 4 companies (Basf, Lvmh,

[11] We tested for cointegration separately for the pre-crisis and in-crisis periods. The results clearly suggest that the two sub-samples are too short. In the pre-crisis period 10 companies have only one cointegrating relationship, whilst in the in-crisis period most companies have two cointegrating relationships, and none of the companies has three cointegrating relationships.

Marks&Spencer and Telenor). Hence, for these 4 companies, we are able to perform a price discovery analysis with the full model (*Model I*) comprising equations (1) to (7).[12] For other 4 companies (Carrefour, Casino Guichard, Renault and Vodafone), we only find two cointegrating relationships. These companies are analysed with *Model II*. Finally, we find only one cointegrating equation for the last 4 companies (Stora Enso, Upm, Vivendi and Volkswagen) which are studied with *Model III*.

For the companies included in *Model II* and *Model III*, we have to re-define the VECM given in equations (1)-(7). We notice that, for all the companies in *Model II*, the two cointegrating equations do not include the equity market. Thus, in the *Model II* specification of the VECM we have three markets only, namely the CDS, bond and option markets and cointegrating equations (5) and (6). For companies in *Model III*, we find that for Upm the cointegrating equation is (6) while for Stora Enso is (7). For Vivendi and Volkswagen the only non-stationary series are the CDS and bond spreads which means that their cointegrating equation necessarily will include these two markets.

Following Blanco et al. (2005), we also test restrictions on the significant cointegrating equations of the three models. The theory says that the four markets we analyse should price credit risk equally in the long term. In other words, their credit spreads should be cointegrated with cointegrating vector [1, -1, 0], which means that the coefficient of the option implied spread should equal -1 and the constant term in each cointegrating equation should equal zero. If this is not the case, three explanations are possible: (a) different markets price credit risk differently; (b) at least one market in a given cointegrating equation incorporates non-transient factors which are unrelated to credit risk; (c) at least one market includes non-transient measurement errors.

Results of the test on the restrictions imposed on the cointegrating vectors are reported in Table 3. We cannot reject the null hypothesis for 3 of the 4 companies in *Model I* for the cointegrating vectors defined in equation (5) and (7) at the 1% level and we never reject the null for the cointegrating vector defined in equation (6). For companies in *Model II*, we cannot reject the null, at the 1% level, for 3 (out of 4) companies for the cointegrating vector defined in (5), whereas we have no rejection of the null for 2 companies for the cointegrating vector defined in (6). Instead, rejection of the null, at the 1% level, is always suggested for companies in *Model III*. Overall, except for the companies in *Model III*, the markets price credit risk equally in several cases.

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[12] Interestingly, Forte and Peña (2009) also find that they can perform a complete price discovery analysis for only 4 companies (included in their *Model I*) out of 17 companies in their sample.

These findings are not unexpected since the option implied spreads based on the Merton model, while adequately tracking changes in credit quality may not reproduce the exact level of credit spreads observed in the CDS and bond markets. However, since our analysis of price discovery is based on credit spread changes the results reported in Table 3 are not a matter of concern.

5.1 Price discovery analysis

Only *Model I* allows us to perform a complete analysis of price discovery across the four markets. A price discovery analysis in *Model II* can be performed only for CDS, bond and options. The analysis for the companies studied with *Model III* will be restricted to the two markets included in the only cointegrating equation considered.

The main results of this paper are based on the implementation of *Model I*. The estimates of the error correction coefficients (λ's) are shown in Table 4. Coefficients can be looked at in pairs for a preliminary assessment of price discovery. For example, λ_{11} and λ_{41} give an indication of the relationship between the option and CDS markets. In particular, if λ_{11} is negative and significant and λ_{41} insignificant, then the option market leads the CDS market. Similarly, if we are interested in the leading role between the bond and option markets or the equity and option markets, we should focus on λ_{22} and λ_{42} or λ_{33} and λ_{43} respectively. We observe that before the crisis period, the long term inter-linkages among the markets are weaker as the number of statistically significant error correction coefficients decreases as compared to the crisis period. Overall, the analysis of the VECM estimates clearly shows a more dominant role of the option market over the other markets and this is especially true during the crisis period. To determine the extent of the price discovery that takes place in each market relative to the others we employ the information share (IS) indicator of Hasbrouck (1995) and the GG measure of Gonzalo and Granger (1995). Table 5 shows the IS mid-point and GG estimates for the companies analysed with *Model I*. Panel A of Table 5 reports the results for the whole sample. As in previous studies (see, for instance, Baillie et al., 2002 and Forte and Peña, 2009), we shall consider the IS mid-point to draw our conclusions[13]. The IS indicates that 44% of price discovery occurs in the option market, 27% in the bond market, 23% in the CDS market, and 10% in the equity market.

