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Unveiling Sovereign Effects in European Banks CDS Spreads Variations

Marc Peters and Hugues E. Pirotte

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JEL Classifications: G12, G21, G33.

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Abstract

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1 Introduction

The objective of this paper is to analyze the determinants of credit default swap (CDS) spreads for a sample of European banks over a period comprising the banking crisis from January 2006 to December 2011, thereby observing both normal and stressed market conditions. In particular, this paper tests variables specific to the banking industry and gives a focus to possible link with sovereign's credit standing.

CDS belong to the family of credit derivatives and are over-the-counter (OTC) financial instruments that transfer the credit risk related to a certain underlying asset between two

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counterparties without transferring the underlying asset itself. They thus enable counterparties, mainly financial institutions and banks, to efficiently manage their credit exposures (including those resulting from credit valuation adjustments or CVA) and diversify their credit risk portfolios. The easiness with which CDS contracts can be traded by financial institutions and banks have largely contributed to the fast growing expansion[1] of the related market, up to a peak of USD 62,2 trillion outstanding notional in December 2007 (ISDA Market Survey). Following the subprime crisis and considering increasing efforts in trade compression and clearing, the outstanding notional of CDS contracts has decreased steadily since 2008. According to the ISDA market analysis published in December 2012[2], the CDS market represents an adjusted notional outstanding of USD 24,3 trillion as of June 30, 2012.

In a CDS agreement, one party (the protection buyer) pays a periodic fee (usually expressed as a percentage - in basis points - of the notional value and called “spread” or “premium”) to another party (the protection seller) obliged to compensate for the default (or the occurrence of a similar contractually defined credit event) of the reference entity. The contract terminates either at maturity or earlier should a specified credit event occur. Typical credit events include failure to meet payment obligations when they are due and bankruptcy. They are defined in standardized agreements developed by the ISDA. Following the failure of Lehman Brothers in September 2008 and the consecutive G20 decisions, standardization and central clearing of CDS agreements are noticeably increasing. This will hopefully contribute to the enhanced transparency and information quality of such market[3].

By contrast to cash instruments, CDS can be traded without actually trading or owning the referenced underlying asset. This property enables financial institutions and banks to increase their exposures to credit risk or to speculate by notably selling “naked” CDS. Such speculative operations were under the spotlight during the recent sovereign crisis because of their potential detrimental effects on the overall stability of the financial system. Reinforcing the short-selling policies of European Member States, the European Commission consequently forbid written “naked” CDS[4] on sovereigns.

Since the price of a CDS (i.e. its spread) reflects the credit quality of the referenced underlying asset[5], this derivative instrument should be able to serve as a market-based indicator for detecting possible changes in credit risk. This intuition gave rise to the development of market-implied ratings and other similar indicators increasingly used by financial institutions and banks in their day-to-day risk management process as a

[1] Cf. Giglio S. (2011) : *The main reason for this growth in gross terms is that, due to the high liquidity of the CDS market, the easiest way to adjust the exposure to credit risk has been to enter new CDS contracts (possibly offsetting the existing ones) rather than operating directly in the bond market or cancelling CDS agreements already in place.*

[2] Based on BIS June 2012 semi-annual statistical release published in November 2012.

[3] For a reference regarding regulatory initiatives in this field, see Regulation (EU) N°648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories.

[4] See Regulation (EU) N°236/2012 of the European Parliament and of the Council of 14 March 2012 on short selling and certain aspects of credit default swaps.

[5] As perceived by the market.

complement to more traditional credit reviews and to external credit ratings[6]. This evolution is also noticeable for banking supervisors and central banks that are monitoring the financial health of the banking system by tracking CDS spreads evolutions. Hence, correctly understanding the drivers for those evolutions is key in order for policy setters and supervisors to take, with the necessary caution, the appropriate policy decisions and regulatory actions.

So far, while the literature has been quite rich in terms of explaining the determinants of CDS spreads for non-financial firms[7], their interactions with credit ratings as well as the price formation of such spreads by comparison to credit spreads or stock prices, very little has been done specifically in the field of financial institutions or banks in particular. Additionally, the time period generally analyzed remains quite limited and does generally not encompass both normal and stressed market conditions.

Following the 2007 subprime crisis and the consecutive bankruptcy of Lehman Brothers in September 2008, banks have been exposed to a continuous weakening of their financial health. Due to a general mistrust in the financial system and considerable uncertainties as regards certain valuation practices, market liquidity and funding liquidity were put under particular pressure. This was especially the case for Europe. In order to maintain commercial banks in going concern, central banks and governments were called for rescue. Several banking groups were recapitalized or became publicly held.

The positive response from the market was unfortunately temporary. Such measures of last resort, transferring the financial risks from banks to sovereigns, created a destructive spiral between the rescued banks and their respective governments, turning a financial turmoil into a sovereign crisis. In an attempt to break the vicious circle, the European Central Bank (ECB) introduced in October 2011 a first Longer Term Refinancing Operation (LTRO) assorted with an easing of its collateral requirements. Two months later, the ECB announced measures to support bank lending and money market activity, including two other LTRO's. Finally, in August 2012, the ECB had to announce its firm commitment to intervene in the government bond market through the Outright Monetary Transactions (OMT) programme to ease the market and political tensions. To our knowledge, the existing literature has not yet studied the influence of existing governmental supports on the determinants of CDS spreads for European banks, nor its dynamic through time.

Our results globally confirm the findings from the existing literature regarding the lack of significance of the structural model and its breakdown in times of stress. In addition, we confirm the importance of macro-economic components such as the general level of interest rates and the general state of the economy, particularly in times of stress. We find that before the crisis period the micro- and macro-components are predominant in the determination of CDS spread variations while the influence of countries' CDS becomes more important when entering further into the crisis period. Interestingly, southern European countries are the first to become significant at the start of the crisis. Progressively, all countries' CDS become increasingly significant, overweigh all other explanatory variables

[6] This use seems to provide an objective indicator. But since prices of CDS comprise both a credit risk premium and a market risk aversion component, it can also create potential self-fulfilling prophecies when these market-based implied measures are also used for collateral haircuts definitions.

[7] For example, see Collin-Dufresne et al. (2001).

and remain so even after the crisis period, thereby suggesting the focused attention of market participants for the sovereign dimension.

The remainder of this paper is organized as follows. Section 2 reviews previous works on the determinants of CDS spreads and their relations to (bond) credit spreads, stock prices or ratings. Section 3 describes our data set and presents our main assumptions. Section 4 describes the various steps in the methodology used to assess the determinants of CDS spreads and discusses the intuition regarding the selected explanatory variables. Sections 5 and 6 present our results. Section 7 concludes.

2 Literature Review

This section provides an overview of the existing literature in relation to our analysis, alongside three axes: (1) the link between traditional (bond) credit spreads and their derivatives-based measure through CDS, (2) the link between (semi-static) ratings and implied ones from CDS prices, and (3) the lead-lag informational analysis between these various markets.

2.1 The determinants of credit and CDS spreads

A first stream of the literature examines the determinants of credit and CDS spreads, starting from a Merton-type of structural model (see section 4 for further insight), and completing his approach through the introduction of other explanatory variables, usually related to the general state of the economy.

Looking at credit spreads, Collin-Dufresne et al. (2001) note the importance of macro-variables and the limitation of structural models that focuses on firm-specific variables only, a large portion of credit spread changes being found related to non-credit risk factors. This confirms many findings after the emergence of the first credit pricing theories that credit risk is probably predominantly systematic rather than specific. This has been further confirmed while analyzing the CDS market. Gilchrist et al. (2011) for instance demonstrated the importance of considering the business cycle perspective in explaining the determinants of credit spreads. Similarly, Berndt et al. (2005) suggest that CDS spreads are likely not attributed to credit risk alone and Annaert et al. (2013) notably conclude that liquidity and global economic variables are important to explain CDS variations. More recently, Keiler and Eder (2013) investigate the degree of systemic risk and the importance of potential spill-over effects in the banking system by analyzing the determinants of CDS spreads using spatial econometric approach. Such technique enables them to look at the existing cross-sectional interactions and to distinguish between three main components: a systemic one, a systematic one and an idiosyncratic one. The systemic factor is found highly significant for the CDS market. This confirms the intuition of Giglio (2011) that analyzes the evolution of the joint default risk of large banks during the financial crisis using the basis between CDS spreads and bond spreads as a proxy. His conclusion however underlines the importance of idiosyncratic risk in observed spreads' spikes, notably in early 2008.

In the context of this review, it is interesting to note a specific niche of the literature that analyzes the explanatory power of Merton's based structural models developed by the industry. While remaining model-specific, their conclusions could provide useful guidance for our research. Hence, through the estimation of default risk premia from US corporate bonds, Berndt et al. (2005) find that the expected default frequencies from the Moody's KMV model explain a large proportion of the cross-sectional variation in CDS spreads. However, substantial variation is noted for a given default probability. This suggests some caution in interpreting the predictive power of CDS spreads. Similarly, using the CreditGrades model, Byström (2006) finds that theoretical and empirical spread changes are significantly correlated. The correlations indicate a close relationship between the stock market and the CDS market and also indicate some predictive ability of the tested model. In this paper, we will follow a comparable approach in the sense that, close to the KMV setting, we will calculate the theoretical concept of "distance-to-default" based on Merton's model for each bank in our sample and compare it to the observed single-name CDS spread variations. By doing so, we will determine the explanatory power of the theoretical model and further complete our analysis through additional control variables that have notably been found useful in the existing literature or are deemed relevant in the context of financial institutions.

More recently, the literature has also had the opportunity to test the stability or relevance of previous results by analysing the determinants of CDS spreads before, at the beginning (see Alexopoulou et al. (2009)) and during the financial turmoil. Di Cesare and Guazzarotti (2010), using a methodology close to Byström (2006), provide a useful study using a sample of US non-financial companies in the period between January 2002 and March 2009. Similar to Collin-Dufresne et al. (2001), they have found that CDS spreads are driven by a common factor, which cannot be explained by indicators of economic activity, uncertainty and risk aversion. In addition, it results from their findings that, considering a stressed environment, the leverage becomes much more significant than volatility in explaining the changes in CDS spreads. Using monthly CDS spreads of 41 major banks and 162 non-banks, Raunig and Scheicher (2009) find that banks were perceived as being less risky than non-banks before the sub-prime crisis. During the crisis period, their results become broadly similar for banks and non-banks.

One of the few research performed specifically on banks and covering the period after the subprime crisis is provided by Annaert et al. (2013). Analyzing the determinants of CDS spread changes for 32 listed euro area banks over the period 2004 – 2010, they find an increasing explanatory power of the variables suggested by structural credit models after the crisis period. Similarly, market liquidity became significant in the aftermath of the crisis. They also confirm the findings of Collin-Dufresne et al. (2001) and Gilchrist et al. (2011) about the significance of general economic conditions. We note however that they do not estimate directly the output of the structural credit models but instead use an approximation of their components in their regression setup. In addition, they approximate liquidity using on the one hand the CDS bid-ask spread for the bank-specific component and on the other hand the swap and corporate bond spreads for the market-wide component. In this paper, we try to estimate the structural model output directly and opt for an indicator of liquidity based on the LIBOR-OIS spread that might be considered in our view as better depicting the possible situation on the interbank market, especially in terms of trust and confidence between financial institutions.

2.2 On the relation between CDS spreads and ratings

Considering CDS spreads as "pure" indicators of default probabilities, a second stream of research analyzes the predictive power of CDS spreads and the relationship with external ratings. For instance, Hull et al. (2004), considering both CDS and credit spreads, and Norden and Weber (2004), considering CDS spreads and stock prices, showed that the CDS market is usually very effective in anticipating rating changes, especially downgrades. While not specifically focusing on the interaction between spreads and ratings, the role of ratings in explaining the level of spreads for a given firm cannot be neglected. At this stage, our sample mainly consist of investment-grade banks (there is actually only one non-investment grade bank in our sample). Hence, an extension of the present paper could consider the enrichment of the sample in order to introduce a differentiation between investment-grade and non-investment grade firms, possibly via the use of dummy variables or via sub-sampling by ratings.

Interestingly, Hull et al. (2004), when analyzing the relationship between CDS spreads, bond yields and credit rating announcements, additionally confirm the theoretical relationship between CDS spreads and credit spreads. Similar conclusions have also been found by Blanco et al. (2005) and Zhu (2006), even if some deviations are noted and the explanatory power of the related variables is usually found weak.

