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Introduction

Assessing the credit risk of the European banking and sovereign sectors has never been more necessary. Today's anxious financial markets reflect to a large extent the ramifications of the recent banking and sovereign debt crises. On the other hand, grasping the strong connection between the banking and sovereign sectors is crucial in understanding the risk transmission mechanisms between the two sectors and preventing future downturns.

In view of growing concerns about financial stability, this thesis revolves over two major objectives. The first objective relates to exploiting option pricing models to generate bank and sovereign credit risk indicators and is pursued in chapters One and Two. The second objective is about determining the extent to which key institutions, namely the credit rating agencies and the ECB contributed to curing or hampering the European banking system. Chapter Three and Chapter Four address the latter theme. All through this thesis, we lay stress upon the connection between banks and sovereigns.

Chapter One focuses on the banking sector and the banking crisis. The potential of banks to undermine financial stability underlines the necessity for regulators to quantify their credit risk through reliable indicators. The chapter examines whether the information contained in deep-out-of-the-money put options can be combined with information CDS contracts to estimate default arrival rates. Using a sample of European banks, we exploit a theoretical link between the equity deep-out-of-the-money put options with a view to gauging their credit riskiness .In addition, we analyse the differences between the estimated default arrival rates and those rates emanating from the market (historical default arrival rates) and find the financial guarantees provided by governments to systemically important institutions to be a significantly important factor in explaining those differences. Ultimately, the results suggest that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks but can serve, at times, as early warning signals.

In view of the Eurozone debt crisis, Chapter Two investigates the impact of the credit risk of Eurozone member countries on the stability of the Euro. In the absence of a common euro bond, euro-area credit risk is induced though the credit default swaps of the member countries. The stability of the euro is examined by decomposing dollar-euro exchange rate options into the moments of the risk-neutral distribution. We document that during the sovereign debt crisis changes in the creditworthiness of member countries have significant impact on the stability of the euro. In particular, an increase in member countries' credit risk results in an increase of volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. We find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. We propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure and show that our results are robust to this change in measure. Noticeable is the fact that during the sovereign debt crisis, the creditworthiness of countries with vulnerable fiscal positions is the main risk-endangering factor of the euro-stability.

Chapter Three approaches the question of credit risk along with the relationship of banks and their governments from the perspective of credit rating agencies. It examines the response of credit risk measures of European banks and macro-financial indicators to changes in bank-specific and sovereign credit ratings. Rather than looking separately at how sovereign and bank credit rating actions influence asset prices, we place the focus on confronting the impact of sovereign rating actions against bank-specific rating actions on an array of bank-related variables. We find evidence that the credit risk measures of banks react more to changes in the sovereign credit ratings than those endured by the bank itself. Similarly, changes in sovereign ratings spur more reaction amongst macro-financial indicators. These effects are accentuated during the sovereign debt crisis period and by the occurrence of multiple-notches downgrades. Another significant finding is that the widening gap between bank and sovereign ratings causes the credit risk and macro-financial variables to soar. Ultimately, the paper casts light on how the connection between European banks and their sovereigns is perceived by the financial markets.

Finally, Chapter Four sheds light on the role of the ECB in counteracting the crisis. The unprecedentedly high borrowing costs of banks along with the armada of interventions by the ECB (and kin institutions) to prevent a financial haemorrhage underpin the motivation of this chapter to re-visit the connection between default probabilities à la Merton and borrowing costs for a sample of large European banks . In doing so, the chapter also investigates the ramifications of the ECB's interventions on the health of the banking system. Furthermore, and building on Merton's model, it proposes a simple measure of credit spreads that accounts for the nature of the credit risk profile of large financial institutions. The findings are unequivocal and suggest that higher default probabilities significantly explain the deteriorating ability of banks to borrow from the financial markets. More importantly, there is an increase in the degree to which default probabilities explain borrowing costs when policy measures undertaken by the ECB are incorporated. Conversely, the effect of the liquidity interventions is ambivalent: While liquidity measures directed towards the banking system have a curing effect on the borrowing costs of banks, those related to sovereigns seemingly have an impeding effect.

Chapter One* :

CDS Contracts versus Put Options: A robust relationship?

1.1 Motivation

The Chicago Board Options Exchange argues in a report published in March 2009, that deep out the money options (DOOM options henceforth) can be used by investors as a “viable” and “liquid” alternative to CDS contracts[1]. Various reasons are put forward to defend this idea. Firstly, both derivatives tend to behave in the same way, particularly in times of credit crisis. Secondly, DOOM options occasionally prove to be a better indicator of credit deterioration than the CDS market. The last set of reasons is tied to the transparent feature and relatively low transaction costs of DOOM options as opposed the opaque nature and high transaction costs of CDS contracts. The whole CBOE argument is based on the work of Carr and Wu (2011). A paper where the authors propose a robust theoretical linkage between these two derivatives. In view of growing concerns about credit protection solutions, this study relies on the same model so as to verify the story put forward by the CBOE. It seems relevant to investigate the extent to which combined information contained in DOOM put options and CDS contracts can be used in the pricing of credit risk. More precisely, we exploit an existing theoretical link which proves an equivalence between a DOOM put option and a CDS contract to back out default arrival rates which are typically extracted from CDS contracts only. In this sense, we take a different empirical approach than Carr and Wu’s (2011): We do not place the focus on computing unit recovery claims values extracted from a CDS contract and comparing them to values of unit recovery claims extracted from a DOOM option. Rather, we are interested in using the theoretical linkage between these two types of

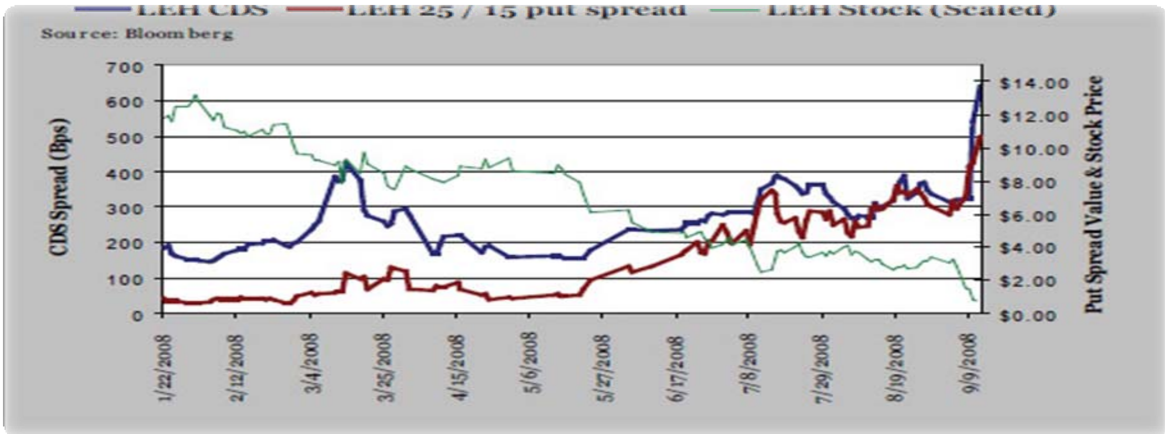
[1] http://www.cboe.com/micro/doom/doomquickreference.aspx

derivatives, and hence the combined information from CDS and DOOM options to provide estimates of default arrival rates.

The model underlying the study is a 'simple' theoretical link between DOOM American put options on a company's stock and a credit insurance contract on the company's bond. The key underpinning of the model is the presence of 'default corridor' [A,B] the stock price cannot penetrate. Before default the stock price remains above a barrier B before sliding below a barrier A<B after default. Under this condition a spread between two American put options struck within the corridor replicates a credit contract whose pay-off is only possible before the option expires. The most desirable attribute of the model is that the replication is materialized regardless of the details of the stock price dynamics before and after default, the interest rate dynamics, and specifications about default arrival rate, provided that the stock price is located outside the default corridor. A legitimate question arises regarding the likelihood of such a default corridor. The question is partly answered by a body of literature which models default as a strategic decision. In other words, debt holders have an incentive to spur or cause default while the value of the stock is still greater than zero, B>0 . Papers addressing the topic of strategic default include Leland and Toft (1996); Anderson, Sundaresan (1996) ; Mella-Baral and Perraudin (1997) and Broadie, Chernov, Sundaresan (2007). On the other hand, Car and Wu (2011) justify the assumption of the escalation of the stock price from above B to below a lower barrier by costs which are inherent to the bankruptcy process.

Futhermore, the authors clearly spell out that when the company is viewed as too big to fail (TBTF), default does not occur even when the stock price falls below the strike price of the DOOM option due to the existence of government guarantees. However, we take a particular interest in examining systemically important European banks. Our Argument is that Lehman

Brothers collapsed despite being deemed TBTF. Thus, we would like to treat a sample of systemically important banks as though they would not be bailed out in the event of a default and analyse how their default arrival rates behave across time. In fact, the awareness of the systemic importance of certain institutions grew after the collapse of Lehman Brothers. Our interest in this type of banks is also justified by an empirical observation by the CBOE based on our reference model. As the plot below shows, during the crisis period of September 2008 to January 2009, the put spread and CDS spread of Lehman Brothers behaved in quite an identical fashion:



Source: http://www.cboe.com/micro/doom/doomquickreference.aspx

Thus, we apply the theoretical link of Carr and Wu (2011) and confront information about put spreads with that of CDS spreads for a sample mainly composed of systemically important institutions. More importantly we gauge the credit riskiness of such institutions, before and during the financial crisis, through the estimation of their default arrival rates.

In a second stage of our analysis we will attempt to take into account the government guarantee component provided to systemically important banks to judge whether it is necessary incorporate it to our estimation of their default arrival rates. We estimate government guarantees using the same approach as Gray and Jobst (2011)[2] and gauge their effect on the credit risk of the banks' composing our sample, and more specifically on the differences between the estimated and historical default arrival rates.

From an academic perspective, several studies[3] demonstrate an empirical Link between CDS contracts and stock options. To cite a few, *Acharya and Johnson (2007), Berndt and Ostrovnaya (2008*) investigate the impact of announcement of negative credit news on both credit default swap (CDS) and options market. The empirical findings show that both the CDS and the option market react prior to the announcement of negative credit news. But, options prices reveal information about forthcoming adverse events at least as early as do credit spreads. *Cao et al. (2010***)** show that the implied volatility (IV) explains CDS spreads not only because it forecasts future volatility, but also because it captures a time-varying volatility risk premium. *Avino et al. (2011)* investigate the price discovery process in single-name credit spreads obtained from four markets: bonds, credit default swaps, equities and equity options on European data from January 2006 to July 2009. Using a VECM of changes in credit spreads, they find that during the crisis, the option market lead the three other markets (so the option market lead the CDS market). This is confirmed by the strong volatility spillovers observed from the option market to the other markets. *Bekkour and Lehnert(2011)* work on a large European sample *and* demonstrate that the CDS market leads the option market. This pattern have only emerged during the recent financial crisis. Before the crisis the option market is found to lead the CDS market.

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[2] See also the April 2014 *Global Financial Stability Report,* Gray et *al.(*2008), Gray and Malone 2008 (book)

[3] See also Campbell and Taskler (2002), Benkert (2004) and Alexander and Kaeck (2008).

While is ample empirical literature looking at the relationship between stock options and CDS contracts, the main feature of these studies is that they exploit the informational aspect of the markets where these derivatives are traded and attempt to determine the direction in which information flows. Yet, the flaw with this approach is that it ignores that information extracted from the tails of the distribution is likely to reveal more about the behaviour of the markets it describes. The more interesting movements happen at the level of the tail where troublesome options can be found. That is why our data selection process is designed to extract information from the tail distribution of put options.

On the other hand, research tackling this relationship from a pricing perspective is scarce. Merton's model (1974)[4] establishes a link between corporate bond spread and stock return volatility. Despite providing a good foundation, the link is mainly based on the strong assumption whereby asset value follows a Geometric Brownian Motion and volatility is held constant. Hull, Nelken and White (2004), propose a link between CDS spreads and stock option prices through a modification in the estimation of Merton's framework .The calibration proposed by the author is nonetheless static. Carr and Wu (2010) Design a dynamic framework capable of joint estimation and valuation of put options and CDS contracts inherent to the same firm. The model decomposes the total risk on an individual stock into two components: risk in the return variance rate under normal market conditions and risk in the default arrival rate. Using data on stock options and CDS spreads they disentangle the two sources of risks and identify their respective market prices. Unlike in Carr & Wu (2011) the default arrival rate is stochastic. Nonetheless, its estimation procedure based on the Kalman Filter is costly and complex.Therefore, we opt for the framework of Carr and Wu (2011) – explained earlier- to infer default arrival rate estimates.

[4] See also Merton (1973, 1976)

The objective of our study differs from that of Carr and Wu's (2011). Indeed, we do not seek to calibrate the CDS data in the model to prove that the CDS recovery claim is equivalent to the DOOM put option .Instead, we use the theoretical link to estimate a variable of interest, i.e, the default arrival rate. We do so with a specific focus on European the banking sector to gauge its credit riskiness. Altogether, our results indicate that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks but can serve, at times, as early warning signals. Furthermore, our findings suggest that higher financial guarantees from their sovereign display a lower default risk and hence have a lower CDS spread along with a lower estimated default arrival rate. Ultimately, the government guarantee explains the differences in the level of estimated default arrival rates across banks as well as the observed differences between estimated (i.e derived from Carr&Wu 's model) and historical (CDS spreads scaled by (1-recovery rate)) default arrival rates.

The remainder of the paper is organised as follows. Section 2 exposes the underpinning theoretical framework along with the estimation procedure. Section 3 describes the data and the related statistics. Section 4 outlines the main results and discusses their implications on the risk profile of the banks in our sample. Section 6 concludes the paper.