But, when looking at the two sub-samples, the price discovery measures vary considerably. Before the crisis, the IS indicates that 40% of price discovery takes place in the equity market, 34% in the option market, 21% in the CDS market, and very little, only 6% in the bond market. During the financial crisis,

[13] To save space, we do not report the upper and lower bounds of the IS measure. However, their range is narrow which suggests that the reported midpoint is a reasonable estimate of the price discovery in each market.

the IS measure in the equity market dramatically reduces to 10%, in the option market it increases to 47%, in the CDS market it stays constant at 21%, while in the bond market it increases markedly to 27%. It is apparent that the findings for the whole sample are mainly driven by the crisis period. The most striking result is the role of the option market both before and during the crisis. In the pre-crisis period, it contributes substantially to the price discovery of credit risk although not as much as the equity market. On the other hand, during the crisis period, according to the IS measure, the option market dominates price discovery while the equity market is the least important. Interestingly, the bond market is the least important before the crisis while it becomes the second most prominent one during the financial crisis.

One possible explanation for the dominance of the option market in crisis periods is the proliferation of trading strategies which attempt to exploit the higher levels of volatility in the markets. Most of these strategies are based on the use of options (Neftci (2008) and Hedge Funds Review (2006)). When uncertainty in the market is high, market participants are less willing to take on directional bets and then prefer to trade volatility. Hence, they either seek to buy insurance to protect their positions against adverse movement in prices (hedgers) or try to profit from large fluctuations, either positive or negative, which are usually observed in these scenarios (speculators). Both types of investors can achieve their aims by leveraging up positions in options.

The other finding of our analysis refers to the increasing role of the bond market in price discovery during the crisis. This may be related to the liquidity problems - faced by market participants during the recent financial crisis, as they were forced to deleverage their corporate bond positions to re-pay their short term exposures, as discussed in Bai and Collin-Dufresne (2011).

The dramatic fall in the price discovery of the equity market during the crisis may be due to a substantial increase in hedging costs. Das and Hanouna (2009) show that equity hedging costs increase when markets are volatile. When stock prices fall, hedge ratios rise, thus determining an increase in hedging costs, worsened by the presence of frictions such as illiquidity in the equity market. This could be a reason why, under such circumstances, professional investors may channel their trades via different trading venues such as bond and option markets. In fact, if an investor wants to hedge his short CDS position, he may buy put options or short the underlying reference bonds, in addition to selling equity.

A second possible reason for the lesser role of the equity market relative to the other markets during the crisis may be related to the presence of informed trading and insider trading documented for the derivatives markets by Pan and Poteshman (2006) and Acharya and Johnson (2007). In particular, the former study focuses on the option market and document how information on option trading volumes could help predict the future movements of equity prices, which supports the greater importance of options in the price formation process. The latter study highlights how insider trading could be the reason of the superiority of the CDS market over the equity market in terms of information revelation in presence of negative credit news.

Often the two measures of price discovery give consistent results in the pre-crisis analysis. This is not the case, in some instances, for the crisis period. In particular, during the crisis, the option market appears to be leading the price discovery according to the IS measure, whereas it shows a low GG value (10%). The study of Yan and Zivot (2007) sheds light on this occasional lack of consistency.[14] Their decomposition of the GG and IS indicators shows that GG takes into account only the price response of a market to transitory shocks, whereas IS considers price responses to both permanent and transitory shocks[15]. Yan and Zivot (2007) conclude that GG and IS can be used in combination to disentangle transitory and permanent effects, but that only IS is an indicator of "the relative informativeness of individual markets". They argue that a high IS combined with a low GG measure for a given market is likely to suggest that the price discovery role of that market is dominant because it responds mainly to fundamental shocks rather than transitory shocks.

Our evidence of the alternating dominant roles of the stock and option markets is consistent with the findings of Alexander and Kaeck (2008), who show that option implied volatilities are the main determinant of CDS price changes in high volatility regimes while equity market returns are the leading determinant during stable markets. The dominant role of the equity market during stable periods is also in line with the results of Forte and Peña (2009) and Norden and Weber (2009). Our findings support those of Berndt and Ostrovnaya (2008) and Cao et al. (2010), who document the importance of the information flow from the option market to the CDS and equity markets. Finally, as in Zhu (2004) and Blanco et al. (2005) we observe that in the pre-crisis period the bond market is dominated by the CDS market in terms of price discovery. However, a the opposite is true during the crisis as both price discovery measures, IS and GG, attribute a substantial price discovery role to the bond market. The increasing importance of price discovery in the bond market during the recent financial crisis is also documented by Bai and Collin-Dufresne (2011), who look at a sample of US companies, The analysis of *Model II* gives further support to the results obtained above. For this model we directly report the IS and GG measures in Table 6. We can see that, in the pre-crisis period, the IS measure indicates that 18% of price discovery takes

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[14] There has been a lively debate on the correct interpretation of the GG and IS measures. Generally, the IS measure seems to be the proper measure to assess the amount of information generated by each market. For more on this topic, see the special issue (issue 3, 2002) of the *Journal of Financial Markets*.

[15] Hasbrouch (1996) generally defines as temporary any "lagged adjustment toward the new permanent price" that is formed as new information reaches the market.

place in the option market, 31% in the bond market, 53% in the CDS market. During the crisis, the IS increases to 69% in the option market, decreases to 20% in the bond market, and decreases to 12% in the CDS market.