2.3 Price discovery process

A third stream of the literature looks at the price discovery process and analyzes the lead-lag relationship between the CDS market and the bond market or the stock market. In this vein, Byström (2005) suggests that the CDS index spread narrows when stock prices rise and vice versa, the latter leading the price discovery process, and observes a significant correlation between the stock price volatility and the CDS spreads[8]. He finally finds a significant positive autocorrelation in the iTraxx market. Blanco et al. (2005), while testing the theoretical equivalence of CDS prices and credit spreads, suggest that CDS prices react more to firm-specific variables (equity returns and implied volatilities), especially in the short term, and that CDS prices tend to lead the price discovery process. According to Zhang et al. (2006), this quicker reactivity of CDS prices in the short term may be partly due to the absence of funding and short-sale restrictions in the derivatives market[9]. Consistent with Collin-Dufresne et al. (2001), they find that most of the variance in both CDS prices and credit spreads remains unexplained and possibly influenced by a common factor.

Zhu H. (2006) compares the pricing of credit risk in the bond market and the CDS market. He finds that the theoretical parity relationship is satisfied and that CDS spreads tend to respond more quickly to changes in credit conditions in the short run. These conclusions are similar to Blanco et al. (2005). Fung et al. (2008) find a dependence between the lead-lag

[8] This is in line with the implementation of Merton-like models where the implied information from stock prices is used as an input.

[9] We would thus expect the recent European regulation on short-selling to influence this conclusion. This could be further analyzed in a later study.

relationship and the credit quality of the underlying reference, the CDS market playing a more prominent role in terms of volatility spillover. Using weekly data of European financial and non-financial firms over the period January 2004 – October 2008, Alexopoulou et al. (2009) confirms the existence of a long-run relationship between the CDS and the corporate bond markets where the CDS market tends to lead the price discovery process. Following the financial turmoil in the summer 2007, the paper interestingly notes an increased sensitivity of CDS spreads to systematic risk while bond markets priced in more information about liquidity and idiosyncratic risk. These results are consistent with those of Norden and Weber (2004) and Zhu (2006).

Intuitively, given the role of CDS, credit risk should be the main determinant of CDS spreads. However, the existing academic literature has already demonstrated that other factors, having a more systematic nature, such as general economic conditions but also liquidity, plays a role. Recently, Giglio (2011) or Keiler and Eder (2013) further suggest the importance of a systemic factor.

Building on this literature and focusing on the European banking sector, this paper intends to further analyze the determinants of CDS spreads, starting from the distance-to-default parameter based on Merton's structural model, then introducing additional explanatory variables, as suggested by the existing literature and also including some variables deemed specific to the financial sector (such as the LIBOR-OIS spread and the tier 1 ratio), and finally investigating the possible influence of the related sovereigns (being the main systemic driver possibly determining the changes in CDS spreads for banks).

This paper contributes specifically to the existing literature by (1) completing the few studies performed on the bank CDS determinants; (2) analyzing the link between banks and sovereigns through the crisis cycle via the introduction of country variables; and (3) suggesting policy implications from our results.

3 Data

3.1 Data description

After cleaning the data, notably ensuring a balanced panel, our final dataset is composed of a sample of 16 quoted European banks[10] over the period from January 2006 to December 2011. For these banks, we have obtained weekly euro-denominated CDS mid-quotes from Bloomberg (313 data points for each bank), representing a total of 5.008 observations.

We have considered the 5-year maturity CDS contracts, being the most frequently traded, which is common to the existing literature in this field. CDS quotes result from an aggregation of multiple submissions by contributors. Hence, the quality of the information available may affect the results of our analysis. However, Mayordomo et al. (2010) have

[10] The list of selected banks is the following: Deutsche Bank AG (DE), Commerzbank AG (DE), BNP Paribas (FR), Société Générale (FR), Crédit Agricole SA (FR), ING Groep NV (NL), UBS AG (CH), Credit Suisse Group AG (CH), Banco Santander SA (ES), Intesa Sanpaolo (IT). UniCredit SpA (IT), Banco Bilbao Vizcaya Argentaria SA (PT), HSBC Holdings Plc (UK), Barclays Plc (UK), Lloyds Banking Group Plc (UK), The Royal Bank of Scotland Group Plc (UK).

analyzed six major sources of corporate CDS prices: GFI, Fenics, Reuters EOD, CMA, Markit and JP Morgan. Their results suggest that the CMA database offers the best quality information as their quotes lead the price discovery process in comparison with the quotes provided by other databases. Since Bloomberg incorporates CMA data feeds, we are comfortable about the quality of the data used in our study.

For each bank in our sample, we have obtained the weekly stock prices from Datastream. On this basis, we have calculated the related stock returns as well as the weekly historical volatility of stocks. In parallel, considering the importance of volatility parameters as emphasized notably by Benkert (2004) and Zhang et al. (2006), we use a GARCH methodology to determine the volatility dynamics of stocks used in the determination of our structural model in order to capture the full feature thereof.

As in Collin-Dufresne et al. (2001), the risk-free rate is proxied by the 10-year EMU bond index[11] and the slope of the yield curve is estimated through the spread between the 10-year EMU bond index and the 2-year EMU bond index[12]. Other variables reflecting the general state of the economy include the stock index return (Eurostoxx 50) and the stock index volatility (VSTOXX), both obtained on a weekly basis from Datastream.

Bank specific information, such as the number of shares outstanding as well as the balance sheet information (total liabilities, equity, cash and due from banks) necessary for the calculation of the bank's asset value and the bank's debt value under the structural model or the tier 1 ratio, comes from Bankscope. Such information was only available at year-end. See sub-section 4.1 for further details on the computation of the structural model and the approach we have followed to compensate for the static aspects of this data.

Following Zhu (2006) we have ensured the consistency in currency denomination between all our variables and the CDS contracts. We have also taken care of possible differences in quotation unit standards.

In the context of the analysis of the possible influence of sovereigns on banks' credit default spreads, we have downloaded from Bloomberg the weekly euro-denominated CDS mid-quotes for the corresponding sovereigns, in which banking groups' headquarters are located. In this latter case, we are confronted to an incomplete dataset[13] for which some missing observations have been replaced by the previous available quote.

3.2 Stationarity

As pointed out by Di Cesare and Guazzarotti (2010), *models in first-differences are generally preferred notably regarding possible problem of non-stationarity of the processes for CDS spreads.*

[11] Note that Benkert (2004) suggests that the exact choice of the maturity is immaterial according to his results and analysis.

[12] Benkert (2004) suggests that the construction of a slope proxied as the difference between a long and a short rate could induce multi-collinearity. This is however not emphasized nor presented as introducing particular bias by the rest of the literature.

[13] This is similar to Benkert (2004) that was confronted to a frequently interrupted time series with frequent periods of missing or outdated observations. An identical situation has been described by Zhang et al. (2005). While the situation massively improved because of the rapid growth of the CDS market, missing information seem to remain structurally present in particular for non-USD denominated series.

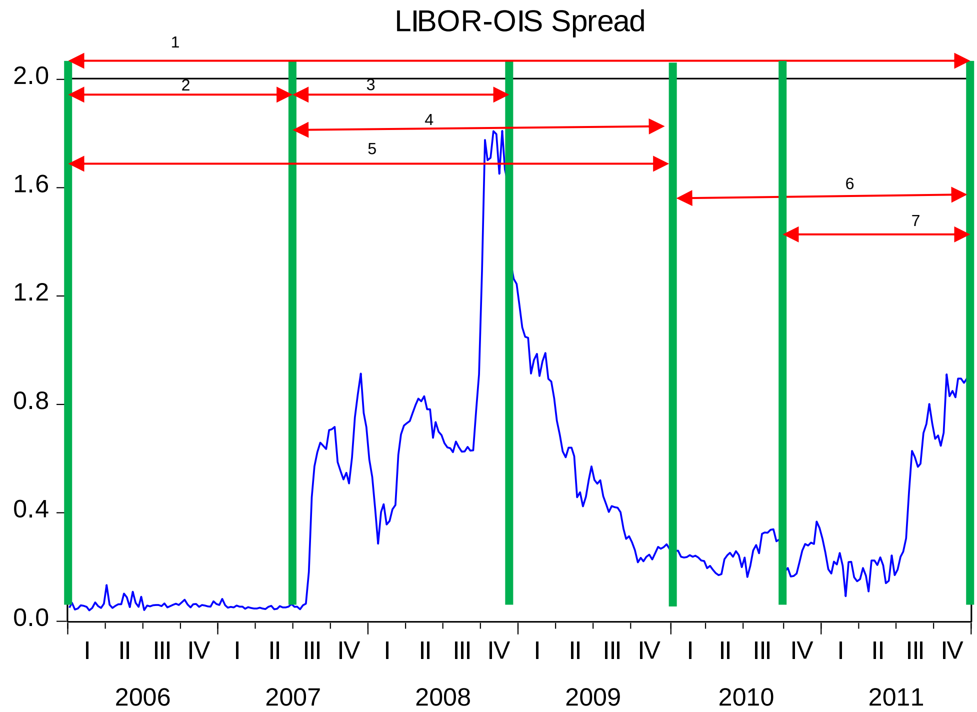
All variables used in our regressions have been tested (see sub-section 4.2 for the model specification). The detailed results of our tests are not presented in this document for the sake of simplicity but are available on demand. Finally, all variables are considered in first-differences with the exception of the (usual) following ones: the slope of the yield curve, stock returns, and the stock index return.

The resulting final selection of first-difference variables is different from Collin-Dufresne et al (2001) only for the case of the slope of the yield curve but we have followed coherently the results of our tests, based on our sample period.

3.3 Sample and sub-samples

Our analysis is run according to the methodology described in the following section and according to a decomposition of the entire sample period in sub-sample periods identified on the basis of the LIBOR-OIS evolution through time as represented in the following graph.

Figure 1 - LIBOR-OIS Spread time decomposition. Chart representing LIBOR-OIS weekly spread data from January 2006 to December 2011. Seven subsamples are defined on the graph conditional on the various tranches of behaviour of the spread.



Hence, the sub-sample periods identified are the following ones:

Table 1 **Identified sample periods** This table shows the various periods of time identified through the visual analysis of the LIBOR-OIS spread chart (Figure 1) and corresponding to various phases of the evolution of the crisis.		
Sample n°	Reference period	Time span

1	Full	5 January 2006 to 29 December 2011
2	Pre-crisis	5 January 2006 to 28 June 2007
3	(Subprime) Crisis (1^{st})	28 June 2007 to 20 November 2008
4	(Subprime + Lehman-effect) Crisis ($1^{st}+2^{nd}$)	28 June 2007 to 31 December 2009
5	Pre-crisis and Crisis ($1^{st}+2^{nd}$)	5 January 2006 to 31 December 2009
6	Post-crisis ($1^{st}+2^{nd}$), incorporating the banking liquidity stress and state aids	31 December 2009 to 29 December 2011
7	Similar to 6 but more focused on the banking liquidity stress and state aids	30 September 2010 to 29 December 2011

We note here that sub-samples 3, 5 and 7 will be mainly used for our robustness checks and the analyses performed under section 6 regarding possible sovereign effects.

4 First developments

The natural starting point for analyzing CDS determinants lies in the structural models based on Merton (1974). So far, most of the literature empirically testing such models use proxies for the embedded firm-specific elements of the model, mainly the leverage ratio and asset volatility.

We opt for an alternative approach, trying to estimate directly the theoretical model output. Hence, inspired by Collin-Dufresne et al (2001) and Annaert et al. (2013) but following a methodology suggested by Di Cesare and Guazzarotti (2010), we first determine the distance-to-default component generated by an application of Merton's structural model (1974) and Black & Scholes (1973). Our analysis starts then by comparing such output with the observed historical CDS spreads. Though Byström (2006) found that theoretical and empirical spread changes are significantly correlated[14], the literature suggests an incomplete determination of the observed spread by the theoretical one. Consequently, this first analysis is further completed by controlling for additional explanatory variables as suggested by the existing literature and notably related to general market conditions.

Our analysis of the possible influence of the sovereigns' credit standing on related variations of banks' CDS spreads run in Section 6 will offer a more systemic perspective to the classical approach developed so far.

4.1 A structural model variable: the distance-to-default

Theoretical background

The existing literature mainly distinguishes two broad approaches for modelling credit spreads: reduced-form models and structural models.

[14] We note here that such observation should likely be nuanced (if not invalidated) in the case of financial institutions for which the level of leverage is particularly high, thereby further influencing the outcome of the theoretical model.

The first category, widely used by practitioners for pricing credit risk, considers that default occurs at a certain randomly defined time in the future. Credit spreads are generally inferred from the historical probabilities of default associated with the firm's rating class and transition matrices provided by well-known rating agencies such as Moody's and Standard & Poor's. This could be seen as a top-down approach aimed at calibrating prices on the related implied default probability and loss-given-default.