1.2 Methodology

Our estimation of the default arrival rates (Lambda) relies upon the framework of Carr and Wu (2011).We start off by outlining its major points of the framework . The authors develop a 'simple' theoretical link between DOOM American put options on a company's stock and a credit insurance contract on the company's bond. Under certain conditions the following relationship holds:

$$Up(t,T) = Uc(t,T) \quad (1)$$

$$\Rightarrow \quad \frac{Pt(K2,T) - Pt(K1,T)}{K2 - K1} = \int_t^T e^{-(r+\lambda)} ds \quad (2)$$

$$\frac{Pt(K2,T) - Pt(K1,T)}{K2 - K1} = \lambda \frac{1 - e^{-(r+\lambda)(T-t)}}{r + \lambda} \quad (3)$$

Where :

Up(t,T) is the unit recovery claim inferred from a DOOM put option

Uc(t,T) is the unit recovery claim inferred from a credit contract

Pt(K2,T)-Pt(K1,T) is the spread between two observable put option prices at time t $K2 - K1$

K2-K1 is the strike difference.

R is the interest rate

λ is the risk neutral default arrival rate

T is the expiry date

The key assumption underpinning the model is the presence of 'default corridor' **[A, B]** the stock price cannot penetrate. Before default the stock price remains above a barrier B before sliding below a barrier **A≤K1<K2≤B** after default. Under this condition a spread between two American put options struck within the corridor replicates a credit contract whose pay-off

is only possible before the option expires. The most desirable attribute of the model is that the replication is materialized regardless of the dynamics of the stock price before and after default, the interest rate dynamics, and specifications about default arrival rate. This implies that not only pricing of the option becomes less complex but also the inference of risk measures such as default probabilities and default arrival rates proves more parsimonious.

While Car and Wu (2009) use the theoretical linkage to show empirically that the values of credit contracts generated by CDS contracts and American put options co-move strongly, we exploit the linkage from a different angle. We use the relationship in equation (3) to infer the parameter λ , which represents the default arrival rate, based on the scaled spread in the pricing of two DOOM put options (left hand side of equation (3)). The spread corresponds to the cost of replicating a standardized default insurance contract paying 1 if the company defaults prior to T and 0 otherwise.

In order to determine a default corridor **[A, B]** in a discrete setting we work with the two lowest strike prices with non-zero bids for the highest possible time to maturity on the same trading day.

We first estimate the prices of the American put options [5] according the Bjerksund-Stensland (1993)(a) and (2002) option pricing model. Basically, the computer efficient method presented in the latter paper provides a simple approximation of the value of an American call and put options by dividing maturity into two periods, each with a flat early exercise boundary. This way, a lower bound to the option value is obtained.

[5] Working with historical prices leads to noisy results

In the context of complete continuous-time Black-Scholes economy, the price of the underlying asset St at a future date t will be:

$$St = Sexp\{(b - 0.5\sigma^2)t + \sigma Wt\}$$

Where :

S is the spot price

$b<r$ is the drift rate w/r to the equivalent martingale measure. (b) is regarded as a cost of carry

— is the volatility

Ωt is Wiener process

The value of an American call with maturity T and strike K and a given feasible strategy within the stopping date τ € [0.T] can be written as:

$$C(S,K,T,r,b,\sigma) = supEo[exp\{-r\tau\}(St - K) +]$$

The relationship in equation (4) can be transformed to obtain the value of the put option such that :

$$P(S,K,T,r,b,\sigma) = C(S,K,T,r - b,-b,\sigma)$$

Once put options are estimated, and assuming constant recovery rates R^b the inference of the default rate arrival (λ) becomes possible. We take two routes with this regard: One implying the use of historical volatilities and the second involving the estimation of an implied volatility surface with a view to curing the issue of noise in the data. However, the cost of estimating an implied volatility surface does not lead to any improvements in the results.

1.2.1 (λ) using estimated option prices and historical volatilities :

All variables in equation (3) are known apart from the parameter of interest. However, it is not possible to find a close form solution without having recourse to optimization technique. We set a starting value[6] of λ= 1 and we obtain a numerical value for $Up(t,T)$ (The unit recovery contract inferred from puts options) and $Uc(t,T)$ (The unit recovery contract inferred from a credit contract). Hence, on each trading day, we obtain a pair of (Up, Uc).

The optimization problem consists simply of minimizing the following objective function:

$$Up(t,T) \leq Uc(t,T) \qquad (4)$$

$$\Rightarrow \min\big(Up(t,T) - Uc(t,T)\big) \qquad (5)$$

This allows us to obtain a time series of optimal solutions for (λ), the default arrival rate corresponding to each trading day from 01/01/2006 to 31/12/2009[7].

1.2.2(λ) using estimated option prices and estimated volatilities :

In a second stage, the same methodology is applied for the Lambda inference except that we estimate implied volatilities for the American option according to the model of Bjerksund-Stensland (2002)

[6] We perform the optimization with various starting values and the results remain unchanged.

Important are the assumptions about: rate structure , stock specification and the continuous dividend yield (we chose a negligible level)

With a view to eliminating part of the noise inherent to option data, we further estimate a volatility surface. We use a modification of the prominent ad-hoc Black-Scholes model of Dumas, Fleming and Whaley (1998). Expect that our IVs are not Black -Scholes-related but are generated from a model for American option pricing

$$IV_i = \alpha_0 + \alpha_1 \text{delta} + \alpha_2 \text{delta}^2 + \alpha_3 T + \alpha_4 T^2 + \alpha_5 \text{delta} \quad T \qquad (6)$$

The regression we had for each date t and put option i , we have one observation of delta (based the theoretical model), and T . We obtain the coefficients of the equation through OLS which allows us to have a new IV for each put option. The resulting implied volatilities are then used to infer option prices, which are in turn used for the optimization in equation (5). The use of an estimated volatility surface does not necessarily to an improvement in our results. Therefore, we only present the results using historical volatilities and estimated option prices.

Once the default arrival rates λ are inferred based on the linkage between DOOM put options and the credit protection contract, we can compare them to default arrival rates which are computed solely based on the credit protection contract such that :

$$k = \lambda(1 - R^b)$$

$$\lambda(t,T) = {k(t,T)}/{(1 - R^b)} \qquad (7)$$

k are the historical CDS spreads

R^b *is the recovery rate fixed at 40%*

The obtained new time series represents historical default rates which are confronted the estimated default arrival rates with a view to comparing the 'prediction power' of each type of indicator.

In a second stage of our analysis we will attempt to take into account the government guarantee component provided to systemically important banks and relate it to our estimation of their default arrival rates. We conjecture that government guarantees might well explain the differences in levels of default arrival rates. Essentially, banks enjoying higher financial guarantees from their sovereign should display a lower default risk and hence have a lower CDS spread along with a lower estimated default arrival rate. Furthermore, we are interested in determining whether government guarantees explain the observed differences between the estimated default arrival rates and those rates emanating from the market, i.e. historical default arrival rates (results 4) .The underpinning argument is that the implicit put option derived from the equity price reflects the total expected loss of the bank net of any financial guarantee while the put derived from the CDS captures the expected loss retained by the bank after accounting for financial guarantees. The difference between these two puts defines the scope of government guarantees.

Following Gray and Jobst (2011), the estimation of the implicit guarantee is possible by combining the market-implied expected losses induced through the contingent claim framework $P_E(t)$ (i.e. Merton's implicit put option) and information from the credit default *swap markets, specifically the put option value using a CDS,* $P_{CDS}(t)$ *which is a measure of* expected default net of any financial guarantee. Hence, the combination of the two types of implicit puts allows us to disentangle between the fraction of expected losses covered by the government$\alpha(t)\ P_E\ (t)$, which represents the government implicit guarantee (i.e. contingent government liability) and the expected loss borne by the bank and translated in its CDS spread$(1-\alpha(t))P_E\ (t)$ according to the equation below:

$$\alpha(t) = 1 - \ P_{CDS}(t)/P_E\ (t) \qquad (8)$$

Where $P_E\ (t)$, the market-implied expected loss is given by the Black-Scholes- Merton equation for the value of an implicit put option :

$$P_E\ (t) = Be^{-r(T-t)}\Phi(-d_2) - A(t)\ \Phi(-d_1)$$

A(t) is the asset value of the bank with strike price B which represents a distress barrier.

On the other hand , $P_{CDS}(t)$, is the expected loss net of financial guarantees.

$$P_{CDS}(t) = \left[1 - \exp\left(-\left(\frac{S_{CDS}(t)}{10{,}000}\right)\left(\frac{B}{D(t)} - 1\right)(T-t)\right)\right] Be^{-r(T-t)}$$

Once the implied government guarantees are retrieved we relate the difference between the estimated and historical default arrival rates of bank *i* at time *t* to the corresponding government guarantee *i* at time *t* through the following panel regression with fixed effect[8]

$$|\delta\lambda|_{it} = a + b\delta GG_{it} + X_{it} + s_{it} \quad (9)$$

Where $|\delta\lambda|$ is the difference between the estimated and historical default arrival rates in absolute value (Lambda E – Lambda H).

δGG_{it} is the government guarantee in first differences computed as (alpha*equity put option)

X_it is a set of two controls : Size as measured by market capitalization and VSTOXX which as measure of the risk appetite of the financial markets.

In addition we run two more panel regressions[9] to verify the relationship between the implied government guarantee and the estimated default arrival rates on the one hand, and the implied government guarantee and the CDS spread on the other. We expect the relationship to be negative and significant in both instances implying that banks with higher financial government guarantees display less default risk.

$$\delta Lambda_{Eit} = a + b\delta GG_{it} + X_{it} + s_{it} \quad (10)$$

$$\delta s_{CDSit} = a + b\delta GG_{it} + X_{it} + s_{it} \quad (11)$$

[8] We run a Haussmann test and reject the null hypothesis that the efficient random effects estimators are the same as the consistent fixed effect estimators (significant p-value = 0.000, p<Chi2=18.2)

[9] We run a Haussmann test and reject the null hypothesis that the efficient random effects estimators are the same as the consistent fixed effect estimators (significant p-value = 0.000, p<Chi2=43.98 , p-value = 0.000, p<Chi2=42.23 for Lambda E and s respectively)

Where[10] $\delta Lambda_{Eit}$ is the estimated default arrival rate of bank i in first differences at time t , δs_{CDSit} its CDS spread in first differences and δGG_{it} is the government guarantee in first differences computed as (alpha*equity put option)

X_it is a set of two controls : Size as measured by market capitalization and VSTOXX which as measure of the risk appetite of the financial markets.

1.3 Data Collection and Statistics

1.3.1 Data Collection

Our study spans from January 2006 to December 2009 and thus covers a pre-crisis and a crisis period. We work on a sample of large European banks. The American put options data as well as the stock data is from Thomson Reuters tick database while the CDS spreads are from Bloomberg[11]. The options data on Thomson Reuters is displayed in the form of RIC symbols which stands for 'Reuters Instrument Code' , This code encompasses information about the month-letter for the option type (Call / Put) and its strike price and the exchange identifier. The expiry date needs to be computed from complementary information. We also extract mid quotes of 14:30 p.m along with the corresponding stock prices. We extract data at this point of the day because the highest value of options trading occurs around this time.

To start with, we set a reference time series of trading days from 02/06/2006 to 30/12/2009. In constructing the sample of DOOM options, we apply a number of selection criteria. We sort the data so that for a given put option, on a given trading day, we end up with the two lowest strike prices for the highest possible time to maturity. Maturities which are lower than 200 days are discarded. The combination of low strikes and high maturities is supposed to ensure that the put options are 'deep' enough and are struck within Carr and Wu 's (2011) default

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[10] The Augmented Dickey Fuller test shows the presence of a unit root and so we work with first differences.

[11] We use the German government interest rate the spot interest rate found on Bloomberg.

corridor. Indeed, As pointed out by the authors, we are not apt of identifying this corridor ex-ante because we do not have put quotes for a continuum of strikes. Therefore, we deal with the discrete nature of strikes by selecting the lowest (K1, K2) with non-zero bid quotes and non-zero open interest rate such that K2 > K1. The non-zero(mid) bid quote and non-zero open interest rate conditions are meant to ensure the option is actually traded. Another crucial condition for the model to be implemented is that the stock represents an upper barrier B for (K1, K2) and escalades to a lower barrier A= 0 upon default such that : A<K1<K2<B. In addition, the estimated delta of the American options of our sample is lower than 15% and is another condition to help identify options struck within the corridor. We apply this filtering procedure to a sample of 50 banks and obtain 15 banks which match the requirements for the model implementation. However, the assumption related to the non-penetration of 'default corridor' is intermittently violated by some banks of our sample. When plotting the Strike prices (K1, K2) along with the underlying asset prices (B) of each bank, we observe banks that have asset prices which never penetrate the 'default corridor' throughout the whole period of our study namely : BARC, CNKG, CRDI,DBKG, KBC, , STAN,. And, banks for which the asset price penetration of the corridor is barely ostensible, this the case of : ERTS and CSGN. The plots which can be found in appendix 3, describe the evolution of those three variables throughout our study period for each bank and so periods over which this particular assumption is violated can be visualized.

In addition, we retrieve over-the counter- CDS quotes at 5 years maturities due to their reliability.

An additional set of data is required for the estimation of the implicit government guarantee which is obtained by recovering the difference of an implicit put option from equity and implicit put option using a CDS derivative. For 12 banks of our sample we retrieve information from Bloomberg about equity prices, the number of shares outstanding and government bond yields, the S&P 500 index, quarterly book values of short and long-term debt. The implied equity risk premiums are downloaded from Damodaran website (http://pages.stern.nyu.edu/~adamodar/).

1.3.2 Statistics

The number of banks which match our filtering criteria amounts to 15 over a period of 3 years (2006 through 2009). At maturities which are no lower than 200 days, we have 1044 observation for each bank.

Table 1 reports summary statistics calculated based on the banks' time series mean values for default arrival rates, CDS spreads and strike prices K1 and K2. The mean value for the CDS is 44 bp with a standard deviation of 61%. The strikes prices K1 and K2 have mean values of 12,80 and 13,93 and standard deviations of 14,80 and 16,26. The mean on the mean values of the stocks prices is around 66 with a high standard deviation of around 1144. This gives us an indication of the large differences among the banks of our sample.