In *Model III* (results reported in Table 7) we have one cointegrating relation and only two markets are considered. The restrictions in the analysis caused by the exclusion of two of the four markets and the fact that the restrictions on the cointegrating vector are rejected at the 1% level (as shown in Table 3) imply that *Model III* findings should be taken with caution. For Upm, our estimates show that the bond market has a dominant role over the option market (according to both GG and IS) in both pre-crisis and crisis periods but less so in the latter. For Stora Enso we find that the option market has a leading role over equity in the pre-crisis period with a IS measure of 62% but it is dominated in the crisis period. For Vivendi and Volkswagen, where the only cointegrated markets are CDSs and bonds, the bond market leads the CDS market both before and during the crisis[16].

5.2 Volatility spillovers across CDS, bond, equity and option spreads

In order to detect volatility spillovers between the four markets, we focus on the significance of the off-diagonal elements defined in matrices A and B in equation (10). For instance, if we are interested in measuring volatility spillovers from the option market to the CDS market, we will have to look at the significance of a_{41} and b_{41}, where a_{41} measures innovation spillovers in terms of squared residuals and b_{41} measures volatility spillovers in terms of conditional variance. Table 8 reports the frequency with which spillover parameters are statistically significant for the companies included in *Model I*.[17] If we focus on frequencies equal to or greater than 75%, we can clearly see how volatility spillovers are more frequent from the option market to the other markets during the crisis period. However, before the crisis, the option market is less responsible for volatility spillovers towards the other markets, whereas the frequency of significant spillovers from the CDS to the equity market is substantial (with a frequency of 75%).

5.3 GARCH models: a new application for price discovery

[16] For *Models II* and *III*, we also analysed the short-term price discovery patterns from VARs based on changes in the spreads (excluding the error correction terms). Results, in general, confirm the leading role of the option market in the crisis period and are available from the authors on request.
[17] Estimation results of the full BEKK (1,1) model are available on request.

As discussed in the model Section we propose a new way to generate time varying IS measures based on a GARCH specification of the error terms in our VECM. In Figure 1, we show our daily IS measures for Marks&Spencer over the whole sample. The results highlight the usefulness of point-in-time estimates of price discovery as it allows us to capture a greater variety of patterns than an analysis based on a simple split of the sample into two sub-periods. Indeed, the period preceding the crisis is mainly characterised by the dominant role of the equity market in line with the price discovery results discussed in Section 5.1. However, we can see that in the first part of the crisis period the equity market still plays the leading role in price discovery until June 23, 2008. Then, in the heat of the crisis, immediately before and after the default of Lehman Brothers, the option market takes a clear lead. Finally, from the second quarter of 2009, when the crisis subsides and stock markets start to recover, the equity market bounces back to its pre-crisis dominant role.

6. Robustness tests

6.1 Alternative model for options data

In the analysis we have used option implied spreads obtained from CreditGrades, a structural credit risk model. As a robustness test, we redo our calculations with a reduced form model based on Merton (1976) and discussed in Hull et al. (2005). Details are shown in Appendix B. The alternative model uses two option implied volatilities as the only inputs to derive option implied spreads, and no accounting data. Its main disadvantage is that the resulting implied spreads often overestimate market spreads. However, in our analysis we focus on credit spread changes rather than levels. So the higher level of the spreads should not be a problem. In addition, in the cointegrating equations, where levels are used, the constant term can capture differences in levels between the implied and observed spreads.

We implement the reduced form model for companies in *Model I* only. Again, the IS and GG measures are calculated for the whole sample, the pre-crisis and the crisis periods. Our (unreported) results confirm the dominance of the equity market in the period preceding the financial crisis, followed by the CDS and the bond market[18]. However, during the crisis period, the option market is more important than both the CDS and equity markets, the latter showing the least role in price discovery, in line with our results from section 5. We also redo our analysis of spillover effects with the new series of option implied spreads estimated with the reduced form model. The results are very similar to those shown in Section 5.2.

[18] Results are available on request.

6.2 Three variable model and comparison with previous studies

Previous studies have analysed credit risk price discovery only in three or fewer markets. For instance, Forte and Peña (2009) and Norden and Weber (2009) investigated the comovements of CDS, bond and equity markets. It would be interesting to see how our framework applied to the above three markets compares with previous findings. We run this test on all the companies with the maximum number of cointegrating equations (*Model I*). Consistent with Forte and Peña (2009) and Norden and Weber (2009), we find that, in stable periods, the equity market has the dominant role in price discovery, followed by the CDS market and the bond market. This is reassuring because if we can replicate previous results with our sample then it is reasonable to conclude that our new findings, when including the option market, are not sample specific. Interestingly, during the crisis, which was not investigated in previous contributions, it is the bond market that dominates in the three market analysis. However, as shown in previous Sections, the true role of these three markets in credit risk price discovery can be properly assessed only when the option market is included in the analysis. In Table 9 we compare the 3- and 4-market price discovery measures. It can be clearly seen that the role of the CDS market remains mostly unchanged when the option market is included. On the other hand, the IS measure of the bond and equity markets drop by 14% and 13% respectively in the pre-crisis period. During the crisis period, the fall is even more pronounced at 21% and 19% respectively. An analysis of the behaviour or the GG measure leads to similar conclusions. The above shows that the exclusion of the option market from the analysis leads to an overestimation of the contribution to price discovery of bonds and equities.