The second category, introduced by Merton (1974), is based on the traditional Black and Scholes (1973) option pricing theory to model the value of a firm's equity and debt. Starting from Modigliani and Miller (1958), thereby assuming that the value of a firm is unaffected by its capital structure (composed of equity and debt in this case), a firm's default is deemed to happen when the market value of its total asset falls below a certain threshold, defined by the nominal value of its outstanding debt at maturity. By opposition to reduced form models, these structural models are mostly used in a bottom-up approach aiming at assessing the credit risk exposure through the fundamentals of the firm. In the case of the plain vanilla option-like framework of Merton (1974), the time of examination of default is fixed. When a firm defaults, bondholders receive the value of the firm's total asset. Hence, a firm's capital structure can be seen as a combination of options where shareholders are long a European call option (right to "buy" the firm in going concern) and bondholders are short a European put option (obligation to "buy" the firm in default), both with a strike price corresponding to the above-mentioned threshold.While largely used by the literature to examine the determinants of credit spreads (see Alexopoulou et al. (2009) or Annaert et al. (2013) for a similar statement), structural models are however subject to strong assumptions related notably to the existence of a single debt, the timing of default (at the debt's maturity for the simpler case[15]) and the absence of costs related to the default.

The main necessary inputs to the model are: the risk-free rate, the nominal amount of outstanding debt, the firm's asset value and its volatility. For quoted entities, most of those variables can be found (or obtained) using available information from the stock market and published annual reports. Hence, calculating the distance-to-default component from the theoretical model has required preparatory steps and calibrations as explained in the following paragraphs.

Getting to the distance-to-default (or DD)

Merton (1974) proposes to use back the Black & Scholes (1973) option pricing framework in the following setting:

$$Risky\ debt(D) = Riskfree\ debt - Put\ Option \qquad (1)$$

where the put option can be seen as the value of the limited liability right of shareholders, i.e. the right to default when the asset-liability equilibrium of the firm is not satisfied anymore. Thus:

$$Put\ Option = Fe^{-r_f T} N(-d_2) - V_a N(-d_1) \qquad (2)$$

[15] Some more advanced models of the like propose a barrier option pricing model (Bryis & De Varenne (1997), Pirotte (1999b)).

where, in our context, V_a is the market asset value of the bank, F is the total face value of the debt of the bank (considered simplistically as one single bond issue under Merton (1974)), T is the average maturity of the liability side, σ_a is the asset volatility, r_f is the risk free rate, $N(-d_2)$ (and $N(-d_1)$ respectively) represents the probability of $V_a < F$ at T, and

$$d_1 = \frac{\ln(\frac{V_a}{Fe^{-r_f T}})}{\sigma_a\sqrt{T}} + \frac{1}{2}\sigma_a\sqrt{T}, \quad d_2 = d_1 - \sigma_a\sqrt{T} \tag{3}$$

Overall, the market value of assets is equal to the sum of both market values of equity and debt, namely: $V_a = E + D$, and D is obtained through:

$$D = \underbrace{Fe^{-r_f T}}_{risk\ free\ debt} - \underbrace{N(-d_2)}_{PD}\left[\underbrace{Fe^{-r_f T} - V_a\frac{N(-d_1)}{N(-d_2)}}_{E_0(LGD)}\right] \tag{4}$$

The notion of distance-to-default (DD) is genuinely embedded in the calculation of the structural model (see equation (4) above). $N(-d_2)$ represents the probability of default, and the expression of d_2 relies on the following ratio:

$$DD = \frac{\ln\left(\frac{V_a}{Fe^{-r_f T}}\right)}{\sigma\sqrt{T}} \tag{5}$$

The numerator could be seen as the distance by itself (i.e. the present value of the difference between the value of assets and the value of the debt) and the denominator, $\sigma\sqrt{T}$, could be interpreted as the velocity at which the value of assets could fall below the value of the debt, thereby triggering the default state. Expression (5) was thus named “distance-to-default” and is notably used in practice by KMV Moody’s for example.

The necessary inputs of DD are provided through the following iterative procedure. The key advantage when implementing this model, is to realize that E is traded and thus easily known. E is itself a call option on the same asset-liability structure:

$$E = call(V_a, F, \sigma_a, T, r_f) \tag{6}$$

Thus, it is easy to invert it to get the implied σ_a and V_a. But these makes two unknown variables. The approach used by Pirotte (1999a) relies on Ronn & Verma’s (1986) idea to add a second equation that relates the σ_a (unobservable) to the σ_E (observable):

$$\sigma_{call} = \sigma_E = \frac{V_a\left(\frac{\delta E}{\delta V_a}\right)}{E}\sigma_a = \frac{V_a N(d_1)}{E}\sigma_a \tag{7}$$

Using σ_E and an accounting estimate of V_a as starting points, iterating with (6) and (7) allows to converge to a pair of variables σ_a and V_a. Those are then used in (5) to get the DD corresponding estimate.

In the context of the present paper, we determine the various original parameters through the following data mappings:

- r_f = the yield of the 5-year EMU bond index obtained from Datastream.
- $F =$ the value of each bank's debt (from Bankscope). The value of the debt (F) is obtained by subtracting the book values of "equity" and "cash and due to banks" from the total liabilities.
- $T =$ 5-year maturity to remain consistent with the maturity underlying the observed CDS instruments.
- E = obtained by multiplying the weekly quotes obtained from Datastream with the number of shares outstanding obtained from Bankscope.
- V_a(book value) = sum of F and E.

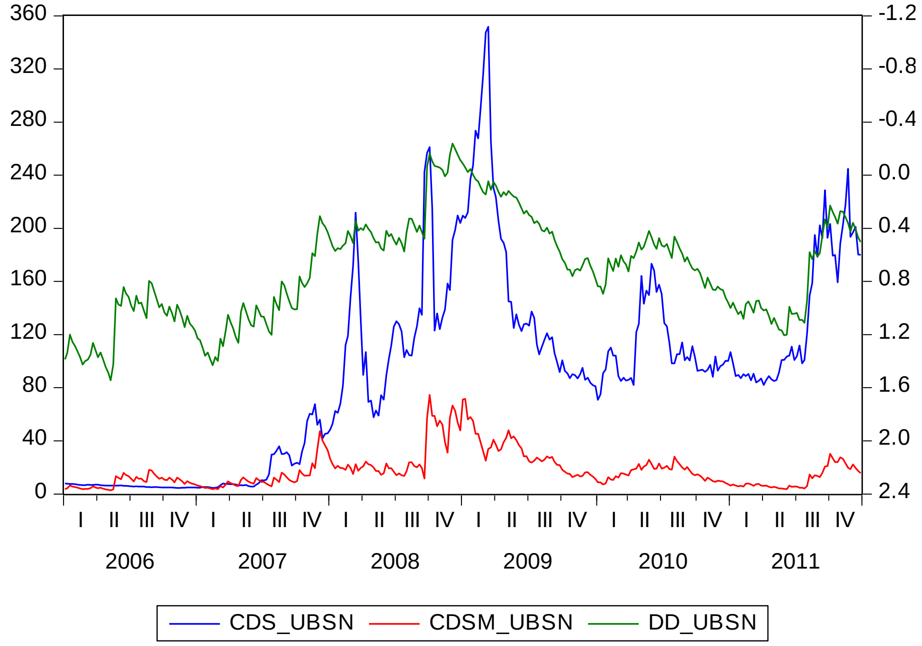
Along with the fact that *DD* is a notion more commonly used by practitioners in monitoring exercises and is relatively straightforward in its interpretation (facilitating the analysis thereafter), using *DD* enables us to somehow alleviate the limitations of Merton (1974), being those of Black & Scholes' (1973) framework. Indeed, technically speaking, such framework requires in particular the normality assumption of asset returns and the pricing of the credit risk premium by the market as defined through the value of a put option. In practice, V_a is not directly traded (which makes the no-arbitrage framework of a limited application) and the credit risk premium seems to be exponentially increasing with lower ratings, much more than what the Black & Scholes pricing produces. In the end, the idea is not to test Merton's model *per se* but to obtain a good theoretical proxy as an ingredient in the determination of the market CDS prices.

We note here that, as can be seen from equation (5), the distance-to-default is mainly influenced by the stock volatility and the leverage (i.e. the ratio between the value of assets and the value of the debt), the latter being particularly important for financial institutions like banks. This particularity has to be kept in mind when analyzing the contribution of these two elements to the observed CDS spreads.

The following table provides an illustration of the relationship through time between the observed CDS spreads, the theoretical CDS spreads[16] (both left scale) and the distance-to-default component (right scale) for UBS AG.

[16] Calculated for illustrative purpose.

Figure 2 - Evolution of observed CDS, theoretical CDS and DD. This chart provides a comparison of the evolution of both the observed and the computed CDS weekly spreads as well as the "quasi" distance-to-default measure (DD) in the Merton's sense.



4.2 Model specification

Based on (most) explanatory variables used in the existing literature (highlighting the rather idiosyncratic or systematic nature of the considered variables) and considering two complementary variables, deemed specific to the banking sector (i.e. the Libor-OIS spread and the Tier 1 ratio), we test the determinants of observed CDS spreads variations using a balanced panel regression (with fixed effects) under the following form:

$$\Delta CDS_{i,t}^{obs} = \gamma_i + \beta_{1,i}\,\Delta DD_{i,t} + \beta_{2,i}\,\Delta Rf_t + \beta_{3,i}\,Slope_t + \beta_{4,i}\,\Delta LIBOIS_t + \beta_{5,i}\,MRet_t + \beta_{6,i}\,\Delta MVol_t + \beta_{7,i}\,HRet_{i,t} + \beta_{8,i}\,\Delta HVol_{i,t} + \beta_{9,i}\,\Delta Tier1_{i,t} + \varepsilon_{i,t} \quad (8)$$

where, $\Delta CDS_{i,t}^{obs}$ is the first-difference of the observed CDS spread for bank i at time t, γ_i represents the intercept for bank i, $\beta_{1\ to\ 9,i}$ are the regression coefficients for bank i, and $\varepsilon_{i,t}$ is the corresponding residual.

where, idiosyncratic (or firm-specific) variables are represented by: $\Delta DD_{i,t}$ being the first-difference of the theoretical distance-to-default calculated for bank i at time t, $HRet_{i,t}$ being the weekly bank stock return (often used by the literature as a proxy for the leverage), $\Delta HVol_{i,t}$ being the weekly change in bank's equity volatility calculated from the weekly stock quotes obtained from Datastream.

We also introduce the Tier 1 ratio as a specific idiosyncratic parameter for the bank industry in our regression. The Tier 1 ratio represents the level of regulatory capital a bank is holding in order to face the risks of its activities (or its risk-weighted assets). We could expect markets to incorporate this information in the anticipation of the credit standing of banks, thereby possibly influencing the CDS spread of the related banks.

where, systematic variables are represented by:

- For the general level and structure of interest rates: ΔRf_t is the weekly change of the risk-free rate at time t proxied by the 10-year EMU bond index obtained from Datastream and $Slope_t$ represents the term structure slope at time t proxied by the spread between the 10-year EMU bond index and the 2-year EMU bond index;
- For the general business climate: following Collin-Dufresne et al. (2001), Zhu (2006) and Annaert et al (2013), we include $MRet_t$ being the market wide stock index return at time t based on the weekly Eurostoxx 50 data obtained from Datastream and following Berndt et al (2005) and Annaert et al (2013), we use $\Delta MVol_t$ being the weekly change in the stock index volatility at time t based on the weekly VSTOXX data obtained from Datastream to measure market wide implied volatility;
- Finally, considering that our study aims specifically at the banking industry, we opt for the spread between Libor and OIS as a proxy for the general state of the banking system[17] but also as a reflection of possible market wide liquidity strains. This approach is similar to Keiler (2013). $\Delta LIBOIS_t$ represents thus the weekly change in spread at time t between Libor and OIS.

Our approach is purposely progressive, testing first each explanatory variables separately and then considering all variables together following the above regression set-up for the combined effects. This approach also enables us to take account of possible colinearity issues and, consequently, select the independent variables that will be used in section 6. All our regression results exhibit a Durbin-Watson statistic between 1.5 and 2.5 thereby suggesting the absence of significant autocorrelation problems. To compute the p-values for our estimated coefficients, White (1980) heteroskedasticity-robust standard errors are used. To account for possible endogeneity issues, we have performed Granger causality tests on our variables. The results globally comfort us with the set-up of our regression in the absence of cointegration.

The following table provide the intuition on the expected relationship for the control variables used in the current set up of our model.

[17] The Libor-OIS spread is considered, notably by A. Greenspan, as *a barometer of fears of bank insolvency*.