Table 2 reports statistics related to the strike prices of the DOOM put options used in the calibration of the model along with the underlying stock prices. Despite the fact that the banks composing our sample share the common feature of being large and/or systemically important banks, the descriptive statistics show considerable difference among these banks. A major difference has to do with the volatility of the stocks. The UK banks (Barclays, RBS and Standard Chartered) have on average the most volatile stocks. Dexia and KBC have the least volatile stocks. The same applies to the mean value of stock prices of these banks. RBS has the maximum stock value (4430.91) and BBVA has the lowest (12.18). Interestingly, In terms of mean, the British banks also have very low strike prices together with German banks : STAN (0.77,094) ; BARC(1.3, 1.40); RBS (4.86, 4.93) , DB (1.97,1.96); CBKG(0.59, 0.67). Another estimate worth of comparison is the skew statistics. This estimate is negative for the put option of some banks suggesting that investors perceive a downward risk and seek protection by buying put options.

1.4 Empirical Results

Table 3 describes the summary statistics of estimated, historical default arrival rates and CDS spreads. There are visible differences in the estimates of each bank. The mean for the CDS ranges from 18 bp to 79bp, whereas it ranges from 248% to 23% for the estimated default arrival rates. According to the descriptive statistics the banks with the most volatile stocks and the deepest out of the money strike prices are not necessarily the banks for which the default arrival rate is highest.

The first set of results reported in table 3 is characterized by dramatic differences across banks. The highest mean values of estimated default rates are registered by CSGN (248%), Barclays (197%), STAN (153%), whereas the lowest mean values are registered by CBKG (23%), ERSTE (30%).The mean value computed based on the cross section of the default arrival rates mean value of the banks of our sample is around 49%. When computing summary statistics based on the mean estimates of all bank, we obtain a standard deviation from the mean of 63,70 % which indicates that there are considerable differences in the level of default arrival rates across banks.

The standard deviation values also give us an indication for the volatility of our estimates and hence the degree of variation in the credit risk of the banks composing our sample. The sharpest variations are observed for CAGRA, CSGN, KBC with standard deviations of 150.79, 149, 104.84 respectively and corresponding minimum and maximum values of (33;609),(44;656),(14;539). (table3)

The plots displayed in Figure 3 clearly show that the estimated default arrival rates constitute a less noisy measure than the historical default rates. The historical measure being largely based on information stemming from the CDS market is bound to have liquidity issues leading to noisy information. Therefore, combining information from the CDS market together with information from the put option market appears to improve the quality of information about the default risk of the financial institution composing our sample.

In the following section we discuss the patterns observed in our estimated default arrival rates and confront them to major events of the financial turmoil that marked the period of our study 2006 -2006. We do so with a view to finding evidence of the ability of our estimates co move with the patterns of the financial markets or provide warning signals as to the deterioration of the credit profile of the financial institutions.

Figure 3 shows that the default arrival rates increased around beginning of 2007 which precedes the start of the credit crunch with BNP Paribas being the first bank to declare exposure to subprime mortgage risk through the collateralised debt obligations. In the following month, the British bank Northern Rock (albeit not part of our sample) faces liquidity strain and causes the first bank run in Britain in 150 years. Banks displaying heightened default arrival rates include Deutsche Bank, Dexia, Unicredit, Barclays, , Erste Group Bank, Credit Suisse. For RBS and Standard Chartered, the increase in the estimate before the credit crunch is slightly less stable but still intelligible.

In the case of BNP Paribas, we do not observe an increase in our credit risk estimates prior to the burst of the credit crunch crisis. Admittedly, this may be due to the fact has BNP Paribas already announced its troublesome situation with regard to the valuation of CDOs to the financial markets thus becoming one of the institutions which played a major role in triggering the subprime crisis.

More pronounced spikes occurred in early 2008, Before Lehman Brothers spread off panic in the financial markets worldwide by filing for bankruptcy. We observe the spikes notably for Credit Agricole, BNP, Credit Suisse and BBVA. Over this period, the subprime crisis in the US was intensified by a series of events, the most consequential being the purchase of Bearn Stern by JP Morgan in March 2008 ,followed by the US government bail-out of Fanny Mae and Freddie Mac in September prior to the collapse of Lehman Brothers the same month. In the particular case of RBS where we only possess data for 2006 and 2007, we observe a sharp and abrupt rise of default arrival rates towards the end of 2007. RBS happens to be one of the banks which were bailed out in October 2008 by the British government to prevent a collapse of the banking sector in the UK. The observation of spikes prior to the intensification of the crisis suggests that our estimated default arrival rates could potentially send early warning signals. In the case of some banks no spikes are observed but the increase in our estimates is very clear and the trend appears more upward than downward for the following months (Barclays, UniCredit, ING Group) .Hence, when not providing early warning signals, our estimates reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks.

Sharp spikes are also observed towards the beginning of 2009. However for most banks the default arrival rates appear to decrease gradually after the increase or stabilize towards the end of the year. One should note that this period was marked by the start of recovery of European banks thanks to the various interventions carried out by governments and central banks. An example of such interventions is the 5tn dollars global stimulus package issued on the G20 meeting in April2009. However, an interesting observation emerges for 2009. Indeed BBVA displays a trend upward throughout year. This coincides with the Spanish sovereign being hit during the sovereign debt crisis starting in October in Greece. One could argue that the rising default arrival rates of BBVA suggests the worry of the markets about a struggling sovereign potentially unable to bail out their banks.

The second part of our analysis involves the estimation of financial government guarantee[12]. The purpose of that is to look at the extent to which this component help explain the differences in levels between the estimated and historical default arrival rates. Government guarantee also help explain the dramatic differences across the banks of our sample. The level of financial guarantee provided by the governments -reflecting primarily the ability of a sovereign to bail out a troubled blank- plays a role in reducing the default risk of the bank. Figure 5 represents the times series plot of the Government guarantees. Around the beginning of 2008 we observe a rise in levels which supposedly reflects the intervention of European governments to prevent banks from suffering the effect of the US credit crunch. The rise in level is however more pronounced towards the beginning of 2009, a period where the financial crisis repercussions spread to Europe and were amplified by the start of the sovereign debt crisis.

Table 4 reports regression analysis (Equation 9 through 11) relating to the government guarantee component. The First equation (9) relates differences between estimated and historical default arrival rates to government guarantees. The coefficient is negative and significant. The higher the level of guarantee, the lower the difference in levels between the two types of default arrival rates. This is in line with the fact that CDS spreads represent the default exposure of the bank after taking into account the government guarantee. Put differently, a higher government guarantee, results into a lower the CDS spread, and so we

[12] The estimation of the government guarantee involves the estimation of a faction alpha (α) such that $\alpha(t)P_E\ (t)$. While the alphas should never be negative from a conceptual viewpoint .This factor takes a negative value for a very limited number of observations in our sample but it worth pointing out reasons which may be at the origin of this deviation from theory, these include: Differences between the put option values of the Merton model may differ from the put option values from CDS spreads due to, e.g., illiquidity in CDS markets, distortions in pricing due to irrational behaviour, recovery value perceived as different from the 40% used in pricing CDS, the effects of government interventions such as capital injections that dilute banks' equity.

obtain a higher historical default arrival rate which in turn reduces the differences between the historical and estimated default arrival rates.

Equation (10) and (11) verify the relationship between the government guarantee variable and default risk indicators, namely our estimates of default arrival rates and CDS spreads. In both instances we find strong evidence of the expected relationship (negative and significant coefficients), that is, banks with higher guarantees have less default risk.

We introduce size and an indicator of the risk appetite of the European financial markets and our results remain unchanged.

1.5 Conclusions

The contribution of this work is twofold. First, we contribute to the literature linking CDS spreads to put options. Second, and more importantly we exploit the theoretical link between these two derivatives to estimate the default arrival rate in an innovative way. We do so with a specific focus on European the banking sector to gauge its credit riskiness. Altogether, our results indicate that the estimated default arrival rates do not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks but can serve, at times, as early warning signals. Furthermore, our findings suggest that higher financial guarantees from their sovereign display a lower default risk and hence have a lower CDS spread along with a lower estimated default arrival rate. Ultimately, the government guarantee explains the differences in the level of estimated default arrival rates across banks as well as the observed differences between estimated (i.e derived from Carr&Wu 's model) and historical (CDS spreads scaled by (1-recovery rate)) default arrival rates.

A practical goal of the paper is to verify whether combined with information from the CDS market, DOOM put options could prove to be an alternative indicator of credit deterioration instead of solely relying on CDS derivatives deemed to have an opaque nature.

Table 1 : List of Banks

Bank Code	Bank Name	Ticker
BARC	Barclays	BARC:LN
BBVA	Banco Bilbao Vizcaya Argentaria	BBVA:SM
PNPPA	BNP Paribas	BNP:FP
CAGRA	Credit Agricole	ACA:FP
CBKG	COMMERZBANK	CBK:GR
CRDI	UniCredit SpA	UCG:IM
CSGN	Credit Suisse Group AG	CSGN:VX
DBKGn	Deutsche *Bank*	DBK:GR
DEXI	DEXIA	DEXB:BB
ERST	ERSTE Bank Group	EBS:AV
ING	*ING DIRECT*	INGA:NA
KBC	KBC Bank	KBC:BB
RBS	*Royal Bank of Scotland* (*RBS*)	RBS:LN
STAN	Standard Chartered *Bank*	STAN:LN
UBSN	UBS	UBSN:VX

Table 2: Summary statistics calculated based on the banks time series mean values for default arrival rates, CDS spreads and strike prices K1 and K2

	Estimated Lambda	CDS	Stock	K1	K2
Mean	49,31	44,73	655,37	12,80	13,95
STD	63,70	61,06	1144,57	14,80	16,26
Q1	52,85	59,73	29,18	7,11	7,41
Median	79,21	73,38	64,12	11,61	13,55
Q3	128,58	116,26	230,64	29,80	33,91
Skew	1,13	1,77	3,36	0,57	0,57
Kurto	0,70	2,93	11,85	-1,20	-1,21
Min	23,34	49,84	12,18	1,13	1,24
Max	248,03	264,88	4430,91	42,20	47,52

Table 3: Summary statistics of strikes prices and stocks prices

	Mean	Median	STDEV	Min	Max	Q1	Q3	Skew	Kurto
				Barclays					
K1	3,30	4,20	1,48	0,48	6,4	1,70	4,20	-0,47	-1,19
K2	3,61	4,20	1,56		6,5	2,30	4,60	-0,47	-1,15
S	667,53	688,49	277,90	72,32	1086,74	439,19	926,48	-0,32	-1,16
				BBVA					
K1	27,37	17,00	17,70	9	80	14,50	38,00	1,07	-0,17
K2	29,82	17,50	19,33	9,75	80	15,00	42,00	0,97	-0,51
S	12,18	13,01	3,30	4	17,16	10,02	14,95	-0,57	-0,82
				CAGRA					
K1	23,17	24,50	10,13	4,8	50	14,76	31,48	0,30	-0,10
K2	23,77	25,84	10,49	4,8	50	14,76	32,00	0,04	-0,94
S	20,37	21,35	8,00	6,11	32,71	12,85	27,99	-0,20	-1,53
				CBKG					
K1	1,13	1,40	0,66	0,13	2,79	0,48	1,60	-0,18	-1,19
K2	1,24	1,59	0,75	0,13	2,39	0,36	1,80	-0,28	-1,37
S	123,56	149,50	64,90	13,51	223,38	44,49	175,13	-0,38	-1,35
				CRDI					
K1	32,22	38,00	15,66	6,4	76	17,00	48,00	-0,26	-1,24
K2	37,99	44,00	18,46	6,4	90	20,00	54,00	-0,37	-1,04
S	337,72	390,23	133,00	51,61	632,81	235,58	443,68	-0,43	-1,02
				DBKG					
K1	4,15	4,00	2,28	0,74	9,2	1,20	6,00	-0,11	-1,31
K2	4,02	4,20	2,36	0,72	9,2	1,20	6,60	-0,07	-1,27
S	66,25	75,10	24,62	15,535	107,162	44,94	86,09	-0,41	-1,06
				DEXIA					
K1	11,61	14,00	6,30	0,8	20	4,40	18,00	-0,43	-1,49
K2	12,48	16,00	6,67	1	21	4,80	19,00	-0,46	-1,50
S	13,08	16,08	6,84	1,03	22,46	5,31	18,94	-0,40	-1,49
				ING					
K1	16,31	16,00	9,55	1,23	25	4,80	24,00	-0,09	-1,72
K2	13,81	20,00	10,11	1,6	30	6,00	25,00	-0,16	-1,50
S	17,30	19,79	8,17	1,91	27,61	7,40	24,60	-0,49	-1,37
				KBC					
K1	41,80	44,00	28,55	4,4	88	10,00	72,00	0,09	-1,67
K2	45,15	41,00	30,44	4,8	92	11,00	76,00	0,05	-1,70
S	102,51	89,50	69,04	5,5	223,38	32,20	168,12	0,18	-1,43
				RBS					
K1	10,20	13,50	5,36	1,67	17	4,00	14,00	-0,68	-1,30
K2	10,67	13,50	5,44	1,83	18	4,83	14,50	-0,72	-1,25
S	4430,91	4908,72	2940,02	145,49	8512,39	754,64	7144,26	-0,25	-1,59
				UBS					
K1	11,12	5,80	7,80	1,6	44,82	4,40	18,68	0,47	-0,66
K2	13,55	6,40	10,51	1,6	85,91	4,80	22,41	0,87	1,55

S	37,98	30,36	22,02	8,57	71,147	16,52	62,37	0,24	-1,67
				BNP					
K1	42,20	48,00	13,59	12	76	36,00	49,61	-0,63	-0,23
K2	47,52	54,57	15,22	14	90	40,00	54,57	-0,35	0,06
S	64,12	68,08	16,37	20,77	91,6011	54,56	76,25	-0,71	-0,22
				CSGN					
K1	39,89	59,69	37,75	3,8	119,38	4,60	59,69	0,50	-1,02
K2	41,70	43,77	34,13	4	139,28	5,20	67,65	0,28	-1,09
S	38,11	38,54	10,19	14,81	55,86	31,15	46,30	-0,26	-0,81
				ERSTE					
K1	3,30	3,20	2,04	1	9,5	1,60	4,80	0,88	0,12
K2	3,48	3,40	2,09	1	9,5	1,70	5,00	0,88	0,04
S	38,18	41,99	14,07	6,59	57,93	28,73	49,51	-0,60	-0,78
				STAN					
K1	11,51	11,50	0,98	10	17	11,00	12,00	0,99	3,57
K2	11,93	12,00	1,16	10	17,5	11,00	13,00	0,62	1,54
S	1263,52	1247,23	123,80	1024,6	1652,85	1176,39	1339,15	0,66	0,23

Note: Table 2 reports summary statistics of the DOOM put options strikes K1, K2 along with the underlying stock price S for each bank over the period of January 2006 to December 2009.