7. Conclusions

This paper analyses price discovery and volatility spillovers in credit spreads obtained or implied from the option, CDS, bond and equity markets. Our main finding is that the option market leads the price discovery during periods of market turmoil while it is less important but still relevant in tranquil periods. In line with recent studies, the equity market represents the main venue for credit risk price discovery under stable market conditions. However, we find that it has a minor role in periods of high volatility. A new finding relates to the bond market which, while being the less relevant in stable periods, acquires a major role during crisis periods, contributing more to price discovery than the CDS and the equity markets. The CDS market is important in both stable and turbulent conditions, but its role is not predominant. Consistent with the price discovery results, the relevance of the option market in crisis periods is clear even when we investigate volatility spillovers across markets. Robustness tests confirm our findings and, more importantly, show that previous studies that ignore the option market may misrepresent the price discovery process. Finally, we introduce a time-varying measure of price discovery based on a multivariate GARCH model. This measure highlights the variability of the information flow across markets and confirms its high sensitivity to changing market conditions.

Appendix A

CreditGrades Model

According to the model, the recovery rate L follows a lognormal distribution with mean $\bar{L}$ and standard deviation λ where

$$\bar{L} = EL \text{ and} \tag{A1}$$

$$\lambda^2 = Var \log(L) \text{, such that} \tag{A2}$$

$$LD = \bar{L} D e^{\lambda Z - \lambda^2 / 2}, \tag{A3}$$

Z is a standard normal random variable which is known at the time of default only. The company's asset value is assumed to follow a geometric Brownian motion:

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t \tag{A4}$$

where μ is the asset drift, σ is the asset volatility and W is a standard Brownian motion.

The survival probability of the company at any time *t* is given by the probability that the asset value (A4) does not hit the barrier defined in (A3) before time *t*:

$$P(t) = \phi(-\frac{A_t}{2} + \frac{\log(d)}{A_t}) - d \cdot \phi(-\frac{A_t}{2} - \frac{\log(d)}{A_t}) \tag{A5}$$

where

$$d = \frac{V_0 e^{\lambda^2}}{\bar{L} D} \text{ and} \tag{A6}$$

$$A_t^2 = \sigma^2 t + \lambda^2 . \tag{A7}$$

The asset value and asset volatility can be proxied by market observables parameters. In fact, it can be assumed that at time $t = 0$:

$$V = S + \bar{L}D \text{ and} \tag{A8}$$

$$\sigma = \sigma_S \frac{S}{S + \bar{L}D} \tag{A9}$$

such that (A6) and (A7) can be transformed as:

$$d = \frac{S + \bar{L}D}{\bar{L}D} e^{\lambda^2} \text{ and} \tag{A10}$$

$$A_t^2 = (\sigma_S \frac{S}{S + \bar{L}D})^2 t + \lambda^2 \tag{A11}$$

where S is the stock price, σ_S is the stock volatility, D is the debt-per-share, $\bar{L}$ is the global recovery rate and λ is the percentage standard deviation of the default barrier. Finally, the survival probability is converted to a credit spread as follows:

$$EIS = r(1-R) \frac{1 - P(0) + e^{r\xi}(G(t+\xi) - G(\xi))}{P(0) - P(t)e^{-rt} - e^{r\xi}(G(t+\xi) - G(\xi))} \tag{A12}$$

where $\xi = \frac{\lambda^2}{\sigma^2}$ (A13)

and, following Rubinstein and Reiner (1991),

$$G(u) = d^{z+1/2}\phi(-\frac{\log(d)}{\sigma\sqrt{u}} - z\sigma\sqrt{u}) + d^{-z+1/2}\phi(-\frac{\log(d)}{\sigma\sqrt{u}} + z\sigma\sqrt{u}) \tag{A14}$$

with $z = \sqrt{1/4 + 2r/\sigma^2}$. (A15)

In particular, an estimate of the asset volatility can be obtained by using the following relationship[19]:

[19] See Stamicar and Finger (2006) for a comprehensive discussion on different ways to extend the original CreditGrades model.

$$\sigma_S = \sigma(1+\frac{\bar{L}De^{rt}}{S}) \tag{A16}$$

where σ_S is a daily time series of ATM equity option implied volatilities. By inverting the formula and solving for the unknown asset volatility σ, we can calculate an option-implied spread (OIS) by using again equation (A12).

Appendix B

The reduced form model is based on the seminal work of Merton (1976), where the stock price is allowed to follow a jump-diffusion process:

$$\frac{dS}{S} = (\mu - \theta k)dt + \sigma_E dz + dq \tag{B1}$$

where dq is a Poisson process with intensity θ and jump size k.