Table 2
Expected relationships in the data

This table summarizes the expected relationships between the various control variables and the dependent variable, i.e. the evolution of the CDS spread, according to the theory and previous empirical evidence, and presents the major related papers.

Control variables	Expected Relationship	Rationale
$\Delta DD_{i,t}$	Negative	The deterioration of the credit standing of a counterparty would result in a broadening of the related CDS spreads but the distance-to-default would tighten.
$HRet_{i,t}$	Negative	Following Annaert et al. (2013), we expect a negative relation between stock returns and credit spreads. A booming period exhibiting high stock returns should comfort investors about the financial health of a firm and the existence of future profitability. Hence, the default probability should be lowered. On the contrary, credit spreads are expected to increase with leverage. Indeed, as explained by Annaert et al. (2013), if the stock returns fall, the leverage in terms of market value will increase (the market value of firms' assets being proxied by the stock returns; the leverage being the debt-to-asset ratio).
$\Delta HVol_{i,t}$	Positive	Higher volatility is expected to generate higher credit spreads as a reflection of increased uncertainties and risk that the default threshold could be triggered. We thus expect a positive relationship between our indicators of volatility and the spreads. This is confirmed from a pure option-pricing perspective.
$\Delta Tier1_{i,t}$	Negative	We could expect a negative relationship with the CDS spread. Indeed, a comfortable Tier 1 ratio should in principle be reassuring about a bank's ability to withstand losses and continue to meet its financial obligations in going-concern.
ΔRf_t	Negative	As underlined by Annaert et al. (2011), *interest rates are positively linked to economic growth and higher growth should, ceteris paribus, imply lower default risk*. We thus expect a negative relationship between the risk-free rate (proxied by the 10-year EMU index bond) and the credit spread.
$Slope_t$	Uncertain	Similar to Collin-Dufresne et al. (2001), we have introduced the slope of the yield curve as an indicator of the possible future evolution of the general state of the economy. A positive slope is associated with a positive view on the evolution of the economy and hence with a low default probabilities. We thus expect a negative relationship between the slope and the credit spreads. However, Di Cesare and Guazzarotti (2010) underline the uncertainty associated with the expected sign of this coefficient. They notably point out that: *the increase in expected future interest rates may reduce the number of profitable projects available to a company and, in turn, increase credit spreads*. They further suggest that: *a higher level for the slope would imply, ceteris paribus, a lower level for the short-term interest rate which is usually associated with worsening economic conditions and higher credit spreads*.
$\Delta LIBOIS_t$	Positive	Regarding market wide liquidity, possible tensions in the banking system will be reflected in a certain scarcity of this resource. The Libor-OIS spread being an indicator for such tensions, we expect a positive relationship between the Libor-OIS spread and the credit spreads.
$MRet_t$	Negative	Stock index return and stock volatility index have been widely used in the literature as proxies for the general business climate. A positive business climate, exhibiting high stock index return and low stock volatility index, will be associated with lower default probabilities and hence a low level of credit spreads. We thus expect a negative relationship between stock index return and credit spreads as well as a positive relationship between stock volatility index and credit spreads.
$\Delta MVol_t$	Positive	

5 First results

5.1 Descriptive Statistics

Table 3 represents the descriptive statistics for all variables used in regression (8) presented above. It corresponds to a balanced sample over a 5-year period from 5 January 2006 to 29 December 2011. There are in total 5008 observations divided into 16 cross sections.

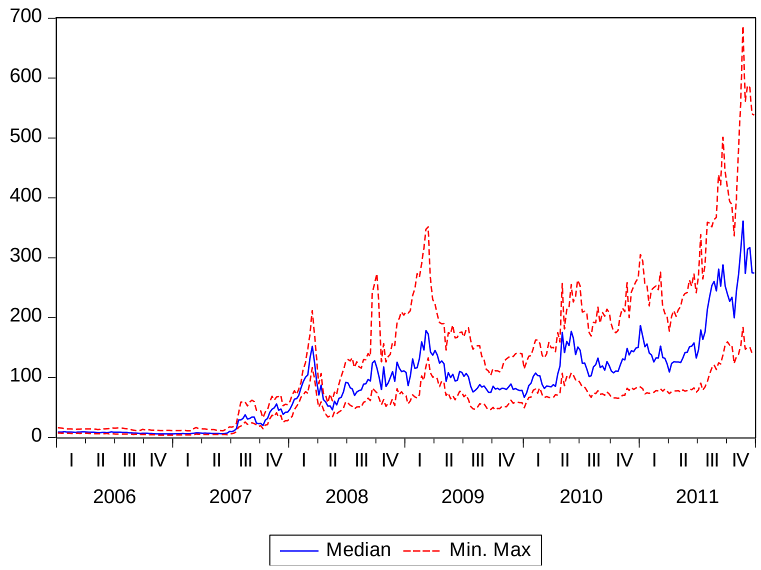
Table 3 comes here

We note that CDS spreads exhibit substantial cross-sectional differences and time variations (see Table 4 and Figure 3 here below for bank by bank market CDS spreads descriptive statistics and illustration). This is summarized by Figure 4 that shows a steadily increasing trend since the first quarter of 2007.

Table 4 comes here

Figure 3 comes here

Figure 4 - European CDS spread evolution for all banks. Weekly spread data from January 2006 to December 2011. The chart provides the median, min and max boundaries.



We also note a significant level of cross-sectional correlation, as shown in Table 5 for the Spearman rank-order correlation, possibly indicating the influence of common systematic and systemic factors.

Table 5 comes here

5.2 Correlations

The following tables provide the average correlations between the variables used in equation (8) above over four sample periods as defined on the basis of the LIBOR-OIS spread evolutions (i.e. samples 1 "full", 2 "pre-crisis", 4 "crisis" and 6 "post-crisis"). This review of the correlations can already inform us about the possible relationships between variables and their evolutions through time as well as providing us with a first intuition about the results.

Full sample period (5/01/2006 – 29/12/2011)

<u>*Table 6 comes here*</u>

The correlations between the explanatory variables and the observed CDS spread variations have signs that are consistent with the intuition. We already note particularly low correlation level between the observed CDS spread variations and the distance-to-default variations. We also observe a noticeable relationship between the observed CDS spread variations and the market index return (almost 50%), the market volatility index (around 24%) and the individual stock return (almost 46%).

Not surprisingly considering the set-up of the structural model, we observe a strong relationship between the distance-to-default and the individual stock volatility, i.e. about 49%.

Finally, we note the relationship between the LIBOR-OIS spread variations and the stock market variables.

Pre-crisis period (5/01/2006 – 28/06/2007)

<u>*Table 7 comes here*</u>

The correlation between the explanatory variables and the observed CDS spread variations have signs that are consistent with the intuition, except for the slope and the tier 1 ratio.

The correlation between the observed CDS spread variations and the distance-to-default variations remain low but however slightly increasing in the pre-crisis period. The relation between the observed CDS spread variations and the market index return as well as the market volatility index changes seems irrelevant before the crisis (while the correlation between the observed CDS spread variations and the individual stock return remains relevant – but lower – around 20%).

We continue to observe the relationship between the LIBOR-OIS spread variations and the stock market variables.

In crisis period (28/06/2007 – 31/12/2009)

<u>*Table 8 comes here*</u>

The correlation between the explanatory variables and the observed CDS spread variations have signs that are consistent with the intuition, except for the LIBOR-OIS spread variations (GLIQ). As expected, the correlation between the observed CDS spread variations and the distance-to-default is decreasing in crisis period (likely due to the presence of volatility breakdowns during crisis periods that are not reflected correctly in the theoretical setup).

We also note that, unsurprisingly, times of stress increase the correlation between variables. In particular, we observe an increasing correlation between the observed CDS spread variations and the market index return (almost 35%), the general level of interest rates and the slope of the term structure of interest rates (respectively 22% and 14%) and the individual stock return (about 38%). This tends to suggest the increasing importance of macroeconomic variables in times of stress.

Post-crisis period (31/12/2009 – 29/12/2011)

<u>*Table 9 comes here*</u>

Interestingly, in the post-crisis period, the correlation between the explanatory variables and the observed CDS spread variations have signs that are again consistent with the intuition.

The correlation between the observed CDS spread variations and the distance-to-default is increasing in comparison with the crisis period and, interestingly, up to a level higher than before the crisis. We note also that the crisis has likely exacerbated the correlation between the observed CDS spread variations and the LIBOR-OIS spread variations as well as the other market variables (i.e. the market index return and the market volatility index variations). Unsurprisingly, the theoretical model remains massively influenced by the market and stock volatilities.

We thus note consequently that, in the post-crisis period, the correlation between variables seems to have been generally exacerbated by the crisis period.

5.3 Regression results: individual variables

First, we regress individually the observed credit default spreads to each explanatory variables considered in equation (8) over the full sample period from January 2006 to December 2011.

The results for these individual regressions are summarized in table 10.

<u>*Table 10 comes here*</u>

Comments on the idiosyncratic variables

The results from these individual regressions are globally consistent with the existing literature. Regarding the structural model output, we note that the estimated parameter is statistically significant over the entire sample period (95% significance level). The related R-squared coefficient is however particularly low. This result suggests that there are possibly other independent variables that could help explaining the changes of observed CDS spreads.

The individual stock return has the expected sign and is statistically very significant (99% significance level). The individual stock volatility is not significant on the tested sample period[18]. Hence, we exclude this variable from our analysis.

The tier 1 coefficient is found not significant[19]. Hence, the Tier 1 ratio does not seem to contribute materially to the determinants of CDS spreads variations and we prefer to exclude it from our analysis at this stage. This lack of significance could be quite surprising. However, recent history tends to illustrate that regulatory ratios are poor indicators of the true financial health of credit institutions (see notably the speech given by Andrew G. Haldane, Executive Director of the Bank of England, at the American Economic Association on 9 January 2011). Such a lack of market trust in prudential ratios should receive adequate attention from prudential authorities, especially in a context where confidence in the banking sector should be restored.

Comments on the systematic variables

Considering that the LIBOR-OIS spread is seen as an indicator of possible tensions on the interbank market, we expect a positive relationship between its variations and the CDS spreads variations. This relation is confirmed and reinforced by the high statistical significance of the related coefficient (99% level).

The sign of the coefficient for the level of interest rates is found consistent with our intuition for the sample period tested. We note that its high statistical significance as well as the importance of the coefficient are consistent with the existing literature (for instance, see Annaert et al. (2013) and Di Cesare and Guazzarotti (2010)). Regarding the slope, the sign of the related coefficient is found consistent with Collin-Dufresnes et al. (2001). The coefficient itself is found highly significant.

The coefficient related to the stock index return is highly significant (at the 99% level) and its sign is consistent with our intuition. The result for the stock volatility index is equally fitting our intuition. The coefficient is found highly significant.

In the next section we run the full regression set-up as represented by equation (8) but considering the elimination of the individual stock volatility and the tier 1 ratio as mentioned above. This enables us to better identify the combined effects of the independent variables and confirm our selection thereof.

5.4 Regression results: all variables

The complete sample, selecting variables

Table 9 (see Appendix 1) presents the results of the following full regression set-up (see equation (9) below) over the entire sample period, from January 2006 to December 2011.

[18] This observation is valid for all but one sample periods tested. We note that the coefficient is only significant at the 95 % level during the pre-crisis period with an intuitive sign.

[19] This observation is valid for all but one sample periods tested. We note that the coefficient is only significant at the 95% level during the pre-crisis period but with a counterintuitive sign.

$$\Delta CDS_{i,t}^{obs} = \gamma_i + \beta_{1,i}\,\Delta DD_{i,t} + \beta_{2,i}\,\Delta Rf_t + \beta_{3,i}\,Slope_t + \beta_{4,i}\,\Delta LIBOIS_t + \beta_{5,i}\,MRet_t + \beta_{6,i}\,\Delta MVol_t + \beta_{7,i}\,HRet_{i,t} + \varepsilon_{i,t} \quad (9)$$

In comparison with the results presented in the previous sub-section, we note some sign reversions or lose of significance. Therefore, before going further with our analysis, our variables need further investigation notably considering possible colinearity issues as suggested by the correlation matrices presented under sub-section 5.2 (see tables 6 to 9)[20].

Further regressions are thus made over the same full sample period in which independent variables are alternatively added or subtracted in order to test for their respective contributions and relevance. In particular, the highest level of correlation across our sample periods concerns $MRet_t$, $\Delta MVol_t$ and $HRet_{i,t}$. Hence, we test successive regressions for those three variables alternatively. The highest level of (adjusted) R-squared will determine the selection of variables.

Similarly, we test $Slope_t$ for which the significance seems to fade away when considered jointly with the other explanatory variables and $\Delta LIBOIS_t$ that exhibits relatively high levels of correlations with the market return and volatility variables[21].