Table 4: Summary statistics of estimated , historical default arrival rates and CDS spreads

	Mean	Median	STDEV	Min	Max	Q1	Q3	Skew	Kurto
Barclay									
Lambda E	**167,34**	197,08	89,80	28,31	322,31	76,96	253,60	0,08	-1,49
Lambda H	**116,01**	101,12	107,90	9,08	435,20	14,38	198,84	0,74	-0,49
CDS	**69,60**	60,67	64,74	5,45	261,12	8,63	119,31	0,74	-0,49
BBVA									
Lambda E	**52,42**	28,29	52,45	13,56	301,85	23,14	63,72	2,80	8,93
Lambda H	**156,51**	155,00	42,79	70,64	295,60	130,00	171,67	0,72	0,66
CDS	**93,91**	93,00	25,67	42,39	177,36	78,00	103,00	0,72	0,66
CAGRA									
Lambda E	**187,86**	121,59	150,79	33,59	609,25	50,73	311,32	0,78	-0,55
Lambda H	**83,07**	71,26	69,69	9,72	276,12	12,22	142,03	0,33	-1,32
CDS	**49,84**	42,76	41,82	5,83	165,67	7,33	85,22	0,33	-1,32
CBKG									
Lambda E	**23,34**	16,48	24,38	4,28	320,68	11,65	28,76	6,23	62,02
Lambda H	**89,78**	98,66	66,87	13,09	274,16	20,32	138,14	0,41	-0,90
CDS	**53,87**	59,20	40,12	7,85	164,50	12,19	82,88	0,41	-0,90
CRDI									
Lambda E	**74,55**	72,27	32,52	25,69	170,67	41,35	91,73	0,61	-0,25
Lambda H	**100,67**	84,16	86,11	12,46	460,39	20,50	158,85	1,03	1,05
CDS	**60,40**	50,50	51,66	7,48	276,23	12,30	95,31	1,03	1,05
DBKG									
Lambda E	**50,64**	43,85	35,93	12,63	265,08	23,72	60,04	2,01	6,19
Lambda H	**98,42**	91,95	75,66	15,92	286,66	21,74	159,21	0,44	-1,08
CDS	**59,05**	55,17	45,39	9,55	172,00	13,05	95,53	0,44	-1,08
DEXIA									
Lambda E	**71,07**	59,85	52,92	12,24	208,53	27,09	96,01	0,96	-0,15
Lambda H	**444,36**	401,38	138,44	160,00	983,33	320,47	522,83	0,78	-0,20
CDS	**264,88**	236,64	84,38	96,00	590,00	189,94	313,46	0,82	-0,20
ING									
Lambda E	**88,32**	65,88	64,48	21,80	281,80	36,17	108,55	1,29	0,81
Lambda H	**119,09**	115,35	77,47	9,54	305,03	50,80	172,27	0,20	-0,82
CDS	**71,45**	69,21	46,48	5,72	183,02	30,48	103,36	0,20	-0,82
KBC									
Lambda E	**103,67**	50,48	104,84	14,26	539,87	28,55	162,90	1,65	3,06
Lambda H	**328,98**	366,67	120,54	96,25	570,83	247,81	429,17	-0,47	-0,84
CDS	**197,39**	220,00	72,32	57,75	342,50	148,69	257,50	-0,47	-0,84
RBS									
Lambda E	**79,21**	68,83	45,76	33,36	240,99	53,92	87,72	2,01	4,13
Lambda H	**122,31**	107,80	112,80	6,61	508,16	12,40	214,18	0,57	-0,70
CDS	**73,38**	64,68	67,68	3,96	304,89	7,44	128,51	0,57	-0,70
UBS									
Lambda E	**88,32**	65,88	64,48	21,80	281,80	36,17	108,55	1,29	0,81
Lambda H	**174,92**	160,04	135,66	9,33	607,80	54,81	230,22	0,85	0,38
CDS	**104,95**	96,02	81,40	5,60	364,68	32,89	138,13	0,85	0,38
BNP									
Lambda E	**53,29**	38,26	36,64	12,13	223,04	22,35	72,85	0,99	0,70
Lambda H	**86,58**	94,43	49,95	10,95	239,21	48,09	119,66	0,07	-0,54
CDS	**51,95**	56,66	29,97	6,57	143,52	28,86	71,80	0,07	-0,54
CSGN									
Lambda E	**248,03**	237,67	149,79	43,89	656,58	117,34	360,86	0,51	-0,75
Lambda H	**143,26**	131,35	94,17	18,33	443,81	76,11	194,79	0,68	-0,04
CDS	**85,96**	78,81	56,50	11,00	266,28	45,67	116,87	0,68	-0,04
ERSTE									
Lambda E	**30,23**	23,72	22,17	4,05	133,18	16,43	33,71	1,53	2,53

Lambda H	**212,62**	205,91	170,51	18,06	803,36	59,17	307,47	0,99	0,95
CDS	**127,57**	123,54	102,31	10,83	482,02	35,50	184,48	0,99	0,95
					STAN				
Lambda E	**153,48**	135,30	47,21	99,91	265,42	118,58	166,00	1,04	-0,10
Lambda H	**238,59**	222,50	124,84	93,50	583,33	129,79	292,71	1,01	0,28
CDS	**143,15**	133,50	74,91	56,10	350,00	77,88	175,63	1,01	0,28

Note: Table 3 reports summary statistics of the Estimated , historical default arrival rates and CDS spreads for each bank. Respectively Lambda E, Lambda H, CDS over the period of January 2006 to December 2009. Lambda E, Lambda H is expressed in % whereas CDS is expressed in basis points.

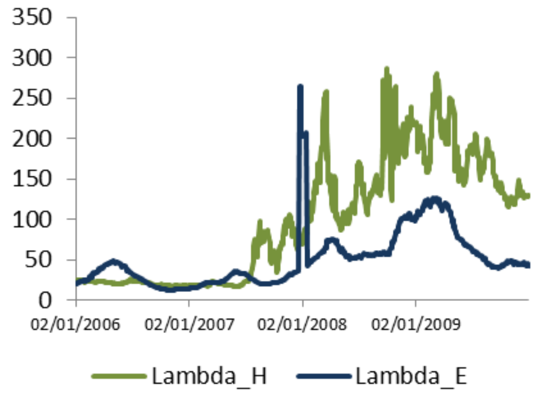
Table 5: Regression results of equations 9 through 11

Variable	Coefficients	
	Model 1 ($\|\Delta\lambda\|$)	
GG	-2.426*** (0.000)	-1.696*** (0.000)
VSTOXX	-	-0.002 ** (0.014)
Size	-	0.883 *** (0.000)
R-squared	*0.164*	*0.175*
	Model 2 (Lambda)	
GG	-3.340*** (0.000)	-0.995 *** (0.000)
VSTOXX	**-**	-0.002 *** (0.000)
Size	**-**	0.598 *** (0.000)
R-squared	*0.316*	*0.381*
	Model 3 (CDS)	
GG	-3.216 *** (0.000)	-0.412 *** (0.000)
VSTOXX	-	-0.002 *** (0.000)
Size	-	1.473*** (0.000)
R-squared	*0.473*	*0.655*

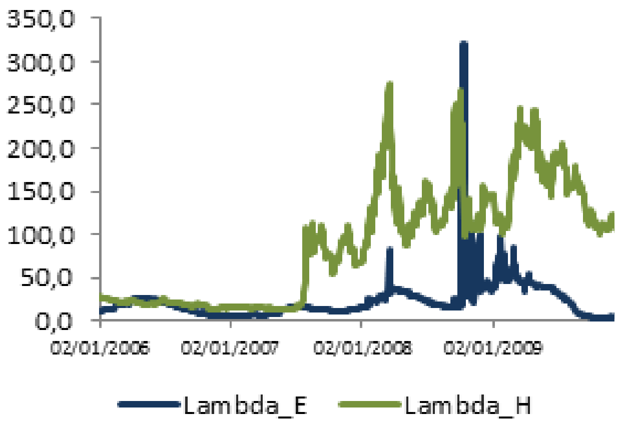
Note: Table 4 reports fixed effect panel regression results over the period 2006-2009. The depend variables are: $|\delta\lambda|$, $\delta Lambda_{Eit}$ and δs_{CDSit} where $|\delta\lambda|$ is the difference between the estimated and historical default arrival rates in absolute value (Lambda E – Lambda H); $\delta Lambda_{Eit}$ is the estimated default arrival rate of bank i in first differences at time t and δs_{CDSit} its CDS spread in first differences
The independent variables are: GG_{it} , size and VSTOXX. δGG_{it} is the government guarantee in first differences computed as (alpha*equity put option); Size as measured by market capitalization and VSTOXX which as measure of the risk appetite of the financial markets.