Hull et al. (2005) assume that, in presence of jumps, the stock price goes always to zero. This, in turn, implies that the company has defaulted. Hence, defaults are assumed to follow a Poisson process with intensity θ in the same fashion as reduced form models (see Duffie and Singleton (1999), among others). Reduced form models are traditionally calibrated on bond data. However, the model used in this paper and detailed in Hull et al. (2005) is calibrated on option data. According to Merton (1976), the price of a put option with strike price K and maturity τ is given by:

$$P = S_0[\kappa e^{-\theta\tau}\phi(-d_2) - \phi(-d_1) + \kappa(1-e^{-\theta\tau})] \tag{B2}$$

where:

$$d_1 = \frac{\theta - \log\kappa}{\sigma_E\sqrt{\tau}} + 0.5\sigma_E\sqrt{\tau}\ , \tag{B3}$$

$$d_2 = d_1 - \sigma_E\sqrt{\tau}\ , \tag{B4}$$

and κ represents the moneyness of the option:

$$\kappa = \frac{K}{S_0}e^{-r\tau}\ , \tag{B5}$$

S_0 being the current stock price and r the risk-free interest rate.

Equating (B2) to the Black-Scholes price of a put option, we obtain:

$$\kappa e^{-\theta\tau}\phi(-d_2)-\phi(-d_1)+\kappa(1-e^{-\theta\tau})=\kappa\phi(-d_2^*)-\phi(-d_1^*) \tag{B6}$$

where $d_1^* = \dfrac{-\log(\kappa)}{v\sqrt{\tau}}+0.5v\sqrt{\tau}$ and (B7)

$$d_2^* = d_1^* - v\sqrt{\tau} \tag{B8}$$

with v defining the implied volatility.

Finally, the credit spread on the debt (in the case of a zero coupon bond) can be recovered using:

$$OIS = -\log\left[e^{-\theta T} + \left(1-e^{\theta T}\right)R\right]/T \tag{B9}$$

As we have two equations in the form of (B6) for each implied volatility and two unknowns (namely, θ and σ_E), the optimisation problem generates two unique solutions.

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Table 1. Descriptive statistics

Descriptive statistics are provided for four series of credit spreads: CDS, bond, equity and option spreadsover the period January 2006 - July 2009. The rating column indicates the lowest and the highest rating assigned to each company by Moody's during the whole sample period. Only one rating is reported when a company's rating did not change.

		Moody's	CDSs				Bonds				Equities				Options			
	Obs.	Rating	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
Basf	396	A1-Aa3	8.5	160	35.5	29.9	0.1	157.2	21.7	29.5	0	1480.5	50.8	152.7	0	1002	34.1	103.4
Carrefour	768	A3-A2	10.5	147.5	39.7	26.6	0.2	582	63.2	84.8	0	865.7	80	173.8	0.1	1046	76.6	155.5
Casino Guich.	832	Baa3	37.5	430	110.4	64.2	47.2	748.6	160.1	125.1	0.2	1200.6	112.6	216.3	13.1	811.3	100.7	117.1
Lvmh	741	Baa2-Baa1	12.5	222.5	55.4	43.8	7.6	270	60.3	54.1	0	884	67	164.5	0	951.4	47.8	129.7
Marks&Spencer	845	Baa1	25.5	560	133.1	124.3	36.5	651.8	171.6	163.4	0	1395.4	173.1	285	0	1296.3	138.8	231
Renault	527	Baa1-Baa2	17	580	126.7	137.9	22.6	816.1	156.4	188	17.8	2382.3	413.6	579.2	28.3	2558.9	411.9	570.7
StoraEnso	518	Ba2-Baa3	29.5	762.5	241.9	214.1	38.4	812.5	270.4	268.9	0.5	1392.3	264.5	362.5	1.5	1466.6	231.2	306.4
Telenor	539	A3-A2	15.5	180	47.6	34.3	18.8	365.3	62.4	70.1	0.1	2011.6	84.5	297.1	1	1186.2	60.9	177.2
Upm	482	Baa2-Baa3	28.5	500	188.8	160.8	36.7	799.5	239.5	248.2	0.1	971.1	218.5	299.8	1.2	1231.2	169.4	236.3
Vivendi	776	Baa2	32.5	275	84.8	47.2	41.5	388.3	117.7	87.2	0	590.2	24.4	93.7	0	780	27.4	89.2
Vodafone	800	A3-Baa1	20.5	217.5	67.5	49.4	21.1	328.6	69.2	59.6	0	828.7	77.4	146.6	0.1	1758.6	75.9	188.8
Volkswagen	651	A3	13.5	412.5	80.3	79.7	16.9	476.7	84.1	102.3	13.8	14769	757.6	2585	32.3	16524	552.1	1186
Mean			21.0	370.6	101.0	84.4	24.0	533.1	123.1	123.4	2.7	2397.6	193.7	446.4	6.5	2551.0	160.6	290.9
St. dev.			9.5	200.1	63.3	60.8	16.1	232.9	77.5	77.6	6.2	3930.0	209.4	685.9	11.7	4427.3	164.1	310.4