<u>*Table 11 comes here*</u>

Following these regressions results, we decide to exclude $\Delta MVol_t$ and $HRet_{i,t}$ from our further analysis due to their strong interactions with $MRet_t$. We also observe a relationship between the latter and both $Slope_t$ and $\Delta LIBOIS_t$. Considering the particular contribution of $MRet_t$ to the explanatory power of our analysis but recognizing the possible relevance of both $Slope_t$ and $\Delta LIBOIS_t$ in the context of our study, we decide to constitute two separate sets of regression, one including $MRet_t$ (called "panel A") and the other including $Slope_t$ and $\Delta LIBOIS_t$ (called "panel B"), for further exploration.

Testing the period samples

Proceeding further with our selection of variables, we test now the different sample periods defined in sub-section 3.3 on the basis of the LIBOR-OIS spread evolution using the following regression set-up.

$$\Delta CDS_{i,t}^{obs} = \gamma_i + \beta_{1,i}\,\Delta DD_{i,t} + \beta_{2,i}\,\Delta Rf_t + \underbrace{\beta_{3,i}\,Slope_t + \beta_{4,i}\,\Delta LIBOIS_t}_{Panel\ B} + \underbrace{\beta_{5,i}\,MRet_t}_{Panel\ A} + \varepsilon_{i,t} \quad (10)$$

Results are presented in Table 10 below for the four non-overlapping sample periods already used in sections 5.2. The other periods identified in sub-section 3.3 have been used for our robustness checks. The related results confirm comments provided below. They are not disclosed but are available on demand.

<u>*Table 12 comes here*</u>

[20] Tables 6 to 9 present correlations matrices for the four main sample periods under review. Correlations above 0.30 have been conservatively considered as potentially creating colinearity issues.

[21] This observation seems to be intuitively correct as both systematic elements reflect the state of the economy, the libor-ois spread being a more specific reflection of the state of the financial system.

Regarding panel A:

- Distance-to-default: the structural model coefficient is of intuitive sign and is statistically significant over all sample periods (90% significance level at the lowest in the pre-crisis period) but the post-crisis period. While the results of an individual regression over the different sample periods are consistent with the existing literature[22] (results undisclosed), the coefficient considered jointly with the panel A variables seems to have increased significance (possibly highlighting residual collinear effects or illustrating the fact that the distance-to-default component is less affected by the restrictive assumptions of Merton's model). Interestingly, this seems to suggest however that the market seemed to show lesser focus on pure idiosyncratic parameters at the exit of the sub-prime crisis.

- General level of interest rates: consistent with the literature, the risk-free rate is found particularly significant in explaining observed CDS spreads. The negative sign is coherent with our expectations. Similar to the results of Annaert et al. (2013) and Di Cesare and Guazzarotti (2010), the importance of the related coefficient increases during the crisis.

- General state of the economy: the sign of the stock index return coefficient is consistent with our expectation for all sample periods tested. The coefficient is found losing its importance during the pre-crisis period. This would confirm that during period of calm, the market is more focused on idiosyncratic parameters and that macro-economic variables are generally disregarded. Such phenomenon is also observed for the general level of interest rates.

Regarding panel B:

- Distance-to-default: in this regression set-up, the structural model coefficient is barely significant. This might confirm the presence of residual collinear effects. However, it does not affect our overall conclusion.

- General level of interest rates: similar results as under panel A.

- General structure of interest rates: the term structure slope is significant over the full sample period as well as during the crisis period, thereby reinforcing our previous statement about the predominance of systematic variables in times of stressed market. The related sign of the term structure slope is found consistent with most of the literature. Indeed, a negative sign is expected but as underlined by Annaert et al. (2013), *many authors find the term structure slope to be ill-behaved*, further underlying that *it either is not significant or its sign depends on the exact regression specification and the choice of other explanatory variables.* Our results nevertheless comfort us in our selection of variables and our approach to deal systematically with colinearity issues.

- General level of confidence on the interbank market: as mentioned earlier, we expect a positive relationship between the LIBOR-OIS spread variations and the CDS

[22] The literature underlines the fact that the restrictive assumptions posed by the theoretical model fails to reflect the market anticipations and imperfections; this phenomenon being exacerbated during a crisis period.

spreads variations. Such relation is confirmed for the full sample and the post-crisis period. In-between, the coefficient is found insignificant. This would seems to suggest that the information contained in the variations of the LIBOR-OIS spread has been integrated by the market from the sub-prime crisis onwards and has become a matter of particular attention for the market participants, especially for the banking industry. Indeed, this observation is consistent with and reflects the fact that liquidity pressures on banks have been increasing from 2009 onwards. We also note in this context the comment provided by Annaert et al. (2013) in their conclusion regarding the uncertainties highlighted by the IMF in its 2007 Global Financial Stability Report concerning the incorrect apprehension of risks and liquidity by the market at the onset of the crisis. This would support the fact that the market requested some time to properly integrate all relevant risk information at that time.

While we are comfortable with our results so far, we note however the sensitivity of the results to the selection of variables and the regression set-up. This is however not peculiar to our study and is common to most of the literature reviewed.

At this stage, we can conclude that the inclusion of additional variables, especially of a more systematic nature during a stressed period, globally improves the regression results and hence contributes to a better specification of the changes in credit default spread values. However, the relatively modest level of (adjusted) R-squared suggests that other factors are still uncovered.

In the next step, we analyse the influence of the sovereign dimension on the credit default spread of banks and see whether and how it contributes to our results.

6 Country effects on banks' credit default spreads

6.1 Model specification

As explained previously, a key objective of this paper is to test the possible influence of the perceived sovereign risk on the credit default spreads of the banks incorporated in the concerned country.

This analysis is performed by applying country dummies ($\delta_i^k, k \in \{UK, FR, SP, DE, CH, NL, IT\}$, taking a value of zero or one) to the available country CDS spreads when corresponding to the country of incorporation of the banks in our sample.

Estimation is based on a balanced panel regression (with fixed effects) under the following form:

$$\begin{aligned} \Delta CDS_{i,t}^{obs} = \alpha_i &+ \beta_{1,i}\,\Delta DD_{i,t} \\ &+ \beta_{2,i}\,\delta_i^{UK}(\Delta CDS_t^{UK}) + \beta_{3,i}\,\delta_i^{FR}(\Delta CDS_t^{FR}) + \beta_{4,i}\,\delta_i^{SP}(\Delta CDS_t^{SP}) \\ &+ \beta_{5,i}\,\delta_i^{DE}(\Delta CDS_t^{DE}) + \beta_{6,i}\,\delta_i^{CH}(\Delta CDS_t^{CH}) + \beta_{7,i}\,\delta_i^{NL}(\Delta CDS_t^{NL}) \\ &+ \beta_{8,i}\,\delta_i^{IT}(\Delta CDS_t^{IT}) + \epsilon_{i,t} \end{aligned} \tag{11}$$

where $\Delta CDS_{i,t}^{obs}$ is the change in the observed CDS spread for bank i at time t, $\Delta DD_{i,t}$ is the first-difference of the theoretical distance-to-default calculated for bank i at time t, ΔCDS_t^{UK} is the change in the observed country CDS spread for the United Kingdom at time t, ΔCDS_t^{FR} is the change in the observed country CDS spread for France at time t, ΔCDS_t^{SP} is the change in the observed country CDS spread for Spain at time t, ΔCDS_t^{DE} is the change in the observed country CDS spread for Germany at time t, ΔCDS_t^{CH} is the change in the observed country CDS spread for Switzerland at time t, ΔCDS_t^{NL} is the change in the observed country CDS spread for the Netherlands at time t, ΔCDS_t^{IT} is the change in the observed country CDS spread for Italy at time t, α_i is the intercept for bank i, $\beta_{1\ to\ 8,i}$ are the regression coefficients for bank i, and $\epsilon_{i,t}$ is the corresponding residual.

All our regression results exhibit a Durbin-Watson statistic between 1.5 and 2.5 thereby suggesting the absence of significant autocorrelation problems. To compute the p-values for our estimated coefficients, White (1980) heteroskedasticity-robust standard errors are used.

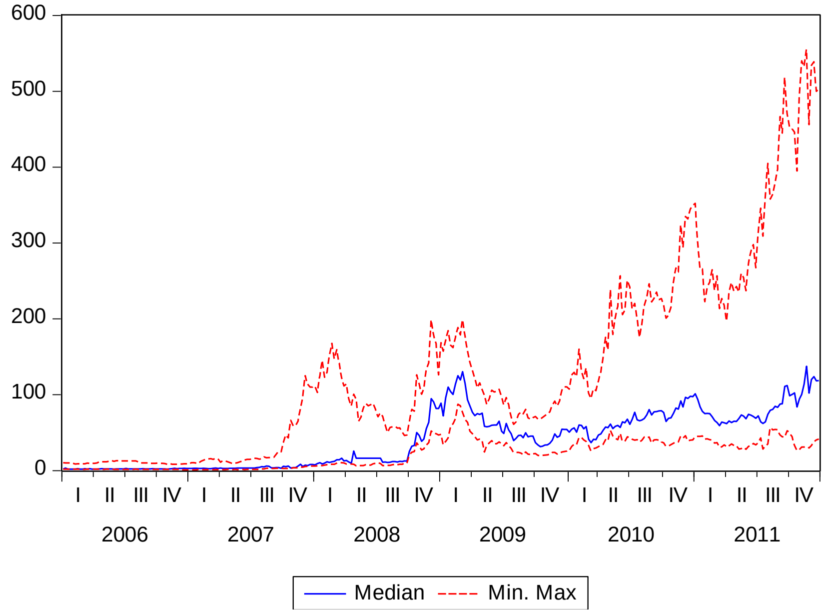
6.2 Data Statistics

The following table represents the descriptive statistics for all raw variables used in the regression (equation 11) presented above. It corresponds to a balanced sample over a 5-year period from 5 January 2006 to 29 December 2011. There are in total 5008 observations divided into 16 cross-sections.

Table 13 comes here

We note that country CDS spreads exhibit substantial differences and time variations across the different countries considered in this study. The particular stress on the southern European countries can be observed in the maximum spreads obtained by Spain (SP) and Italy (IT) while the northern European countries were less affected. In this case again, the level of the spreads is the reflection of the stress on these particular countries at certain point in history. This is illustrated in the following graph in Figure 5.

Figure 5 - **Sovereigns CDS spreads evolution**. Weekly spread data from January 2006 to December 2011. The chart provides the median, min and max boundaries, based on the seven countries involved through the various banks considered.



6.3 Results

Testing a first sample

In a first step, we analyse the relation with the countries over the entire sample period, before the sub-prime crisis starts and from the beginning of our sample period until the end of 2009 (being an intermediary point between the sub-prime crisis and the flow of state interventions in Europe).

<u>Table 14 comes here</u>

Over the entire sample period, the (adjusted) R-squared is relatively high with a value of 38% of the variance explained by the model. With the exception of UK, all coefficients are statistically significant. They overweigh the coefficients associated with the theoretical model.

If we look at the situation before the crisis, we note that the R-squared is remarkably lower with a value of 1,72%. With the exception of Italy (at 99%) and The Netherlands (at 95%), none of the country coefficients is significant. The distance-to-default coefficient on the contrary is significant at the 90% level. This seems to suggest that before the crisis period the market was not worried about the possible link between the sovereigns and the related banks.

If we consider the entire crisis period (that we will decompose later on), we note that the (adjusted) R-squared has increased significantly to a value of almost 14%. The theoretical component is insignificant. All country coefficients are significant. We note however a negative sign and a lesser significance for UK. This seems to suggest that with the crisis, the changes in the banks' credit default spreads have been increasingly influenced by the credit standing of their related sovereigns. This moves could be explained by the "too big to fail" principle by which market participants increasingly expect State interventions in order to maintain (systemic) banks in going concern in such uncertain times.

A more detailed analysis

In a second step, we analyze more in detail the different sub-sample periods as identified earlier on the basis of the LIBOR-OIS spread evolution from 2006 to 2011.

Table 15 comes here

If we now decompose the initial period of crisis, we note that in the first stage of the crisis, the (adjusted) R-squared has slightly improved to about 5%. During this period, the theoretical component is already disregarded. More interestingly, only the coefficients for Italy, Spain and Germany are significant. This could be seen as a confirmation of the European fragmentation and the related focus on the southern countries. This also suggest that Germany has probably been considered at an early stage by the market as an indicator of stability for Europe.