Figure 1: Plots of Estimated versus Historical Default Arrival rates

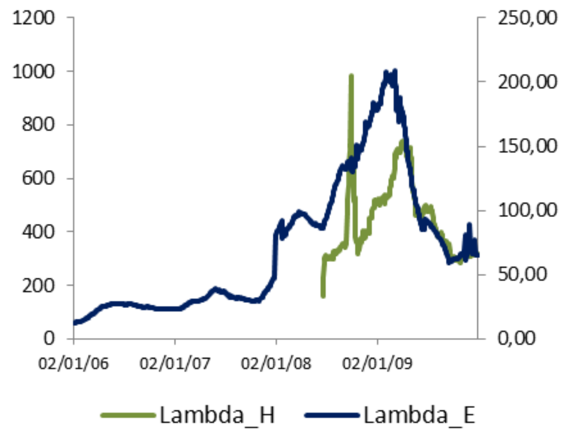
DEUTSCHE BANK



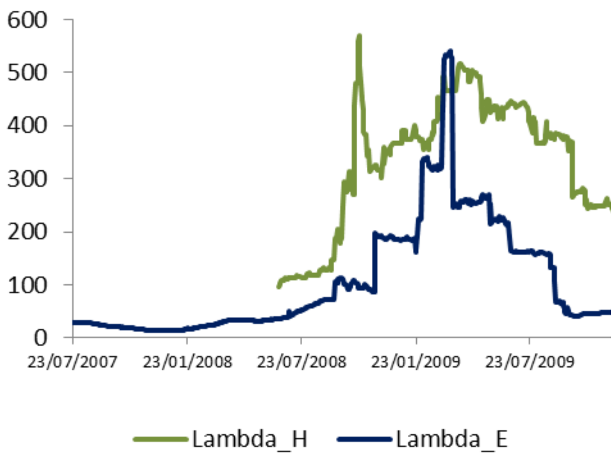
COMMERZBANK



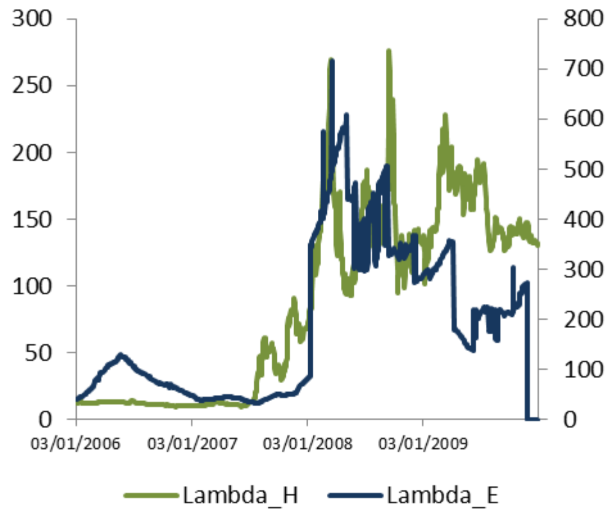
Dexia



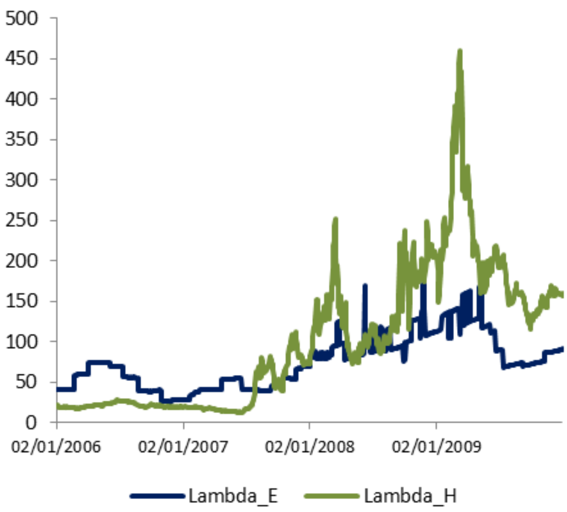
KBC



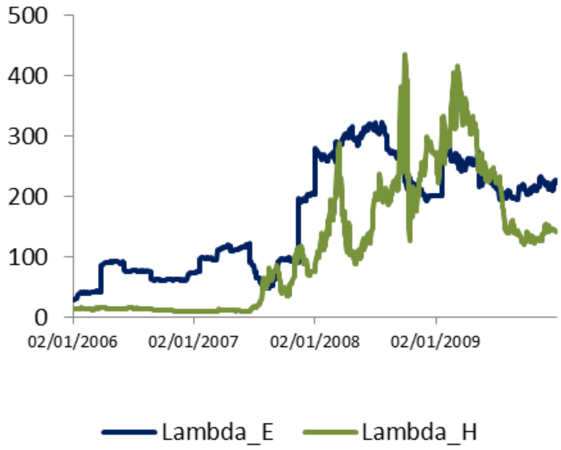
Credit Agricole



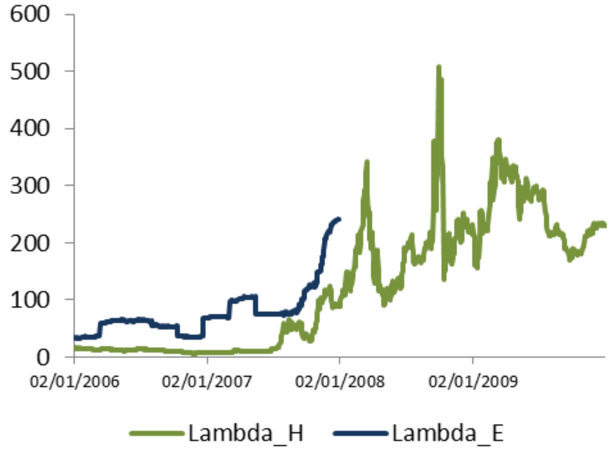
Unicredit



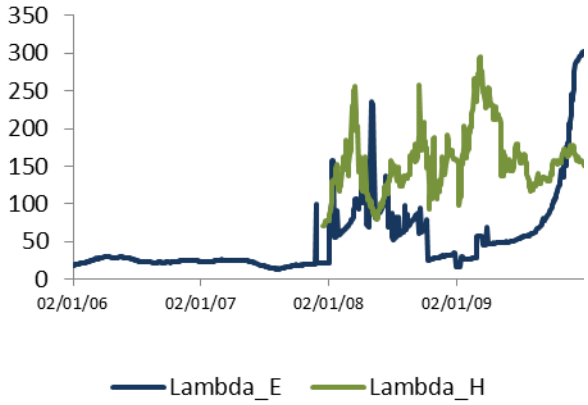
Barclays



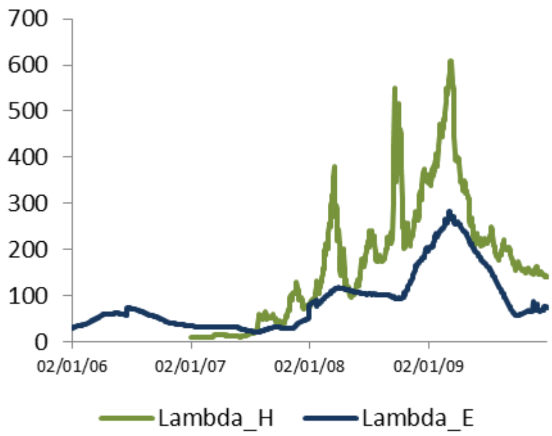
Royal Bank of Scotland



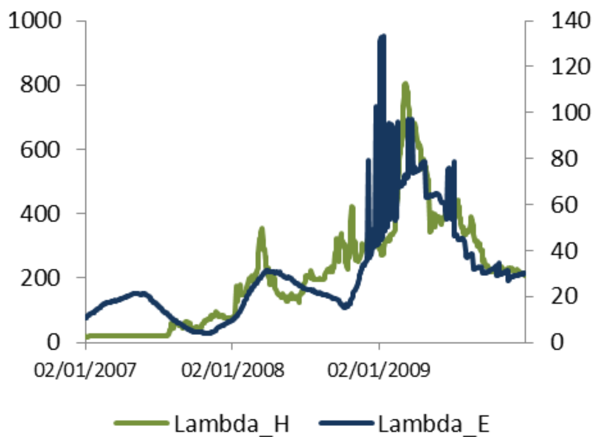
BBV ARGENTARIA



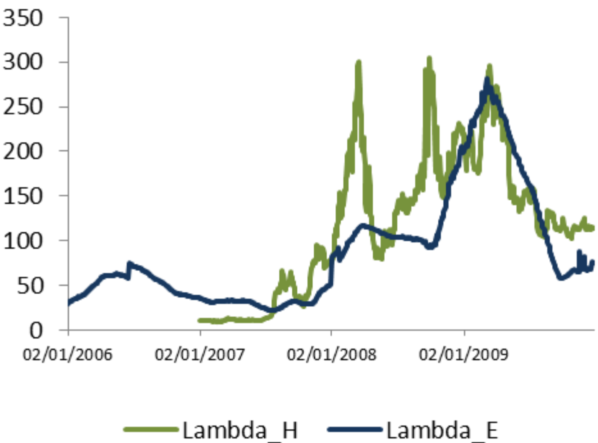
UBS



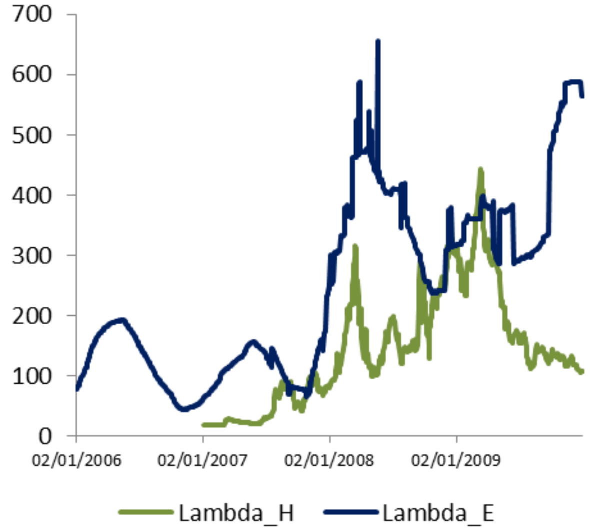
ERSTE GROUP BANK



ING



Credit Suisse



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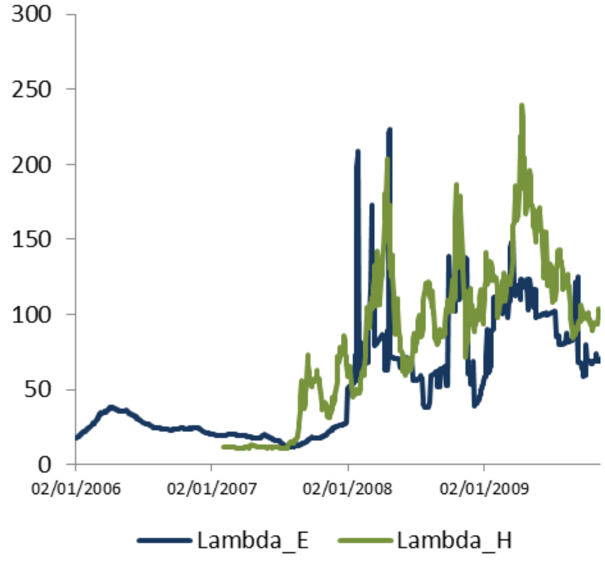


Stan

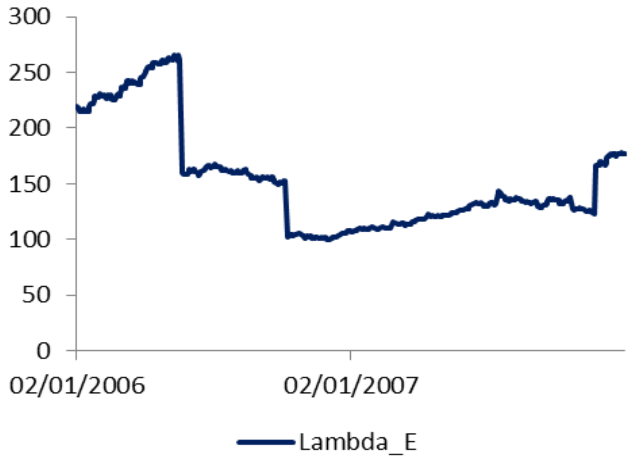
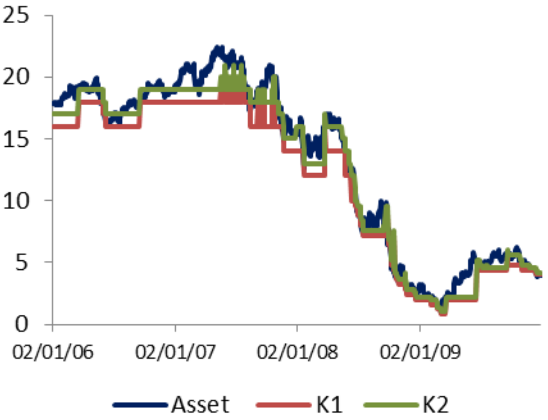
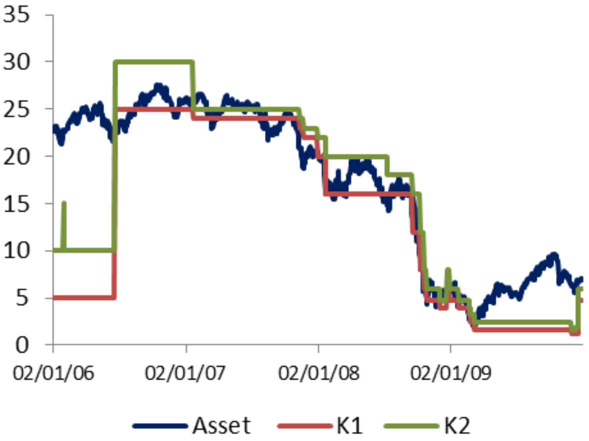