Table 2. Johansen Cointegration Tests

Johansen Trace test statistics are reported for the system of four non-stationary series of credit spreads obtained from the CDS, bond, equity and option markets. The test specification includes a constant in both the cointegration equation and the VAR. The optimal number of lags is chosen according to the Akaike criterion. Columns 2 to 5 show test statistics for a given maximum number of cointegration relations. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	None	At Most 1	At Most 2	At Most 3
Basf	179.23***	82.58***	28.68***	1.77
Carrefour	168.24***	29.80**	10.84	4.32**
Casino Guich.	123.11***	27.01***	2.66	-
Lvmh	198.50***	69.20***	28.25***	3.40*
Marks&Spencer	165.58***	49.78***	16.56**	1.87
Renault	202.56***	67.49***	12.26	1.24
StoraEnso	84.20***	24.02	8.46	1.54
Telenor	202.30***	67.42***	22.06***	0.80
Upm	82.40***	24.70	6.67	1.01
Vivendi	14.47*	0.39	-	-
Vodafone	153.33***	28.22*	7.51	1.63
Volkswagen	29.44***	3.22*	-	-

Table 3. Tests on the Equivalence of Credit Spreads Across Markets

This table reports statistical tests on the equivalence of credit spreads across markets for the individual companies in our sample. For companies in *Model I*, CE1, CE2 and CE3 correspond to cointegrating equations (5), (6) and (7), respectively. For companies in *Model II*, CE1 and CE2 correspond to cointegrating equations (5) and (6), respectively. For companies in *Model III*, CE1 corresponds to cointegrating equation (6) and equation (7) for Upm and Stora Enso, respectively. For Vivendi and Volkswagen $CE1=CDS_{t-1}-\phi_{11}-\phi_{21}BCS_{t-1}$. We test the null hypothesis that the difference between the credit spreads identified by the above cointegrating equations is zero. *, ** and *** indicate rejection of the null hypothesis at the 10%, 5% and 1% level, respectively.

	Restriction on CE1	Restriction on CE2	Restriction on CE3
	[1, -1, 0]	[1, -1, 0]	[1, -1, 0]
Basf	0.56	3.62*	6.58**
Lvmh	2.57	0.11	8.02***
Marks&Spencer	7.33***	0.02	0.11
Telenor	0.74	2.22	0.003
Carrefour	4.09**	3.83*	-
Casino Guich.	1.19	8.00***	-
Renault	9.87***	10.06***	-
Vodafone	2.08	2.17	-
Upm	9.85***	-	-
Stora Enso	16.44***	-	-
Vivendi	11.79***	-	-
Volkswagen	11.91***	-	-

Table 4. Error correction coefficients in *Model I*

Error correction coefficients for the cointegration equations specified in *Model I* are shown for the whole sample, the pre-crisis period (January 2006 - July 2007) and the crisis period (August 2007 - July 2009). The number of lags to include in the VECM estimation for changes in CDS spreads, bond spreads (BCS), equity spreads (EIS) and option spreads (OIS) has been selected according to the Akaike criterion for the whole sample case. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	ΔCDS			ΔBCS			ΔEIS			ΔOIS		
	λ_{11}	λ_{12}	λ_{13}	λ_{21}	λ_{22}	λ_{23}	λ_{31}	λ_{32}	λ_{33}	λ_{41}	λ_{42}	λ_{43}
Panel A: Whole Sample												
Basf	-0.035**	0.035	-0.008	0.081***	-0.094***	-0.044***	-0.231*	1.100***	-0.279***	0.075	0.738**	0.015
Lvmh	-0.048***	0.005	0.005	0.042***	-0.018**	-0.016***	-0.059*	0.055***	-0.039***	-0.227***	0.199***	0.095***
Marks&Spencer	-0.065***	0.042***	0.004*	0.025***	-0.042***	-0.003**	0.006	0.011	-0.030***	0.009	0.086**	0.024***
Telenor	-0.071***	0.051***	-0.001	0.073***	-0.074***	-0.011***	-0.127	-0.002	-0.159***	-0.797***	0.765***	0.058***
Panel B: Pre-crisis period												
Basf	-0.046*	0.019	0.211*	0.002	-0.114**	-0.021	0.005	0.001	0.058*	-0.021	-0.011	0.509***
Lvmh	-0.006	-0.014	0.007	0.077***	-0.066***	0.079***	0.007	-0.003	-0.016	0.003	-0.003	0.003
Marks&Spencer	0.042*	-0.070***	-0.374	0.040***	-0.042***	-0.587*	0.000	-0.001	-0.027*	0.004	0.002	0.360***
Telenor	-0.016	-0.008	-0.005	0.008	-0.046***	-0.004	0.002	0.031	-0.021	0.029	0.039	0.018***
Panel C: In-crisis period												
Basf	-0.037*	0.035	-0.008	0.084***	-0.095***	-0.044***	-0.220	1.121***	-0.283***	0.103	0.749*	0.011
Lvmh	-0.067***	0.012	0.009*	0.114***	-0.072***	-0.028***	-0.062	0.065**	-0.043***	-0.227**	0.205***	0.083***
Marks&Spencer	-0.067***	0.043***	0.004	0.023**	-0.041***	-0.003*	0.003	0.013	-0.031**	0.021	0.083	0.026**
Telenor	-0.089***	0.065**	-0.001	0.100***	-0.095***	-0.012***	-0.160	-0.021	-0.162***	-1.103***	1.021***	0.066**