Then, if we look at a longer crisis period, we observe that other countries are progressively significant and that the (adjusted) R-squared continues to increase up to 14%. This suggests that progressively all European countries have been put under scrutiny by the market, thereby exercising an increasing influence on the perceived riskiness of the associated banks and hence, on the changes in the associated banks' credit default spreads. This could be interpreted as a progressive transfer of the financial risk associated traditionally with banks to the related sovereigns, thereby paving the ground for the sovereign crisis we have gone through (still are in) in Europe.

Interestingly, at the end of the observed period, the theoretical component has an increased significance but remain however overweighed by the countries' coefficients. The (adjusted) R-squared has massively increased to almost 56% and all countries' coefficients are statistically significant. This possibly suggests a change in the market perception by which an increased focus is to be given to sovereign risk (i.e. its on-going capacity to support likely-to-fail banks) and the possible influence of the latter on the going concern situation of a bank.

Testing the full picture

In this last set of regressions, we test all independent variables together according to panels A and B as defined beforehand.

Table 16, Panel A and Panel B, comes here

For both panels, the results confirm the fact that incorporating the sovereign component increased massively the explanatory power of our model with a huge increase of the (adjusted) R-squared up to almost 70% for the last sub-sample period in panel A and 58% for the last sub-sample period in panel B.

We note in particular that at the end of the sample period (i.e. the last sub-sample), the general state of the economy proxied by the stock index return in panel A, the general level of confidence on the interbank market in panel B and the country components in both panels are the most relevant indicators for the variations in CDS spread for banks. Overall, the sovereign effect appears however dominant and consistent across panels.

This tends to illustrate the progressive focus of the market towards the sovereign credit standing even before the increasing number of State interventions across Europe to rescue banks. This phenomenon underlines the anticipation of the market participants in the context of the "too big to fail" principle and the related moral hazard. It occurs gradually through time up to a point where the link between sovereigns and banks could actually not be disconnected any more.

Such analysis also shows that an analysis of the relation between the various determinants of CDS spreads could inform the authorities on possible destructive links that are created and could enable those authorities to take earlier remedial actions or at least to incorporate such effects in their policy decisions. Of course, as mentioned by Annaert et al. (2013), coefficient estimates and statistical significance changes through time (and in function of the precise set-up), thereby underlining the need for complementary indicators.

7 Conclusion

The objective of this paper is to analyze the determinants of credit default swap (CDS) spreads for a sample of European banks over a period from January 2006 to December 2011, thereby observing both normal and stressed market conditions. In particular, this paper gives a focus to variables specific to the banking industry and to possible link with related sovereign's credit standing.

So far, while the literature has been quite rich in terms of explaining the determinants of CDS spreads for non-financial firms, their interactions with credit ratings as well as the price formation of such spreads by comparison to credit spreads or stock prices, very little has been done specifically in the field of financial institutions or banks in particular. Additionally, the time period generally analyzed remains quite limited and does generally not encompass both normal and stressed market conditions. Moreover, to our knowledge, the existing literature has not yet studied the influence of sovereigns on the determinants of CDS spreads for European banks.

Our results globally confirm the findings from the existing literature regarding the lack of significance of the structural model and its breakdown in times of stress. In addition, we confirm the importance of macro-economic components such as the general level of interest rates and the general state of the economy, particularly in times of stress. The absence of significance for the tier 1 ratio in our analysis seems to confirm that such indicator is actually not considered by the market participants as an input in their assessment of the credit worthiness of a financial institution, likely considering it too static.

We note that the model is sensitive to the period sampling as well as the cross-sectional sampling; hence, conclusions should be nuanced when interpreting CDS spreads evolutions in terms of policy decisions.

We find that before the crisis period the macro- and micro-components are generally predominant in the determination of CDS spread variations while the influence of countries

CDS become more important when entering further in the crisis period. Interestingly, southern European countries are the first to become significant as we enter into the crisis. This tends to illustrate the progressive focus of the market towards the sovereign credit standing even before the increasing number of state interventions across Europe to rescue banks. This phenomenon underlines the anticipation of the market participants in the context of the "too big to fail" principle and the related moral hazard. Progressively, all CDS countries become increasingly significant up to a point where the link between sovereigns and banks could actually not be neglected and tends to overweigh all other explanatory variables. Interestingly, once created such link remain persistent and strong in the aftermath of the sub-prime crisis period, thereby suggesting the focused attention of market participants for the sovereign dimension. It also shows that an analysis of the relation between the various determinants of CDS spreads could inform the authorities on possible destructive links that are created and could enable those authorities to take earlier remedial actions or at least to incorporate such effects in their policy decisions along with other indicators.

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Appendix 1: Tables

Table 3
Overall descriptive statistics
This table provides descriptive statistics for the weekly observations of all model variables from January 2006 to December 2011. CDS_t^{obs} represents the bank average CDS spread through time.

	CDS_t^{obs}	DD_t	Rf_t	$Slope_t$	$LIBOIS_t$	$MRet_t$	$MVol_t$	$HRet_t$	$HVol_t$	$Tier1_t$
Mean	93.17106	0.727532	0.034776	0.004915	0.004086	-0.001457	26.58054	-0.004829	0.057247	0.101350
Median	83.83200	0.717913	0.035650	0.004910	0.002624	0.002392	24.10000	-0.001012	0.045262	0.096000
Maximum	687.1040	3.034926	0.043870	0.014060	0.018100	0.103075	87.51000	0.626444	0.327970	0.196000
Minimum	3.800000	-0.888541	0.019750	-0.003980	0.000400	-0.134494	13.06000	-1.234744	0.014132	0.065000
Std. Dev.	82.45262	0.515872	0.006352	0.004182	0.003757	0.032038	11.01491	0.074601	0.043170	0.027208
Skewness	1.540491	0.455940	-0.648714	-0.035411	1.475959	-0.505302	1.742806	-1.631308	2.894621	1.147020
Kurtosis	7.009582	4.242843	2.394307	2.253129	5.450499	4.962358	7.381711	30.96782	14.46982	4.394759

Table 4
Descriptive statistics on the individual CDS spreads
This table provides descriptive statistics for the weekly observations of individual bank CDS spreads from January 2004 to December 2012.

PANEL A	BBVA	Banco Santander	Barclays	BNP Paribas	Commerzbank	Crédit Agricole	Crédit Suisse	Deutsche Bank
Mean	118.7001	113.6154	85.48050	72.75082	88.84102	88.96219	74.16079	75.49654
Median	74.40100	74.82000	82.87900	53.64350	67.20400	76.90650	72.36800	77.47150
Maximum	492.7290	455.6620	278.6370	359.5860	349.1910	403.7800	255.8250	311.6010
Minimum	7.864000	7.627000	5.594000	5.375000	8.125000	6.000000	8.969000	10.15400
Std. Dev.	129.1479	121.5079	75.10492	77.25531	82.33259	90.55566	58.11622	60.69476
Skewness	1.085617	1.097179	0.469724	1.334045	1.088149	1.118641	0.573118	0.617539
Kurtosis	3.059114	3.094771	1.972853	4.021601	3.253311	3.559624	2.248617	2.519607
Observations	468	468	468	468	468	468	468	468

PANEL B	HSBC	ING	Intesa	Lloyds	RBS	SG	UBS	Unicredit
Mean	57.69158	76.02206	109.6019	104.6120	112.1744	93.30570	81.40988	125.4188
Median	58.28900	65.69800	51.78150	77.78300	104.8640	79.02650	85.71550	75.11550
Maximum	183.5300	269.4350	627.8240	375.8280	395.9370	432.0800	351.7920	687.1040
Minimum	4.983000	4.500000	5.922000	3.800000	3.964000	5.969000	4.550000	7.478000
Std. Dev.	46.99229	69.75968	136.5903	103.1351	105.8321	99.85119	74.21894	149.0681
Skewness	0.489522	0.718958	1.659108	0.715519	0.634683	1.301989	0.710290	1.569049
Kurtosis	2.057251	2.481432	4.769449	2.389156	2.330202	3.936761	2.835665	4.643679
Observations	468	468	468	468	468	468	468	468

Table 5

Cross-correlogram of individual bank CDS spreads on the entire sample period

This table provides all cross-correlations for the weekly observations of all model variables from January 2006 to December 2011.

Covariance Analysis: Spearman rank-order
Sample: 5/01/2006 29/12/2011
Included observations: 313

Correlation	CDS_BARC	CDS_CSGN	CDS_DB	CDS_HSBC	CDS_ING	CDS_INTESA	CDS_LLOYDS	CDS_RBS	CDS_SG	CDS_UBSN	CDS_UNIC	CDS_COMB	CDS_BBILBAO	CDS_BNP	CDS_CA	CDS_BS
CDS_BARC	1.000000															
CDS_CSGN	0.963047	1.000000														
CDS_DB	0.950181	0.953566	1.000000													
CDS_HSBC	0.965889	0.964928	0.952199	1.000000												
CDS_ING	0.944771	0.946323	0.944588	0.953346	1.000000											
CDS_INTESA	0.911599	0.887750	0.908768	0.918161	0.954816	1.000000										
CDS_LLOYDS	0.896641	0.849801	0.903358	0.883900	0.909632	0.954706	1.000000									
CDS_RBS	0.919168	0.871840	0.916514	0.908700	0.935566	0.964517	0.987293	1.000000								
CDS_SG	0.921340	0.902976	0.926791	0.922029	0.959083	0.979104	0.965647	0.976305	1.000000							
CDS_UBSN	0.945992	0.962060	0.939723	0.935060	0.892046	0.805360	0.802457	0.819959	0.834005	1.000000						
CDS_UNIC	0.905073	0.875217	0.909978	0.902183	0.933515	0.985582	0.960564	0.964036	0.968251	0.802417	1.000000					
CDS_COMB	0.897913	0.866062	0.902889	0.892656	0.929031	0.952247	0.958151	0.966095	0.965271	0.806051	0.947264	1.000000				
CDS_BBILBAO	0.881626	0.847104	0.882523	0.878740	0.927352	0.979113	0.960980	0.967481	0.974678	0.768809	0.972627	0.950889	1.000000			
CDS_BNP	0.907591	0.887788	0.913032	0.912317	0.947869	0.977924	0.971896	0.979861	0.986656	0.814117	0.966213	0.965163	0.982908	1.000000		
CDS_CA	0.881528	0.856795	0.890817	0.877315	0.926719	0.956998	0.966736	0.970633	0.980127	0.794187	0.946159	0.965939	0.973030	0.983014	1.000000	
CDS_BS	0.888195	0.854980	0.886887	0.887541	0.935366	0.984889	0.957702	0.967309	0.977366	0.774350	0.976570	0.952162	0.997036	0.982289	0.970925	1.000000

Table 6
Cross-correlogram of the variables on the entire sample period

This table provides all cross-correlations for the weekly observations of all model variables from January 2006 to December 2011.

	ΔCDS_t^{obs}	ΔDD_t	ΔRf_t	$Slope_t$	$\Delta LIBOIS_t$	$MRet_t$	$\Delta MVol_t$	$HRet_t$	$\Delta HVol_t$	$\Delta Tier1_t$
ΔCDS_t^{obs}	1.000000	-0.034216	-0.097356	-0.074303	0.059874	**-0.497230**	0.242163	**-0.458675**	0.024305	-0.010023
ΔDD_t	-0.034216	1.000000	-0.020040	0.031033	-0.080841	-0.013459	0.002734	-0.027241	**-0.488789**	0.062231
ΔRf_t	-0.097356	-0.020040	1.000000	0.107456	-0.091214	0.086360	-0.021677	0.083159	-0.016106	-0.137466
$Slope_t$	-0.074303	0.031033	0.107456	1.000000	-0.024460	0.101733	0.000683	0.096779	-0.183914	-0.065042
$\Delta LIBOIS_t$	0.059874	-0.080841	-0.091214	-0.024460	1.000000	**-0.314735**	0.260044	-0.219729	0.058660	-0.081293
$MRet_t$	-0.497230	-0.013459	0.086360	0.101733	-0.314735	1.000000	**-0.732248**	**0.727166**	-0.031534	0.036606
$\Delta MVol_t$	0.242163	0.002734	-0.021677	0.000683	0.260044	-0.732248	1.000000	**-0.507366**	0.036336	0.029890
$HRet_t$	-0.458675	-0.027241	0.083159	0.096779	-0.219729	0.727166	-0.507366	1.000000	0.017294	0.037358
$\Delta HVol_t$	0.024305	-0.488789	-0.016106	-0.183914	0.058660	-0.031534	0.036336	0.017294	1.000000	-0.003756
$\Delta Tier1_t$	-0.010023	0.062231	-0.137466	-0.065042	-0.081293	0.036606	0.029890	0.037358	-0.003756	1.000000

Table 7
Cross-correlogram on the pre-crisis period

This table provides all cross-correlations for the weekly observations of all model variables for the previously defined pre-crisis period.