Figure 2: Plots of daily strikes prices and the underlying asset for each banks

DEXIA



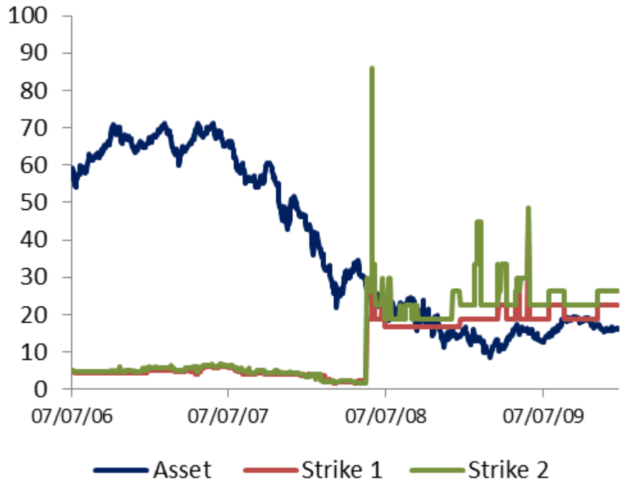
ING



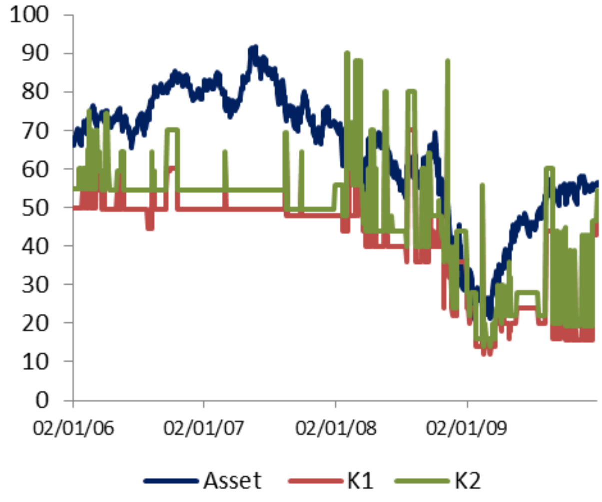
KBC

RBS

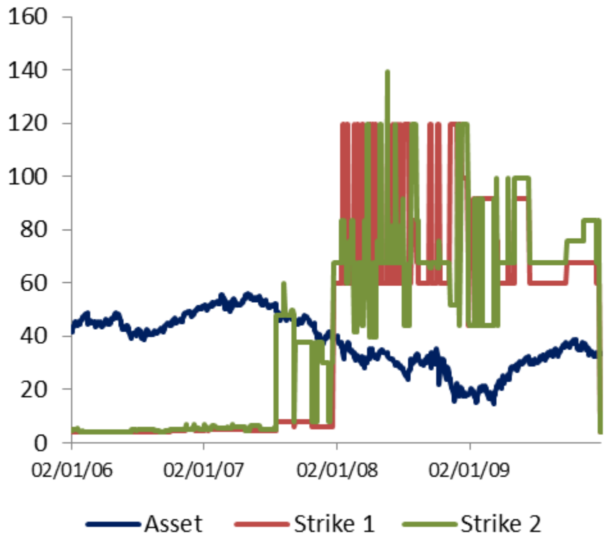
UBS



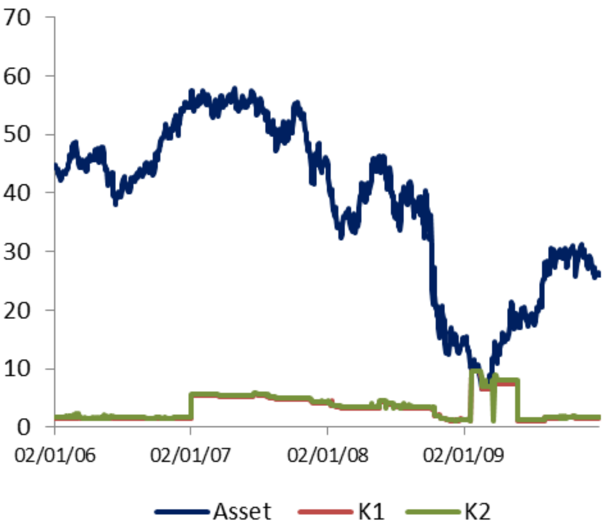
BNP



CSGN



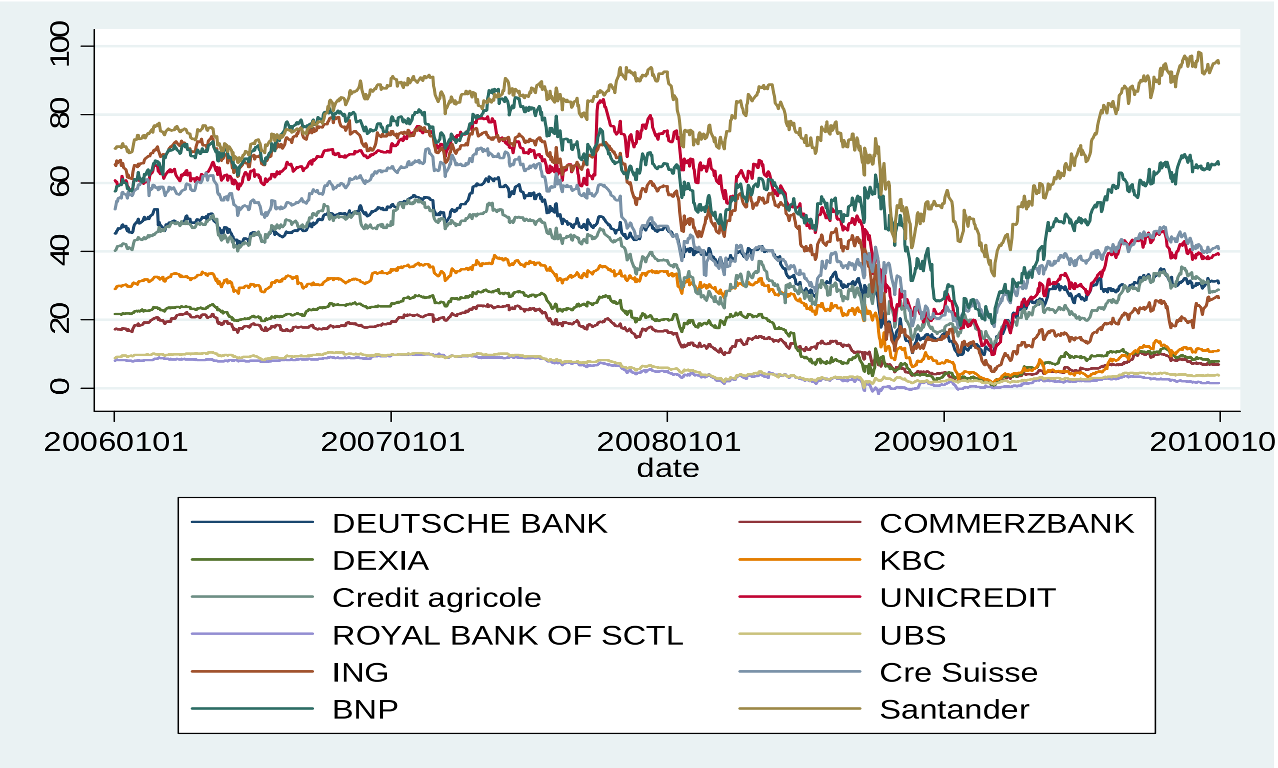
Erste



STAN

Note: Plots of daily strikes prices, K1, K2 and the underlying asset for each banks. The strikes prices K1, K2 are comprised in the 'default corridor' described by the model, which the asset prices should never enter. For certain banks of our sample, this assumption is not materialized throughout the whole period of study.

Figure 3 : Plots of Government Guarantees



Note : The Government guarantees which represents the government implied liability is calculated as alpha*equity put option where alpha is a factor defined as (1- Put on CDS/ Put on equity)

Chapter Two

Euro at Risk: The Impact of Member Countries' Credit Risk on the Stability of the Common Currency**

2.1 Motivation

In view of the current sovereign debt crisis, understanding the dynamics of the credit risk of the euro-area countries proves urgent so as to prevent dire scenarios. At worst, the default of a major country would unleash the currency break-up, ravage the European banking system and ultimately engender a global economic slump. In this study, we view the Eurozone sovereign debt crisis through the twin lenses of sovereign credit swaps and currency option markets. In the absence of Eurobonds, we empirically examine the impact of the credit risk of member countries on the stability of the Euro.

The credit risk of a country can be measured through its sovereign credit default swap (CDS)[13]. Market prices of CDS spreads reflect the perception of financial markets about the economic-political stability of a country, and thus about the creditworthiness of a given sovereign. As shown by Pan and Singleton (2008), the changes in credit risk premiums of sovereign markets which translate into changes in sovereign CDS spreads, do not emanate from changes in fundamentals of the underlying economies. Rather, these variations mirror a change in the risk appetite of market participants in terms of credit exposure. A negative change in the creditworthiness of a sovereign inevitably translates into a depreciation of its currency along with soaring currency volatility. Furthermore, currency option prices are

[13] A sovereign CDS contract provides protection against the non-payment of sovereign debt. Typically, it involves one counterparty agreeing to sell protection to another. The "protected" party pays a yearly premium known as the CDS spread in exchange for a guarantee that in the event of a default, the seller of protection will provide compensation.

instruments which are capable of predicting the changes in the realized volatility of currency returns. Based on data from the Mexican and Brazilian Markets, Car and Wu (2007) establish a relationship between sovereign CDS spreads and currency return volatilities induced through implied-volatilities of currency options and risk reversals[14]. Their results indicate that the sovereign CDS spreads co-vary substantially with the risk reversals. In the same spirit, Hui and Fong (2011) report similar results while focusing on the interconnectivity between the US and Japan sovereign CDS markets and the currency option market characterized by risk reversals of options on the dollar-yen exchange rate. Compared to Japan, The US sovereign credit risk is shown to have a significant impact on the risk reversal. Therefore it is deemed to play a more significant role in the way markets form expectations on the dollar-yen exchange rate.

Turning to the European context, Hui and Chung (2011) document information transmission from the sovereign CDS market to the currency option market. Using implied volatilities of options on the dollar-euro exchange rate as a measure of crash risk, they conclude that the credit risk of the Eurozone is a distinct factor which determines the prices of the out-of-the-money euro put options prices. The recent Eurozone crisis is viewed from various angles by the literature. Azerti et al. (2011) and Alfonso et al. (2011) use the perspective of credit rating agencies and show that sovereign rating announcements have spillovers effect on the European financial markets. They firstly study the response of sovereign CDS spread, banking stock index, insurance stock index and country stock while they secondly focus on the response of government yield spreads. Either way news about downgrades is found to

[14] Risk reversal is the difference in volatility (delta) between similar out-of-the-money call and put options. A positive risk reversal implies that market participants are expecting an appreciation rather than a depreciation of the local currency. The risk reversal conveys information about the skewness of the exchange rate distribution.

have significant spillover effects. However, the linkages with currency option markets are not considered. Another perspective is that of Calice et al. (2011) who analyse the Eurozone crisis by modelling liquidity in the sovereign CDS markets. They find evidence that the liquidity of CDS markets of struggling countries such as Greece, Portugal and Ireland has a substantial impact on sovereign debt spreads. An earlier strand of literature tackles the question of currency crash risk from a macro-economic angle and explains currency crash risk by economic fundamentals. It provides empirical evidence from developing countries of a relationship between macro-economic indicators and weak currencies. Countries with weak fundamentals are less likely to be able to defend their currencies against speculative attacks (Wolff (1987), Eichengreen et al. (1996); Frankel and Rose (1996); Kaminsky et al. (2003) are a few examples).

Our study also relates to a recent strand of literature which attempts to link currency crash risk to the distribution of exchange rate. Notwithstanding the sound models and explanations established by this strand, it does not take into account sovereign credit risk. Brunnermeier et al. (2009) detect negative skewness in the movements of exchange rates involving a low-level interest rate currency and a high-level one. This boils down to saying that carry trade strategies are exposed to crash risk. The authors argue that the skewness is triggered when such strategies take place in an abrupt manner reflecting lower risk appetite and higher liquidity constraints. Currency risk with respect to Carry trade strategies are also examined in work by Fahri et al. (2009).The main risk of these strategies emerges from the value of the exchange rate at the end. The authors propose an exchange model to distinguish between “disaster” and “Gaussian” premia in the currency option markets. The model entails a strong relationship between interest rates, changes in exchange rates and levels of risk reversals. The main empirical implication indicates that disaster premium explains 25% of carry trades returns. In others words, crash risk drives currency returns considerably. Other papers, which find a similar result by analyzing crash risk from the perspective of currency options include the work of Jurek (2009) and Burnside et al. (2011).

Moreover, our study is related to the literature examining the linkage between corporate CDS and stock option markets and the information transmission inherent to these markets. Examples include work by Acharya and Johnson (2007), which presents empirical evidence on the existence of information transmission from the corporate CDS to the stock market. This phenomenon is detected for firms which were subject or are likely to be subject to negative credit news and which maintain strong ties with banks. The analysis of the relation between CDS spreads and implied-volatilities in the work of Cao et al. (2010) shows that the information embedded in the implied volatilities of deep out of the money put options is able to explain the variations in CDS spreads. The skew of the implied volatilities is also computed so as to examine its effect on CDS spreads. Important to note is the fact that this implied volatility is related to the negative tail of the risk neutral probability. Besides, the information embedded in it reflects both future volatility and risk premium.

In an effort to shed more light on the current sovereign debt crisis, our study proposes the use of a sound and state-to-the art measure to assess the stability of the Euro. Based on the framework of Bakshi et al. (2003), the stability of the euro is examined by decomposing dollar-euro[15] exchange rate options into the moments of the risk-neutral distribution. The method is partly used in the recent empirical option pricing literature (see e.g. Bams et al. (2009) and Neumann and Skiadopoulos (2012)). In particular, we compute model-free risk-neutral volatility, skewness and kurtosis measures from the cross-section of currency option

[15] The quotation 'dollar-euro' refers to the amount of dollars needed to obtain one unit of euro.

prices, which allow us to evaluate the stability of the euro. Skewness is typically interpreted as the euro crash risk, while risk-neutral kurtosis as the tail risk of the exchange rate distribution. The first measure gives an indication in which direction market participants are expecting the dollar-euro exchange rate to move. A negative skewness reflects concerns about a depreciation of the euro, which translates into the willingness of investors to pay a higher risk premium for put options relative to call options in order to obtain protection for the potential drop in value. Tail risk refers to the extreme events whose probability is low but whose impact on prices is large should they materialize. In particular, during the European sovereign debt crisis, we expect that possible concerns about the stability of the euro should be reflected in a negative skewness of the dollar-euro exchange rate options. The focus of this study is to examine the impact of the credit risk of Eurozone member countries on the stability of the Euro.

We document that changes in the creditworthiness of a member country on one day have a significant impact on the stability of the euro on the following day. On the one hand, an increase in member countries' credit risk results in an increase of the volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. On the other, we find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. Based on those results, we propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure and show that our results are robust to this change in measure. Noticeable is the fact the creditworthiness of countries with vulnerable fiscal positions is the main, but not the only risk-endangering factor of the euro-stability. While the creditworthiness of the latter countries has a significant impact on the skewness measure (i.e. crash risk) and the stability indicators, healthier countries equally drive the relationship between the creditworthiness and the volatility as well as the kurtosis (i.e. tail risk) of the risk-neutral distribution.

The remainder of this paper is structured as follows: The next section outlines the conceptual framework. Section 3 describes the data and presents some summary statistics. Then, the methodologies with respect to the option pricing aspects and the regression analyses are explained. Subsequently, the empirical results are outlined and discussed. The last section contains concluding remarks.

2.2 A Conceptual Framework

In this section, we attempt to provide a conceptual explanation for the channels through which the sovereign CDS market might impinge on the currency option market. We build on the contingent claim balance sheet framework of (Gray et al. (2007)), which is an adaptation of Merton's contingent claim analysis to the sovereign context. Under this structure, the sovereign balance sheet in Figure 1, representing a combined balance sheet of the government and the monetary authority, can be expressed in terms of foreign currency units (here US Dollar) to analyze the values of assets and liabilities in an international context.

Sovereign assets consist of foreign reserves, net fiscal assets and other public assets. The item "-guarantees" results from subtracting the guarantees to too-big-to-fail entities from both sides of the balance sheet. The value of local currency liabilities in foreign currency terms, $LCL_{\$}$, which comprises local-currency debt and base money, can be viewed as a call option on sovereign assets (in foreign currency terms), $V_{\$Sov}$. The strike price for this option, B_f, is the distress barrier for foreign currency-denominated debt, which is derived from the interest payments and promised payments on foreign currency debt up to time T in the future. Similar to the Black-Scholes-Merton pricing framework for equity, this call option can be expressed as:

$$LCL_{\$} = V_{\$Sov}\, N(d_1) - B_f e^{-r_f T} N(d_2)$$

with

$$d_1 = \frac{\ln(A_{\$Sov}/B_f) + \left(r_f - r_d + 0.5\sigma^2_{\$Sov}\right) T}{\sigma^2_{\$Sov}\sqrt{T}} \quad \text{and} \quad d_2 = \frac{\ln(A_{\$Sov}/B_f) + \left(r_f - r_d - 0.5\sigma^2_{\$Sov}\right) T}{\sigma^2_{\$Sov}\sqrt{T}}.$$

Where r_f and r_d are the foreign and local interest rates, respectively, and $\sigma^2_{\$Sov}$ is the volatility of sovereign assets in foreign currency terms. The local currency debt and money are claims on sovereign assets. In principle, governments can always inflate or dilute local currency debt in case of distress, instead of defaulting on foreign currency debt. Therefore, foreign currency debt can be assumed to be more senior compared to local currency debt. In this line of thinking, local currency liabilities can be considered to be similar to equity issued by firms and multiplied by the exchange rate being the "market cap" of the sovereign[16].

The two unknowns that cannot be observed, but need to be computed are implied sovereign assets, $V_{\$Sov}$ and asset volatility $\sigma^2_{\$Sov}$. Asset volatility $\sigma^2_{\$Sov}$ can be derived by applying Ito's

[16] One can easily make the analogy between the value of local currency debt and the value of equity for a firm. If the market value of assets at time t is the sum of the market value of equity and market value on debt, then equity is modeled as a call option on the assets A with strike price B, which represents the promised debt payments.

lemma to the pricing formula of the call option, suggesting a relationship with the volatility of sovereign "equity", $LCL_{\$}$:

$$LCL_{\$}\,\sigma_{\$LCL} = V_{\$Sov}\sigma_{\$Sov}N(d_1)$$

The local currency liabilities $LCL_{\$}$, can be directly computed from the sovereign balance sheet data using actual exchange rates. The volatility of local currency liabilities, $\sigma_{\$LCL}$, is a function of the volatility of the money base and local currency debt, as well as exchange rate volatility. In case the exchange rate is floating, exchange rate volatility is the major part of uncertainty. The model can be implemented similarly to the Merton model, solving the two equations with two unknown variables. The probability of default of the sovereign is given by N(-*d*2). In order to find the model-implied credit spread, we first need to find the current value of the risky debt with promised payments B_f. From the balance sheet of the sovereign, the value of risky debt D_f can be expressed as the difference between the asset value, $V_{\$Sov}$, and the value of the local currency liabilities $LCL_{\$}$. Then the yield-to-maturity of the risky debt is $y = \frac{\ln\left(\frac{B_f}{D_f}\right)}{T}$ and the model-implied "fair value" of the credit spread is equal to s = y – r_f.