Table 5. Price discovery measures for *Model I*

Information share (IS) and Gonzalo-Granger (GG) measures of price discovery for *Model I* are shown for the whole sample (Panel A), the pre-crisis period (January 2006 - July 2007, Panel B) and the in-crisis period (August 2007 - July 2009, Panel C). Mean (0-1) shows the mean value of the GG measure for CDSs, bonds, equities and options by restricting its values between 0 and 1 as suggested by Blanco et al. (2005). Signif. Mean is the mean GG measure calculated by attributing a value of zero to the individual GG values if they are not significant at the 5% level. For GG estimates: *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	IS (Midpoint)				GG			
	CDSs	Bonds	Equities	Options	CDSs	Bonds	Equities	Options
Panel A: Whole Sample								
Basf	0.61	0.06	0.12	0.34	0.82***	0.17	-0.05**	0.05***
Lvmh	0.11	0.38	0.04	0.47	0.34	0.49***	0.03	0.15***
Marks&Spencer	0.17	0.18	0.2	0.47	0.24	0.54***	0.09	0.13***
Telenor	0.02	0.47	0.04	0.47	0.05	0.90***	-0.03*	0.08***
Mean (0-1)	**0.23**	**0.27**	**0.10**	**0.44**	**0.36**	**0.53**	**0.01**	**0.10**
Signif. Mean					**0.21**	**0.48**	**0.00**	**0.10**
Panel B: Pre-crisis								
Basf	0.28	0.08	0.54	0.09	0.18**	0.06**	0.94**	-0.18*
Lvmh	0.00	0.05	0.11	0.83	0.00	-0.05	0.00	1.04**
Marks&Spencer	0.02	0.04	0.86	0.08	0.00	-0.01	0.96**	0.05
Telenor	0.52	0.05	0.08	0.34	0.54**	0.15	0.06*	0.25**
Mean (0-1)	**0.21**	**0.06**	**0.40**	**0.34**	**0.18**	**0.05**	**0.49**	**0.33**
Signif. Mean					**0.18**	**0.01**	**0.47**	**0.31**
Panel C: In-crisis								
Basf	0.59	0.06	0.13	0.35	0.82***	0.17*	-0.05**	0.05***
Lvmh	0.06	0.35	0.02	0.57	0.32*	0.50***	0.03*	0.15***
Marks&Spencer	0.16	0.18	0.19	0.48	0.23*	0.55**	0.09*	0.13***
Telenor	0.02	0.47	0.05	0.46	0.09	0.87***	-0.03	0.08***
Mean (0-1)	**0.21**	**0.27**	**0.10**	**0.47**	**0.37**	**0.52**	**0.03**	**0.10**
Signif. Mean					**0.21**	**0.48**	**0.00**	**0.10**

Table 6. Price discovery measures for *Model II*

Price discovery measures for *Model II*. Information share (IS) midpoint and Gonzalo-Granger (GG) measures of price discovery for CDS, bond spreads and option spreads are shown for the whole sample (panel A), the pre-crisis period from January 2006 to July 2007 (panel B) and the in-crisis period from August 2007 to July 2009 (panel C). Mean (0-1) shows the mean value of the GG measure for CDSs, bonds and options by restricting its values between 0 and 1 as suggested by Blanco et al. (2005). Signif. Mean is the mean GG measure calculated by attributing a value of zero to the individual GG values if they are not significant at the 5% level. For GG estimates: *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	IS (Midpoint)			GG		
	CDSs	Bonds	Options	CDSs	Bonds	Options
Panel A: Whole Sample						
Carrefour	0.15	0.01	0.85	0.75	-0.06	0.32***
Casino Guich.	0.17	0.14	0.70	0.30	0.42***	0.28***
Renault	0.05	0.01	0.95	-0.16	0.36	0.80***
Vodafone	0.12	0.63	0.25	0.39	0.55***	0.05***
Mean (0-1)	**0.12**	**0.20**	**0.69**	**0.38**	**0.30**	**0.36**
Signif. Mean				**0.00**	**0.24**	**0.36**
Panel B: Pre-crisis						
Carrefour	0.36	0.43	0.21	-0.52**	0.77**	0.74**
Casino Guich.	0.09	0.54	0.43	-0.13*	0.74**	0.39**
Renault	0.65	0.25	0.09	3.18***	-2.36***	0.18
Vodafone	1.00	0.00	0.00	1.03***	-0.03	0.00
Mean (0-1)	**0.53**	**0.31**	**0.18**	**0.50**	**0.38**	**0.33**
Signif. Mean				**0.50**	**0.38**	**0.28**
Panel C: In-crisis						
Carrefour	0.16	0.01	0.84	0.78*	-0.09*	0.31***
Casino Guich.	0.17	0.13	0.71	0.30*	0.42***	0.28***
Renault	0.04	0.01	0.96	-0.34	0.44	0.89***
Vodafone	0.11	0.65	0.25	0.38	0.57***	0.05***
Mean (0-1)	**0.12**	**0.20**	**0.69**	**0.37**	**0.36**	**0.38**
Signif. Mean				**0.00**	**0.25**	**0.38**