	ΔCDS_t^{obs}	ΔDD_t	ΔRf_t	$Slope_t$	$\Delta LIBOIS_t$	$MRet_t$	$\Delta MVol_t$	$HRet_t$	$\Delta HVol_t$	$\Delta Tier1_t$
ΔCDS_t^{obs}	1.000000	-0.056630	-0.037159	0.006964	0.003910	-0.094579	0.057885	-0.200174	0.053703	0.004024
ΔDD_t	-0.056630	1.000000	0.096177	-0.067290	0.084797	-0.068126	0.060456	0.015024	**-0.650410**	-0.007106
ΔRf_t	-0.037159	0.096177	1.000000	0.019651	-0.159345	-0.077897	0.065759	-0.017279	-0.054787	0.012157
$Slope_t$	0.006964	-0.067290	0.019651	1.000000	-0.011543	0.041531	-0.055480	0.082844	-0.035359	0.016181
$\Delta LIBOIS_t$	0.003910	0.084797	-0.159345	-0.011543	1.000000	-0.262339	0.216502	-0.151472	-0.174562	0.009310
$MRet_t$	-0.094579	-0.068126	-0.077897	0.041531	-0.262339	1.000000	**-0.876228**	**0.695691**	0.150104	-0.021001
$\Delta MVol_t$	0.057885	0.060456	0.065759	-0.055480	0.216502	-0.876228	1.000000	**-0.615920**	-0.093497	-0.021296
$HRet_t$	-0.200174	0.015024	-0.017279	0.082844	-0.151472	0.695691	-0.615920	1.000000	0.051284	-0.036136
$\Delta HVol_t$	0.053703	-0.650410	-0.054787	-0.035359	-0.174562	0.150104	-0.093497	0.051284	1.000000	0.014178
$\Delta Tier1_t$	0.004024	-0.007106	0.012157	0.016181	0.009310	-0.021001	-0.021296	-0.036136	0.014178	1.000000

Table 8
Cross-correlogram during the crisis period

This table provides all cross-correlations for the weekly observations of all model variables for the previously defined crisis period.

	ΔCDS_t^{obs}	ΔDD_t	ΔRf_t	$Slope_t$	$\Delta LIBOIS_t$	$MRet_t$	$\Delta MVol_t$	$HRet_t$	$\Delta HVol_t$	$\Delta Tier1_t$
ΔCDS_t^{obs}	1.000000	-0.025765	-0.217019	-0.138335	-0.007746	**-0.345765**	0.059522	**-0.382703**	0.017847	-0.008497
ΔDD_t	-0.025765	1.000000	-0.070911	0.105973	-0.123044	-0.081832	0.095870	-0.098485	**-0.494960**	0.090373
ΔRf_t	-0.217019	-0.070911	1.000000	0.113085	-0.089372	0.203597	-0.118988	0.158574	-0.011963	**-0.460166**
$Slope_t$	-0.138335	0.105973	0.113085	1.000000	-0.006596	0.158693	0.026657	0.138252	**-0.303642**	-0.133058
$\Delta LIBOIS_t$	-0.007746	-0.123044	-0.089372	-0.006596	1.000000	**-0.329692**	0.239647	-0.211352	0.054065	-0.108111
$MRet_t$	-0.345765	-0.081832	0.203597	0.158693	-0.329692	1.000000	**-0.699536**	**0.707593**	-0.015239	0.055937
$\Delta MVol_t$	0.059522	0.095870	-0.118988	0.026657	0.239647	-0.699536	1.000000	**-0.459682**	-0.013184	0.059935
$HRet_t$	-0.382703	-0.098485	0.158574	0.138252	-0.211352	0.707593	-0.459682	1.000000	0.041846	0.037095
$\Delta HVol_t$	0.017847	-0.494960	-0.011963	-0.303642	0.054065	-0.015239	-0.013184	0.041846	1.000000	-0.002315
$\Delta Tier1_t$	-0.008497	0.090373	-0.460166	-0.133058	-0.108111	0.055937	0.059935	0.037095	-0.002315	1.000000

Table 9
Cross-correlogram for the post-crisis period

This table provides all cross-correlations for the weekly observations of all model variables for the previously defined post-crisis period.

	ΔCDS_t^{obs}	ΔDD_t	ΔRf_t	$Slope_t$	$\Delta LIBOIS_t$	$MRet_t$	$\Delta MVol_t$	$HRet_t$	$\Delta HVol_t$	$\Delta Tier1_t$
ΔCDS_t^{obs}	1.000000	-0.067227	-0.059118	-0.055159	**0.172132**	**-0.710093**	**0.479958**	**-0.638011**	0.050654	-0.014298
ΔDD_t	-0.067227	1.000000	-0.049660	-0.039677	-0.070978	0.097958	-0.158787	0.080309	**-0.621987**	0.047090
ΔRf_t	-0.059118	-0.049660	1.000000	0.256711	-0.124095	0.050430	0.026253	0.050802	-0.016629	0.061485
$Slope_t$	-0.055159	-0.039677	0.256711	1.000000	-0.136333	0.074677	-0.045664	0.055486	0.038693	0.046321
$\Delta LIBOIS_t$	0.172132	-0.070978	-0.124095	-0.136333	1.000000	**-0.332353**	**0.327835**	-0.257234	0.107617	-0.021676
$MRet_t$	-0.710093	0.097958	0.050430	0.074677	-0.332353	1.000000	**-0.774751**	**0.809325**	-0.086875	0.031609
$\Delta MVol_t$	0.479958	-0.158787	0.026253	-0.045664	0.327835	-0.774751	1.000000	**-0.616699**	0.147810	-0.019248
$HRet_t$	-0.638011	0.080309	0.050802	0.055486	-0.257234	0.809325	-0.616699	1.000000	-0.068515	0.057087
$\Delta HVol_t$	0.050654	-0.621987	-0.016629	0.038693	0.107617	-0.086875	0.147810	-0.068515	1.000000	-0.018839
$\Delta Tier1_t$	-0.014298	0.047090	0.061485	0.046321	-0.021676	0.031609	-0.019248	0.057087	-0.018839	1.000000

Table 10

Individual regressions for each explanatory variable

Results of the panel OLS regression with fixed effects and White-robust standard errors. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. 312 weekly observations (after adj.) considered for the period 12/01/06 - 29/12/11 over 16 cross-sections. The total amount of observations is 4992.

Variables	**Coefficients**	**(p-values)**	**R-squared**
$\Delta DD_{i,t}$	-4.4976	(0.0458)	0.001393
$HRet_{i,t}$	-91.5187	(0.0000)	0.180748
$\Delta HVol_{i,t}$	44.8914	(0.5160)	0.000635
$\Delta Tier1_t$	-40.0580	(0.5831)	0.000505
ΔRf_t	-1870.1750	(0.0000)	0.009649
$Slope_t$	-263.4800	(0.0000)	0.005168
$\Delta LIBOIS_t$	1473.7830	(0.0081)	0.004224
$MRet_t$	-244.6407	(0.0000)	0.238297
$\Delta MVol_t$	0.8577	(0.0000)	0.055503

Table 11

Overall panel regression results for different sets of variables on the entire period

Results of the panel OLS regression with fixed effects and White-robust standard errors. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. 312 weekly observations (after adj.) considered for the period 12/01/06 - 29/12/11 over 16 cross-sections. The total amount of observations is 4992.

Variables	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)
C	0.146410	0.282427	0.551508	0.867411	0.709363	1.850793	0.709080	0.499361
	(0.6068)	(0.3288)	(0.0505)	(0.0036)	(0.0138)	(0.0000)	(0.0135)	(0.0094)
$\Delta DD_{i,t}$	-7.688975	-7.115202	-7.589763	-7.216152	-6.975728	-3.922719	-5.627187	-7.034749
	(0.0002)	(0.0005)	(0.0003)	(0.0010)	(0.0009)	(0.0790)	(0.0053)	(0.0008)
ΔRf_t	-976.3813	-1007.188	-1152.362	-1324.768	-1190.829	-1671.174	-1044.235	-1212.658
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Slope_t$	38.14634	27.63590	-29.08403	-94.54903	-42.43942	-220.2303	-49.61106	
	(0.4475)	(0.5854)	(0.5682)	(0.0845)	(0.4091)	(0.0004)	(0.3375)	
$\Delta LIBOIS_t$	-2459.924	-2458.063	-2665.379	-1187.952	-2670.018	1204.195		-2674.928
	(0.0001)	(0.0001)	(0.0000)	(0.0506)	(0.0000)	(0.0290)		(0.0000)
$MRet_t$	-295.2458	-352.7811	-201.0634		-259.2814		-241.9448	-259.8261
	(0.0000)	(0.0000)	(0.0000)		(0.0000)		(0.0000)	(0.0000)
$\Delta MVol_t$	-0.903876	-0.931229		0.191576				
	(0.0000)	(0.0000)		(0.0759)				
$HRet_{i,t}$	-34.44489		-36.60064	-87.18604				
	(0.0000)		(0.0000)	(0.0000)				
R-squared	0.296774	0.283328	0.268967	0.191129	0.253757	0.016447	0.242822	0.253638
Adj. R-squared	0.293660	0.280300	0.265878	0.187711	0.250755	0.012689	0.239928	0.250786

Table 12
Overall panel regression results for different subperiods

Results of panel regressions with fixed effects and White-robust standard errors for four (4) different periods, the entire one and three consecutive sub-samples. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. Panels A and B present two different sets of variables given the collinearities existing between these two sets.

	Entire period	Pre-crisis period	Crisis period	Post-crisis period
Sample	12/01/06 - 29/12/11	12/01/06 - 28/06/07	28/06/07 - 31/12/09	31/12/09 - 29/12/11
Observations	312 after adj.	77 after adj.	132	105
Cross-sections	16	16	16	16
Total observations	4992	1232	2112	1680
PANEL A				
Variables	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**
C	0.463513	0.003462	-0.216399	0.930739
	(0.0178)	(0.8255)	(0.4538)	(0.0249)
$\Delta DD_{i,t}$	-5.693304	-0.252578	-8.450753	3.320955
	(0.0048)	(0.0685)	(0.0040)	(0.4864)
ΔRf_t	-1069.446	-29.24189	-4176.176	-490.0011
	(0.0000)	(0.0233)	(0.0000)	(0.0669)
$MRet_t$	-242.5445	-2.707821	-125.1181	-418.5618
	(0.0000)	(0.0009)	(0.0000)	(0.0000)
R-squared	0.242659	0.017353	0.132729	0.449816
Adj. R-squared	0.239918	0.002771	0.125271	0.443854
PANEL B				
Variables	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**
C	1.850793	-0.006888	1.532311	2.449650
	(0.0000)	(0.7333)	(0.0024)	(0.0684)
$\Delta DD_{i,t}$	-3.922719	-0.227677	-4.477229	-8.285378
	(0.0790)	(0.1014)	(0.1333)	(0.1954)
ΔRf_t	-1671.174	-24.46665	-5507.324	-716.9786
	(0.0000)	(0.0352)	(0.0000)	(0.0828)
$Slope_t$	-220.2303	0.796641	-306.5268	-157.1520
	(0.0004)	(0.8308)	(0.0000)	(0.4916)
$\Delta LIBOIS_t$	1204.195	-8.043572	-423.7082	6436.797
	(0.0290)	(0.8890)	(0.4671)	(0.0000)
R-squared	0.016447	0.008267	0.058650	0.031979
Adj. R-squared	0.012689	-0.007280	0.050101	0.020900

Table 13 Descriptive statistics This table provides descriptive statistics for the weekly observations of the seven countries' market CDS spreads, from January 2006 to December 2011.							
	CDS_t^{UK}	CDS_t^{FR}	CDS_t^{SP}	CDS_t^{DE}	CDS_t^{CH}	CDS_t^{NL}	CDS_t^{IT}
Obs.	313	313	313	313	313	313	313
Mean	53.76986	43.84945	111.8385	28.12409	32.24177	32.28709	109.0613
Median	60.00000	24.02100	68.69100	23.21400	32.88500	30.25000	74.10900
Maximum	167.7000	248.7710	484.4440	117.6700	177.9000	137.4900	555.2210
Minimum	1.500000	1.500000	2.554000	2.125000	1.065000	1.065000	5.575000
Std. Dev.	35.66599	51.52663	122.8602	26.44690	33.34825	32.68339	122.3349
Skewness	0.156710	1.642593	1.049342	1.119343	1.578325	1.090918	1.751607
Kurtosis	2.691557	5.626177	3.001031	3.825271	6.605225	3.575493	6.080888