The sovereign CCA model provides a framework for valuing sovereign foreign-currency debt, local-currency debt, foreign currency value of base money and local-currency debt. However, the CCA model is not only useful for the valuation of the different constituents of a sovereign's capital structure, but also for the valuation of other claims such as CDS on foreign currency debt. The book-based 'fair' estimates can be compared with market-based spreads of sovereign CDS's and relative value strategies can be employed. This makes it possible to benefit from capital structure arbitrage strategies using various instruments, FX options and sovereign CDS, in particular. Similarly to the relationship between the volatility skew implied by equity options and CDS spreads, a trade strategy on the sovereign capital structure is to trade currency against the CDS. A "fair value" CDS spread can be obtained from the contingent claims model using currency market information. If currency volatility is expensive relative to observed CDS spreads, resulting in a 'fair value' CDS spread being too high compared to the observed spread, a strategy is to sell currency volatility (e.g. a straddle) and to buy protection. If volatility declines or spreads widen the strategy earns money. Another strategy, if currency volatility is cheap relative to the observed CDS spreads, the strategy is to buy currency volatility and to sell protection. If volatility increases or spreads decline the strategy earns money. Many different sovereign capital structure arbitrage trading strategies are possible using a variety of instruments, including FX spot and forwards, FX options, local-currency debt, foreign-currency debt, CDS on foreign-currency debt, and inflation or indexed debt. These strategies are reasonable because exchange rates (which affect the value of local currency liabilities) tend to co-move with the credit spreads of foreign currency debt. As a result, sovereign capital structure arbitrage also ensures that relevant information from the sovereign CDS market is transmitted into the currency options market. For example, if the sovereign CDS spread increases, the "fair value" model-implied spreads appears to be cheap or the foreign currency appears to be undervalued, the strategy is to buy a put on the local currency and to sell protection. If the local currency subsequently depreciates the strategy earns money. In the European context, it suggests, that relevant information regarding sovereign distress risk might affect the stability of the Euro.

However, one might argue that there are several reasons why the sovereign CCA model is not applicable to European countries. First, countries have direct access to large and liquid markets to issue debt in their domestic currency and that is why European countries have only a relatively small amount of foreign currency debt. Moreover, countries from the Economic and Monetary Union (EMU) have only limited control over the money supply of the European Central Bank (ECB) and, therefore, the analogy between local currency liabilities and equity is not complete. However, countries like Greece are indebted in terms of a currency (the euro) that they cannot print on demand. This makes their local currency debt similar to foreign currency debt. Furthermore, the recent interventions of the European Central Bank give rise to the perception that the member countries jointly took over some control over the money supply. As a result, debt of the member countries can be partly considered to be senior debt, equivalent to foreign currency debt, and partly to be junior debt, equivalent to local currency debt. This suggests that the CCA framework can be used as an ad-hoc model for relative value strategies like sovereign capital structure arbitrage.

2.3 Data & Summary Statistics

Data

We collect data on daily 5-year sovereign CDS spreads for 11 countries: Belgium, France, Germany, Netherlands, Austria, Finland, Greece, Spain, Italy, Ireland, Portugal. The source used to obtain the sovereign CDS quotes is Bloomberg's CMAT portal. In addition, we obtain a complete cross-section of daily over-the-counter dollar/euro option prices together with the underlying spot exchange rates, as well as interest rates for Europe and the US through Thomson Reuters' Tick History system. Our data sample covers the period from September 10th 2007 to January 31st 2012[17]. Our data underwent a rigorous cleaning process in order to obtain the final dataset.

[17] However, we had to reduce the sample period for the regression analysis due to lack of reliable sovereign CDS data for certain countries before September 5th 2008. Nonetheless, our sample period still covers the subprime and the sovereign debt crises.

Currency option prices

We obtain OTC European type dollar/euro option prices quoted in implied volatilities at fixed maturities. We used the 1, 3, 6 and 9 months maturity options, because they are the most frequently traded ones. The option quotes are in terms of implied volatilities for particular put and call deltas categories, which is a common industry practice. The different delta categories cover the complete moneyness range of the currency options, e.g out-of-the-money calls and puts at 10-15-20-25-30-35-40-45-delta and at-the-money-options at 50-delta. Using the available delta- and maturity categories of all option contracts, on each day, we fit a functional form to the observed implied volatilities of the options, which allows us to obtain implied volatilities for every possible delta-maturity combination. That allows us to calculate call and put option prices through the Black-Scholes model. Thereafter, on a daily frequency, we are able to derive the moments of the risk-neutral distribution of the dollar-euro exchange rate options.

Sovereign CDS spread

The sovereign credit default swaps, expressed in basis points, are traded at various maturities of up to 30 years. We retrieve the 5-years maturity quotes for the 11 euro-area countries in the analysis since they are the most liquid.

Summary Statistics

Table 1 portrays the summary statistics of individual countries' CDS spreads. We report summary statistics for the subprime crisis period and the sovereign debt crisis period separately. In line with previous research (Hui and Chung (2011)), we assume that October 14th 2009 was the onset of the European sovereign debt crisis. Therefore, the subprime crisis covers the period from September 5th 2008 until October 13th 2009. The period starting on October 14th 2009 and ending at January 31st 2012 represents the sovereign debt crisis period.

Panel A shows the overall statistics for the full sample and reveals the obvious difference in the creditworthiness of the Euro member countries. Based on the CDS data, one might want to characterize certain countries as healthy countries with stable economic conditions and vulnerable countries with fragile economic conditions. Following this logic, France, Germany, Netherlands, Finland and Austria would belong to the group of healthy countries. In contrast, Ireland, Spain, Portugal, Greece and Italy would belong to the group vulnerable country. We leave Belgium due to its political instability unclassified, while its CDS spread would suggest that it could be included in one of the groups. Panel B and Panel C allow us to compare the CDS spreads during the subprime crisis period and during the sovereign debt crisis. The summary statistics reveal substantial differences in the CDS spreads across countries. These differences are in particular pronounced during the sovereign debt crisis. While the average CDS spreads for the healthy countries shows only a slight increase during the subprime crisis, the increase in spreads was substantial for the vulnerable countries. As shown by panel C, the average value is 39bps for Finland and 1359 bps for Greece.

Tables 2 and 3 report summary statistics of the dollar-euro option prices quoted in terms of 10-delta and 25-delta implied-volatilities of calls and puts. The at-the-money options statistics are only reported once together with the put statistics. Summary statistics are presented for four different maturities. The statistics are computed over a sample period covering the subprime- and sovereign debt crisis period, ranging from September 5th 2008 until January 31st 2012. Overall, the implied volatilities for calls and puts increase with maturity and they are on average higher during the sub-prime crisis.

Figure 2 shows the dollar-euro option smile on February 14th 2012 for maturities of up to 9 months. The graph nicely characterizes the extreme shape of the smile, which characterizes the European sovereign debt crisis period. The smirk-type shape, typically observed for equity options, refers to the negative skewness in the risk-neutral distribution of the dollar-euro exchange rate and, therefore, proxies the crash risk of the euro.

2.4 Methodology

It is industry practice to quote currency options in terms of implied volatilities at particular deltas. The Black-Scholes deltas of European-style call and put options are given by

$$\text{delta}_C = e^{-qT} N\left(\frac{\ln(Se^{(r-q)T}/K) + 0.5\sigma^2 T}{\sigma\sqrt{T}}\right) \quad (1)$$

$$\text{delta}_P = -e^{-qT}\left(1 - N\left(\frac{\ln(Se^{(r-q)T}/K) + 0.5\sigma^2 T}{\sigma\sqrt{T}}\right)\right) \quad (2)$$

where S is the dollar-euro exchange rate, K is the exercise, σ is the implied volatility of the option, r and q are the US and European risk-free interest rates corresponding to the time to maturity (T) of the option and N(.) is the cumulative normal distribution.

Estimating the implied volatility surface

For the empirical analysis, we first use a modification of the prominent ad-hoc Black-Scholes model of Dumas, Fleming and Whaley (1998) to estimate the implied volatility surface of our currency options. We use all available information content in currency option prices for different moneyness (deltas) and different maturities. The aim is to construct a time series of standardized measures (e.g. risk neutral volatility, skewness and kurtosis) that characterize the cross-section of prices and can be compared over time. Rather than averaging the two contracts that are closest to at-the-money or closest to one month maturity, we fit the modified ad-hoc Black-Scholes model to all option contracts on a given day and subsequently obtain the desired functional form of the implied volatility surface. This strategy successfully eliminates some of the noise from the data (see Christoffersen et al. (2010)). We allow each option to have its own Black-Scholes implied volatility depending on the options delta and time to maturity T. We use the following functional form for the options implied volatility:

$$IV_{i,j} = \alpha_0 + \alpha_1 \text{delta}_{C\,i,j} + \alpha_2 \text{delta}_{C\,i,j}^2 + \alpha_3 T_j + \alpha_4 T_j^2 + \alpha_5 \text{delta}_{C\,i,j} T_j, \quad (3)$$

where IV_{ij} denotes the observed implied volatility and $\text{delta}_{C,i,j}$, the delta of a call option for the i-th moneyness and j-th maturity, defined in Equation (1)[18]. T_j denotes the time to maturity of an option for the j-th maturity. It is common practice to estimate the parameters using standard OLS. For every call option delta (or put option delta) and maturity, we can compute the implied volatility and derive option prices using the Black-Scholes model. For example, the implied volatility for an at-the-money short term call option with three month maturity can be derived by setting delta equal to 0.5 and time to maturity T equal to 3/12.

Calculating the moments of the risk-neutral distribution

Having characterized the implied volatility surface of the dollar-euro exchange rate options, we calibrate the moments of the resulting risk-neutral distribution. Bakshi et al. (2003) derive a model-free measure of risk-neutral variance, skewness and kurtosis based on all options over the complete moneyness range for a particular time to maturity T.

[18] For put options, we use the corresponding call delta in the implied volatility regression.

Variance, skewness and kurtosis of the T-month risk-neutral distribution can be computed by

$$Variance_t(T) = e^{rT} V_t(T) - \mu^2$$

$$Skewness_t(T) = \frac{e^{rT} W_t(T) - 3\mu_t(T) e^{rT} V_t(T) + 2\mu_t(T)^3}{\left[e^{rT} V_t(T) - \mu_t(T)^2\right]^{\frac{3}{2}}} \tag{4}$$

$$Kurtosis_t(T) = \frac{e^{rT} X_t(T) - 4\mu_t(T) e^{rT} W_t(T) + 6 e^{rT} \mu_t(T)^2 V_t(T) - 3\mu_t(T)^4}{\left[e^{rT} V_t(T) - \mu_t(T)^2\right]^2}$$

where

$$\mu_t(T) = e^{rT} - 1 - \frac{e^{rT}}{2} V_t(T) - \frac{e^{rT}}{6} W_t(T) - \frac{e^{rT}}{24} X_t(T) \tag{5}$$

$$\mathrm{V}_t(T) = \int_{S_t^{-qT}}^{\infty} \frac{2(1 - \ln(K / S_t^{-qT}))}{K^2} c_t(T,K) dK + \int_0^{S_t^{-qT}} \frac{2(1 + \ln(S_t^{-qT} / K))}{K^2} p_t(T,K) dK$$

$$\mathrm{W}_t(T) = \int_{S_t^{-qT}}^{\infty} \frac{6\ln(K / S_t^{-qT})) - 3\left(\ln(K / S_t^{-qT})\right)^2}{K^2} c_t(T,K) dK$$

$$- \int_0^{S_t^{-qT}} \frac{6\ln(S_t^{-qT} / K)) - 3\left(\ln(S_t^{-qT} / K)\right)^2}{K^2} p_t(T,K) dK$$

$$\mathrm{X}_t(T) = \int_{S_t^{-qT}}^{\infty} \frac{12\ln(K / S_t^{-qT})) - 4\left(\ln(K / S_t^{-qT})\right)^3}{K^2} c_t(T,K) dK$$

$$+ \int_0^{S_t^{-qT}} \frac{12\ln(S_t^{-qT} / K)) - 4\left(\ln(S_t^{-qT} / K)\right)^3}{K^2} p_t(T,K) dK \ .$$

The parameters correspond to the ones used in Equation (1) and (2). c and p refer to call and put prices. Again, rather than averaging the observed implied volatilities of all contracts that are closest to one particular maturity (e.g. 3 month), we derive the Bakshi et al. (2003) risk-neutral moments using the estimated implied volatility surface and the corresponding call and put prices. In the empirical analysis, we focus on the 3 months horizon and calculate the moments of the 3-months risk-neutral distribution.

Regression analysis

The first step in our analysis is to regress daily changes in credit default spreads of country i on contemporaneous and lagged changes in the various moments that we use to characterize the risk-neutral distribution as well as on lagged changes in credit default spreads in order to extract the residual component, hence, we estimate the following equations[19]

$$\Delta CDS_{i,t} = \omega^{Vol}{}_i + \sum_{k=0}^{5} \upsilon^{Vol}{}_{i,k} \Delta Vol_{t-k} + \sum_{k=1}^{5} \psi^{Vol}{}_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}^{CDS,Vol} \quad (6a)$$

$$\Delta CDS_{i,t} = \omega^{Skew}{}_i + \sum_{k=0}^{5} \upsilon^{Skew}{}_{i,k} \Delta Skew_{t-k} + \sum_{k=1}^{5} \psi^{Skew}{}_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}^{CDS,Skew} \quad (6b)$$

$$\Delta CDS_{i,t} = \omega^{Kurt}{}_i + \sum_{k=0}^{5} \upsilon^{Kurt}{}_{i,k} \Delta Kurt_{t-k} + \sum_{k=1}^{5} \psi^{Kurt}{}_{i,k} \Delta CDS_{i,t-k} + \varepsilon_{i,t}^{CDS,Kurt} \quad (6c)$$

We do this for up to five lags to absorb any contemporaneous information transmission and any lagged information transmission. In this way, we are able to identify the information arriving in the CDS market, which is not based on information that has been revealed in the dollar-euro options market. The resulting residuals ε_t can be interpreted as innovations in the CDS market relative to the risk-neutral moments that characterize the market conditions in the currency options market.