Table 7. Price discovery measures for *Model III*

The table shows the information share (IS) and Gonzalo-Granger (GG) measures of price discovery for Model III companies for the whole sample, the pre-crisis period (January 2006 - July 2007) and the in-crisis period (August 2007 - July 2009). Model III (a) includes the bond and option markets only, Model III (b) the equity and option markets only and Model III (c) the CDS and bond markets only.

		IS (Midpoint)		GG	
		Model III (a)			
		Bonds	Options	Bonds	Options
Upm	Whole Sample	0.71	0.29	0.74	0.26
	Pre-crisis	0.98	0.02	1.09	-0.09
	In-crisis	0.7	0.30	0.74	0.26
		Model III (b)			
		Equities	Options	Equities	Options
Stora Enso	Whole Sample	0.99	0.01	0.99	0.01
	Pre-crisis	0.38	0.62	0.37	0.63
	In-crisis	0.99	0.01	1.00	0.00
		Model III (c)			
		CDSs	Bonds	CDSs	Bonds
Vivendi	Whole Sample	0.64	0.36	0.49	0.51
	Pre-crisis	0.24	0.76	0.27	0.73
	In-crisis	0.35	0.65	0.34	0.66
Volkswagen	Whole Sample	0.33	0.67	0.26	0.74
	Pre-crisis	0.03	0.97	-0.37	1.37
	In-crisis	0.31	0.69	0.24	0.76

Table 8. Volatility spillovers

The table shows the frequency of significant (at the 5% level) volatility spillover parameters (a and b in equation 9) across CDS spreads, bond spreads, equity spreads and option spreads for companies in *Model I* based on a multivariate GARCH model. Results are reported for the whole sample, the pre-crisis period (January 2006 - July 2007) and the in-crisis period (August 2007 - July 2009).

	CDS to Bond	CDS to Equity	CDS to Option	Bond to CDS	Bond to Equity	Bond to Option	Equity to CDS	Equity to Bond	Equity to Option	Option to CDS	Option to Bond	Option to Equity
						Innovation spillovers (*a*)						
	a12	*a13*	*a14*	*a21*	*a23*	*a24*	*a31*	*a32*	*a34*	*a41*	*a42*	*a43*
Whole Sample	50%	0%	0%	50%	25%	0%	25%	50%	0%	50%	50%	50%
Pre-crisis	50%	75%	25%	0%	50%	0%	0%	0%	0%	25%	25%	50%
In-crisis	25%	50%	0%	25%	50%	0%	50%	50%	0%	50%	50%	25%
						Volatility spillovers (*b*)						
	b12	*b13*	*b14*	*b21*	*b23*	*b24*	*b31*	*b32*	*b34*	*b41*	*b42*	*b43*
Whole Sample	25%	75%	50%	50%	50%	50%	100%	75%	50%	75%	100%	75%
Pre-crisis	25%	75%	0%	25%	25%	25%	0%	0%	0%	25%	25%	50%
In-crisis	25%	50%	0%	0%	25%	0%	25%	50%	25%	75%	75%	100%

Table 9. Price discovery measures with and without the option market

This table reports the proportion of price discovery - as defined by the information share (IS) midpoint and mean Gonzalo-Granger (GG) measures - that takes place in the CDS, bond, equity markets in the absence of the option market and when it is included in the VECM specification (equations 1 to 4). Results are shown for the whole sample (panel A), the pre-crisis period (January 2006 - July 2007, panel B) and the in-crisis period (August 2007 - July 2009, panel C).

	IS Midpoint				GG			
	CDS	Bond	Equity	Option	CDS	Bond	Equity	Option
Panel A: Whole Sample								
Without options	23%	47%	35%	-	34%	57%	10%	-
With options	23%	27%	10%	44%	36%	53%	1%	10%
Difference	0%	-20%	-25%	44%	2%	-4%	-7%	10%
Panel B: Pre-crisis period								
Without options	27%	20%	53%	-	21%	11%	69%	-
With options	21%	6%	40%	34%	18%	5%	49%	33%
Difference	-6%	-14%	-13%	34%	-3%	-6%	-20%	33%
Panel C: In-crisis period								
Without options	25%	46%	31%	-	35%	57%	10%	-
With options	21%	27%	10%	47%	37%	52%	3%	10%
Difference	-4%	-19%	-21%	47%	2%	-5%	-7%	10%

Figure 1. Time-varying price discovery measure for Marks and Spencer

The Figures show the daily midpoint of the information share (IS) for the equity and option markets (upper panel) and the CDS and bond markets (lower panel) for Marks&Spencer.