Table 14 Sovereign effects – First regressions			
Results of the panel OLS regression with fixed effects and White-robust standard errors. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. Dependent variables include the distance to default and the seven countries' CDS spreads, pre-multiplied by dummy variables so that each bank is affected only by its own country's spread. The entire sample period as well as two others are presented as a first example.			
Sample	12/01/06 - 29/12/11	12/01/06 - 28/06/07	12/01/06 - 31/12/09
Observations	312 after adj.	77 after adj.	208 after adj.
Cross-sections	16	16	16
Total observations	4992	1232	3328
Variables	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**
C	0.291121 (0.1058)	-0.003720 (0.7996)	0.180930 (0.3336)
$\Delta DD_{i,t}$	-2.863934 (0.1237)	-0.230043 (0.0940)	-1.607835 (0.3079)
$\delta_i^{UK}(\Delta CDS_t^{UK})$	-0.003165 (0.9622)	-0.028092 (0.1799)	-0.131745 (0.0833)
$\delta_i^{FR}(\Delta CDS_t^{FR})$	1.478957 (0.0000)	0.089581 (0.1560)	0.872296 (0.0000)
$\delta_i^{SP}(\Delta CDS_t^{SP})$	0.861571 (0.0000)	-0.025562 (0.7686)	0.926798 (0.0000)
$\delta_i^{DE}(\Delta CDS_t^{DE})$	1.614819 (0.0000)	0.041456 (0.5226)	1.034484 (0.0000)
$\delta_i^{CH}(\Delta CDS_t^{CH})$	0.945775 (0.0000)	0.162247 (0.3258)	0.691292 (0.0002)
$\delta_i^{NL}(\Delta CDS_t^{NL})$	0.929959 (0.0000)	0.285354 (0.0501)	0.559831 (0.0013)
$\delta_i^{IT}(\Delta CDS_t^{IT})$	0.775125 (0.0000)	0.253826 (0.0003)	0.715404 (0.0000)
R-squared	0.381209	0.017174	0.140574
Adj. R-squared	0.378345	-0.001539	0.134591

Table 15
Sovereign effects – Detailed subsample analysis

Results of the panel regressions with fixed effects and White-robust standard errors. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. Dependent variables include the distance to default and the seven countries' CDS spreads, pre-multiplied by dummy variables so that each bank is affected only by its own country's spread. Regressions are run for various detailed subsample periods as defined here below in each column.

Sample	28/06/07 - 20/11/08	28/06/07 - 31/12/09	31/12/09 - 29/12/11	30/09/10 - 29/12/11
Observations	74	132	105	66
Cross-sections	16	16	16	16
Total observations	1184	2112	1680	1056
Variables	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**
C	0.911333	0.299457	0.497730	0.514415
	(0.0354)	(0.3106)	(0.1909)	(0.3139)
$\Delta DD_{i,t}$	-1.851486	-2.522351	-6.545288	-11.88988
	(0.5468)	(0.3575)	(0.1875)	(0.0731)
$\delta_i^{UK}(\Delta CDS_t^{UK})$	0.095680	-0.133676	0.516882	0.773844
	(0.2050)	(0.0816)	(0.0000)	(0.0000)
$\delta_i^{FR}(\Delta CDS_t^{FR})$	0.292678	0.871852	1.643385	1.687239
	(0.2144)	(0.0000)	(0.0000)	(0.0000)
$\delta_i^{SP}(\Delta CDS_t^{SP})$	1.176746	0.929641	0.853258	0.828880
	(0.0026)	(0.0000)	(0.0000)	(0.0000)
$\delta_i^{DE}(\Delta CDS_t^{DE})$	0.993974	1.037255	2.100123	2.159775
	(0.0185)	(0.0000)	(0.0000)	(0.0000)
$\delta_i^{CH}(\Delta CDS_t^{CH})$	0.375041	0.690497	1.412817	1.314125
	(0.3804)	(0.0003)	(0.0000)	(0.0000)
$\delta_i^{NL}(\Delta CDS_t^{NL})$	-0.077858	0.560464	1.360213	1.293639
	(0.8778)	(0.0014)	(0.0000)	(0.0000)
$\delta_i^{IT}(\Delta CDS_t^{IT})$	0.668880	0.715866	0.781558	0.891641
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R-squared	0.051668	0.140877	0.528299	0.563891
Adj. R-squared	0.032865	0.131413	0.521748	0.554171

Table 16 – Panel A

Sovereign effects – Full regression with the first set of variables and the country CDS spreads

Results of the panel regressions with fixed effects and White-robust standard errors. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. Dependent variables include the distance to default, the market return, the evolution of the risk-free rate, and the seven countries' CDS spreads, pre-multiplied by dummy variables so that each bank is affected only by its own country's spread. Regressions are run for the entire sample period as well as various subsample periods as defined here below in each column.

Sample	12/01/06 - 29/12/11	12/01/06 - 28/06/07	28/06/07 - 31/12/09	31/12/09 - 29/12/11	28/06/07 - 20/11/08	12/01/06 - 31/12/09	30/09/10 - 29/12/11
Observations	312 after adj.	77 after adj.	132	105	74	208 after adj.	66
Cross-sections	16	16	16	16	16	16	16
Total observations	4992	1232	2112	1680	1184	3328	1056
Variables	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**
C	0.178250	0.005794	-0.184788	0.409644	0.478853	0.117336	0.508753
	(0.2822)	(0.7156)	(0.5030)	(0.2013)	(0.2081)	(0.5072)	(0.2391)
$\Delta DD_{i,t}$	-3.871215	-0.242904	-6.319568	1.217506	-3.154323	-3.248730	-0.828634
	(0.0262)	(0.0791)	(0.0260)	(0.7518)	(0.3134)	(0.0471)	(0.8728)
$\delta_i^{UK}(\Delta CDS_t^{UK})$	0.026203	-0.027023	-0.137272	0.537721	0.022113	-0.127444	0.899078
	(0.6800)	(0.1752)	(0.0574)	(0.0000)	(0.7669)	(0.0795)	(0.0000)
$\delta_i^{FR}(\Delta CDS_t^{FR})$	1.156052	0.083627	0.530991	1.137864	-0.140785	0.594636	1.187521
	(0.0000)	(0.1699)	(0.0003)	(0.0000)	(0.6067)	(0.0000)	(0.0000)
$\delta_i^{SP}(\Delta CDS_t^{SP})$	0.746975	-0.010109	0.712094	0.687523	0.876717	0.754123	0.673851
	(0.0000)	(0.8994)	(0.0000)	(0.0000)	(0.0422)	(0.0000)	(0.0000)
$\delta_i^{DE}(\Delta CDS_t^{DE})$	1.170032	0.019340	0.788338	1.167654	0.821080	0.827741	1.162693
	(0.0000)	(0.7607)	(0.0000)	(0.0000)	(0.0163)	(0.0000)	(0.0008)
$\delta_i^{CH}(\Delta CDS_t^{CH})$	0.609382	0.158381	0.488276	0.581892	-0.079482	0.531664	0.486558
	(0.0000)	(0.3431)	(0.0117)	(0.0000)	(0.8535)	(0.0057)	(0.0004)
$\delta_i^{NL}(\Delta CDS_t^{NL})$	0.510673	0.281127	0.284645	0.512941	-0.527905	0.336239	0.446124
	(0.0000)	(0.0737)	(0.1246)	(0.0001)	(0.2716)	(0.0666)	(0.0012)
$\delta_i^{IT}(\Delta CDS_t^{IT})$	0.662842	0.239300	0.564508	0.602748	0.462442	0.600334	0.709273
	(0.0000)	(0.0009)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)
ΔRf_t	92.72236	-24.41547	-3037.522	750.0509	-8049.861	-1568.689	1682.446
	(0.6599)	(0.0686)	(0.0000)	(0.0052)	(0.0000)	(0.0000)	(0.0000)
$MRet_t$	-155.3773	-2.599590	-91.19509	-276.2614	-18.42774	-80.34734	-279.7208
	(0.0000)	(0.0012)	(0.0000)	(0.0000)	(0.4959)	(0.0000)	(0.0000)
R-squared	0.462146	0.026114	0.200577	0.674923	0.116063	0.188076	0.696095
Adj. R-squared	0.459439	0.005926	0.190996	0.670010	0.096979	0.181929	0.688718

Table 16 – Panel B

Sovereign effects – Full regression with the second set of variables and the country CDS spreads

Results of the panel regressions with fixed effects and White-robust standard errors. $\Delta CDS_{i,t}^{obs}$ is the dependent variable. Dependent variables include the distance to default, the evolution of the risk-free rate, the slope of the term structure of risk-free rates, the evolution of the LIBOIS-OIS spread, and the seven countries' CDS spreads, pre-multiplied by dummy variables so that each bank is affected only by its own country's spread. Regressions are run for the entire sample period as well as various subsample periods as defined here below in each column.

Sample	12/01/06 - 29/12/11	12/01/06 - 28/06/07	28/06/07 - 31/12/09	31/12/09 - 29/12/11	28/06/07 - 20/11/08	12/01/06 - 31/12/09	30/09/10 - 29/12/11
Observations	312 after adj.	77 after adj.	132	105	74	208 after adj.	66
Cross-sections	16	16	16	16	16	16	16
Total observations	4992	1232	2112	1680	1184	3328	1056
Variables	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**	**Coefficients (p-values)**
C	1.036594	-0.006076	1.219107	0.392971	1.249289	1.148424	0.529470
	(0.0005)	(0.7653)	(0.0104)	(0.6806)	(0.0195)	(0.0002)	(0.6072)
$\Delta DD_{i,t}$	-2.778350	-0.214339	-3.769550	-4.849842	-5.038657	-1.630176	-9.179619
	(0.1367)	(0.1217)	(0.1952)	(0.3127)	(0.1148)	(0.3223)	(0.1474)
$\delta_i^{UK}(\Delta CDS_t^{UK})$	-0.013346	-0.028337	-0.183138	0.518921	-0.026100	-0.165665	0.726933
	(0.8407)	(0.1750)	(0.0123)	(0.0000)	(0.7226)	(0.0243)	(0.0001)
$\delta_i^{FR}(\Delta CDS_t^{FR})$	1.477107	0.087537	0.804546	1.647395	0.114394	0.843386	1.693453
	(0.0000)	(0.1661)	(0.0000)	(0.0000)	(0.5909)	(0.0000)	(0.0000)
$\delta_i^{SP}(\Delta CDS_t^{SP})$	0.861711	-0.025563	0.883190	0.853601	1.020907	0.910085	0.829131
	(0.0000)	(0.7678)	(0.0000)	(0.0000)	(0.0042)	(0.0000)	(0.0000)
$\delta_i^{DE}(\Delta CDS_t^{DE})$	1.604819	0.037702	0.979198	2.071039	0.975926	1.002628	2.095478
	(0.0000)	(0.5692)	(0.0000)	(0.0000)	(0.0071)	(0.0000)	(0.0000)
$\delta_i^{CH}(\Delta CDS_t^{CH})$	0.933674	0.165098	0.609314	1.384208	0.211538	0.644140	1.263056
	(0.0000)	(0.3237)	(0.0019)	(0.0000)	(0.5734)	(0.0009)	(0.0000)
$\delta_i^{NL}(\Delta CDS_t^{NL})$	0.921816	0.288646	0.485266	1.356708	-0.230410	0.521039	1.282958
	(0.0000)	(0.0538)	(0.0053)	(0.0000)	(0.6677)	(0.0026)	(0.0000)
$\delta_i^{IT}(\Delta CDS_t^{IT})$	0.774082	0.251157	0.652324	0.778314	0.560780	0.684315	0.887815
	(0.0000)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔRf_t	-13.85223	-20.42375	-3709.444	1059.320	-9137.497	-1903.017	1982.626
	(0.9575)	(0.0895)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)
$Slope_t$	-150.7988	1.371273	-252.4651	7.849519	-48.52069	-223.3842	-37.84343
	(0.0022)	(0.7117)	(0.0000)	(0.9599)	(0.7662)	(0.0000)	(0.8375)
$\Delta LIBOIS_t$	-173.9559	-29.32832	-1141.696	3293.903	-2859.441	-1046.789	3192.759
	(0.7354)	(0.6125)	(0.0534)	(0.0001)	(0.0000)	(0.0661)	(0.0005)
R-squared	0.382779	0.017981	0.172263	0.536228	0.150703	0.161574	0.577635
Adj. R-squared	0.379547	-0.003208	0.161941	0.528933	0.131617	0.154970	0.566963

Appendix 2: Figure

Figure 3 - European CDS spread evolution for each individual bank. Weekly CDS spread data from January 2004 to December 2012 for each individual bank taken separately.