Subsequently, for each country i, we run a regression of changes in the moments of the risk-neutral distributions on lagged innovations in the CDS market and lagged changes in the variable itself, hence, we estimate

[19] We use log-changes for CDSs and simple changes for the other variables, which allow us to compare the results across countries.

$$\Delta Vol_t = \tau^{Vol}{}_i + \sum_{k=1}^{5} \lambda^{Vol}{}_{i,k} \varepsilon_{i,t-k}^{CDS,Vol} + \sum_{k=1}^{5} \theta^{Vol}{}_{i,k} \Delta Vol_{t-k} + \mu^{Vol}{}_{i,t} \quad (7a)$$

$$\Delta Skew_t = \tau^{Skew}{}_i + \sum_{k=1}^{5} \lambda^{Skew}{}_{i,k} \varepsilon_{i,t-k}^{CDS,Skew} + \sum_{k=1}^{5} \theta^{Skew}{}_{i,k} \Delta Skew_{t-k} + \mu^{Skew}{}_{i,t} \quad (7b)$$

$$\Delta Kurt_t = \tau^{Skew}{}_i + \sum_{k=1}^{5} \lambda^{Kurt}{}_{i,k} \varepsilon_{i,t-k}^{CDS,Kurt} + \sum_{k=1}^{5} \theta^{Skew}{}_{i,k} \Delta Kurt_{t-k} + \mu^{Skew}{}_{i,t} \quad (7c)$$

For each of the risk-neutral moments, we examine $\beta^{Vol}{}_i = \sum_{k=1}^{5} \lambda^{Vol}{}_{i,k}$, $\beta^{Skew}{}_i = \sum_{k=1}^{5} \lambda^{Skew}{}_{i,k}$ and $\beta^{Kurt}{}_i = \sum_{k=1}^{5} \lambda^{Kurt}{}_{i,k}$ as measures of impact of countries' i credit risk on the risk-neutral moments of the dollar-euro exchange rate and, therefore, on the stability of the euro. A motivation and detailed discussion of the usefulness of this approach for testing transmission effects can be found in Acharya and Johnson (2007) and Berndt and Ostrovnaya (2008).

2.5 Empirical results

Figure 3 shows the annualized volatility of the daily 3-month risk–neutral distribution together with the dollar-euro exchange rate over the period from September 10th 2007 to January 31st 2012. Figure 4 shows the daily risk-neutral skewness and kurtosis of 3 month options calculated according to Bakshi et al. (2003). Interestingly, during the subprime crisis, the skewness is mainly positive and turns negative during the subsequent European sovereign debt crisis, with a turning point in October 2009, typically found to be the start of the sovereign debt crisis. Kurtosis was much higher and more volatile during the subprime crisis and reaches its peak in December 2008.

Clearly, our risk neutral skewness measure is able to distinguish between turbulent times. During the subprime crisis, our measure is positive reflecting a possible depreciation (crash risk) of the Dollar. Towards mid-October 2009, the skewness measure turns negative, suggesting a change in the market expectations of the euro vis-à-vis the dollar. That is, markets expect the euro to depreciate, which translates into buying put options of the dollar-euro exchange rate. The lower kurtosis exhibited during the sovereign debt crisis is synonymous to “thinner” tails of the risk-neutral distribution of the dollar-euro exchange rate. Therefore, the tail risk of the two currencies seems to be priced in the US. The subprime crisis starting with the burst of the housing bubble in the US had a major impact on the US economy. Figure 2 shows that during the subprime crisis, not only the volatility of the dollar-euro exchange rate substantially increased, but the kurtosis of the risk-neutral distribution, our proxy for tail risk, increased as well. However, during the sovereign debt crisis period the volatility increased, but the tail risk of the two currencies is relatively stable at a low level.

Summary statistics of the dollar-euro exchange rate and the risk-neutral moments are displayed in Table 4. The skewness measure is positive over the sub-prime crisis (0.47) but becomes negative during the sovereign debt crisis (-0.37) reflecting concerns of market participants about the stability of the euro. With respect to the kurtosis measure, the lower kurtosis exhibited during the sovereign debt crisis (5 versus 8 in the prior period) is synonymous to “thinner” tails of the risk-neutral distribution of the dollar-euro exchange rate and, therefore, lower tail risk.

Table 5 summaries our regression analysis results. The reported betas refer to the sum of regression coefficients based on equations (7a) – (7c) and can be interpreted as a measures of impact of countries’ i credit risk on the risk-neutral moments of the dollar-euro exchange rate and, therefore, on the stability of the euro. For the complete sample period, the results suggest that member countries creditworthiness affects the volatility of the dollar-euro exchange rate. An increase in the CDS spreads, indicating worsening credit conditions, has a positive impact on the volatility of the exchange rate. However, the results for skewness and kurtosis are typically insignificant. Once we separate the period into a subprime crisis period and a sovereign debt crisis period, we observe significant differences over time. Looking at the subprime crisis period, our estimates have no statistical significance. The interpretation is that the credit risk of the euro-area member countries as measured by their CDS spreads does not affect the stability of the euro induced through the skewness (Skew) and kurtosis (Kurt) of the risk-neutral distribution of the dollar-euro exchange rate together with the risk-neutral volatility. In contrast, the results during the sovereign debt crisis period are quite pronounced. An increase in member countries' credit risk results in an increased risk-neutral volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. Furthermore, the impact for healthy countries is significantly not different to the impact for vulnerable countries. As result, both vulnerable and healthy countries have an impact on the stability of the euro in the way that higher levels of volatility are accompanied by lower levels of the exchange rate, and in turn, a weaker euro.

However, we find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. Overall, the relationship is negative, suggesting that an increase in countries' credit risk has a negative impact on the stability of the euro.

With respect to the skewness measure, we find statistical significance only among countries belonging to the "vulnerable" group, namely: Ireland, Spain, Portugal and Italy. These coefficients are substantially negative, which entails that the struggling countries drive the euro crash risk. It can be shown that the betas for the healthy countries and the ones of the vulnerable countries are significantly different form each other at the 1% level. Additionally, we performed a principal component analysis on the CDS spreads changes of the healthy countries vis à vis the vulnerable countries. PCA_H refers to the first principal component of the first group and PCA_V refers to the first principal component of the second group. Results presented in Table 5 confirm previous findings and suggest that during the sovereign debt crisis period only the struggling countries drive the euro crash risk. Contrary to what one would expect, the creditworthiness of Greece does not seem to play a looming role in the stability of the common currency. This reflects the fact that currency option markets do not perceive the credit risk of Greece as a major determinant or risk factor for the stability of the euro.

It is interesting to confront these findings with figures published by the Bank for International Settlements (BIS). On a regular basis BIS publishes cross-border claims of BIS reporting European banks. The Eurozone member countries are interlinked throughout the foreign claims their national banks hold. Given this exposure, a default of one country would cause a spread of the crisis to the rest of the member countries. The speed and magnitude of those contagious effects depend on the amount of debt the defaulting country owes to the rest of Eurozone countries as well the way it is connected to their respective banks. Put another way, the higher the foreign exposure of a given country to the banks of other Eurozone countries, the stronger the potential contagion effects. Looking at the BIS figures for the third quarter of 2009, the onset of the sovereign debt crisis, the data suggest that other vulnerable countries like Ireland, Portugal, Spain and Italy account for nearly 16% of foreign claims in European banks[20], while Greece only accounts for a bit more than 1%. Interestingly, we find that the creditworthiness of countries like Ireland, Portugal, Spain and Italy have an impact on the stability of the euro, while the results for Greece are insignificant. Additionally, Figure 5 illustrates the Eurozone debt structure as of the end of June 2011.

[20] European banks refer to domestically owned banks of Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, and the UK.

Each cycle represents the foreign exposure of a given Eurozone country to other member countries as well as its exposure to major economies. The figure shows how a country would influence the rest in the event of a default. The countries of interest are: Greece, Spain, Portugal, Italy and Ireland. With 2tn euro of gross foreign debt, Italy has the highest exposure towards national banks of the Eurozone countries, and those of the U.S, Japan, and the UK. Spain comes second with 1.9tn, followed by Ireland 1.7tn and finally Portugal and Greece at the same indebtedness level of 0.4 tn. Given these amounts and the interlinkages of each country with national banks of the other countries, the creditworthiness of Italy, Ireland and Spain seem to be the main sources of worry regarding the common currency, which is in line with our empirical results. French and German banks together hold 429bn, 243.7bn, 105,8 bn of Italian, of Spanish and Irish debt respectively, whereas they only hold 57.3 of Greek claims. This lends further credence to our results which do not display significance for Greece. In the case of default, France and Germany would be in position to absorb the shock more easily than if Italy, Spain or Ireland were to default. Furthermore, while Portugal and Greece have similar levels of debt, Portugal proves more unsettling because it is more intimately linked to another struggling country like Spain.

A new indicator for currency stability

In the following, we combine the three risk neutral moments into one aggregated risk indicator that characterizes the complete risk-neutral distribution. This allows us to derive one single market-based indicator that measures currency stability from the cross-section of exchange rate options. During the sovereign debt crisis period, this indicator would measure the euro instability. However, the comovements of these three moments are supposed to have a nonlinear impact on the risk-neutral distribution as a whole. Some popular risk measures in risk management, such as Value at Risk (VaR) and Expected Shortfall (ES) constructed from this risk-neutral distribution are expected to be a good indicator of the euro stability. The Gram-Charlier and Cornish-Fisher expansions are tools often used to compute VaR and ES in the context of skewed and leptokurtic return distributions. These approximations use the higher moments of the unknown target distribution to compute an approximate distribution and quantile functions. Simonato (2011) compare these methods with the Johnson System of distributions which also uses the moments as main inputs but is capable of accommodating all possible skewness and kurtosis. In this study, we consider an alternative approach based on the Pearson System (Pearson (1895)), which can be used to model a wide scale of distributions with various skewness and kurtosis. The Pearson System is a family of probability density distributions which includes a unique distribution corresponding to every valid combination of the moments of a distribution. It is possible to find the distribution in the Pearson system that precisely matches the moments of the risk-neutral distribution and to generate a random sample. We calculate the VaR and ES for both lower tail and upper tail at the 1%-quantile from the generated random samples. We construct two euro stability indicators by relating the upper tail of the risk-neutral distribution to the lower tail, e.g. the absolute VaR of the upper 1%-quantile divided by the absolute VaR of the lower 1%-quantile. Clearly, these indicators nicely summarize the imbalances of extreme values of the risk-neutral distribution overall and can be considered to reflect currency stability. For example, a ratio below one indicates a fatter left tail of the distribution compared to the right tail and, therefore, suggests euro instability. Figure 5 shows the stability indicators for the complete period.

We replicate the 2-step regression analysis outlined in Equations (6) and (7) by replacing e.g. the skewness measure by the different stability indicators. The resulting betas are shown in Table 6. VaR ratio refers to the indicator based on the Value-at-Risks measure and ES ratio refers to the indicator based on the expected shortfall measure.

The results suggest that our previous findings are robust to a change of measure for euro stability. Most of the coefficients are insignificant except the ones for the sovereign debt crisis sub sample. During that period, all coefficients are substantially negative, which entails that member countries credit risk have a negative impact on the stability of the euro. But again, during the sovereign debt crisis period the struggling countries drive the instability of the common currency. It can be shown that the betas for the healthy countries and the ones of the vulnerable countries are significantly different form each other at the 5% level for both indicators. The principal component analysis again supports those conjectures. In line with previous findings and contrary to what one would expect, the creditworthiness of Greece does not seem to affect the stability of the common currency significantly.

2.6 Conclusions

In this paper, the recent Eurozone sovereign debt crisis is viewed through the twin lenses of sovereign credit swaps and currency option markets. We empirically investigate the impact of the credit risk of Eurozone member countries on the stability of the Euro. The credit risk of a country can be measured through its sovereign credit default swap (CDS). Market prices of CDS spreads reflect the perception of financial markets about the economic-political stability of a country, and thus about the creditworthiness of a given sovereign. The stability of the euro is examined by decomposing dollar-euro exchange rate options into the moments of the risk-neutral distribution. We document that changes in the creditworthiness of a member country on one day have a significant impact on the stability of the euro on the following day. On the one hand, an increase in member countries' credit risk results in an increase of the volatility of the dollar-euro exchange rate along with soaring tail risk induced through the risk-neutral kurtosis. On the other hand, we find that member countries' credit risk is a major determinant of the euro crash risk as measured by the risk-neutral skewness. We propose a new indicator for currency stability by combining the risk-neutral moments into an aggregated risk measure and show that our results are robust to this change in measure. In line with previous research, these findings apply to the period of the sovereign debt crisis but not necessarily to the subprime crisis period. Noticeable is the fact the creditworthiness of countries with vulnerable fiscal positions is the main, but not the only risk-endangering factor of the euro-stability. While the creditworthiness of the latter countries has a significant impact on the skewness measure (i.e crash risk) and the stability indicators, healthier countries equally drive the relationship between the creditworthiness and the kurtosis (i.e tail risk). As one would expect, Ireland, Portugal, Spain and Italy play a prominent role. However, this does not seem to be the case for Greece, which can be partly explained by the only marginal foreign exposure of European banks to Greece.

Figure 1:
The sovereign balance sheet

Assets	Liabilities	
Foreign Reserves	Foreign-currency Debt	Default-free value of debt minus put option
Net Fiscal Asset		
Other Public Assets	Local-Currency Debt Base Money	Call option
- Guarantees		

Figure 2:
Dollar-euro option smile on February 14th 2012 for various maturities (Source: www.fxoptions.com website)

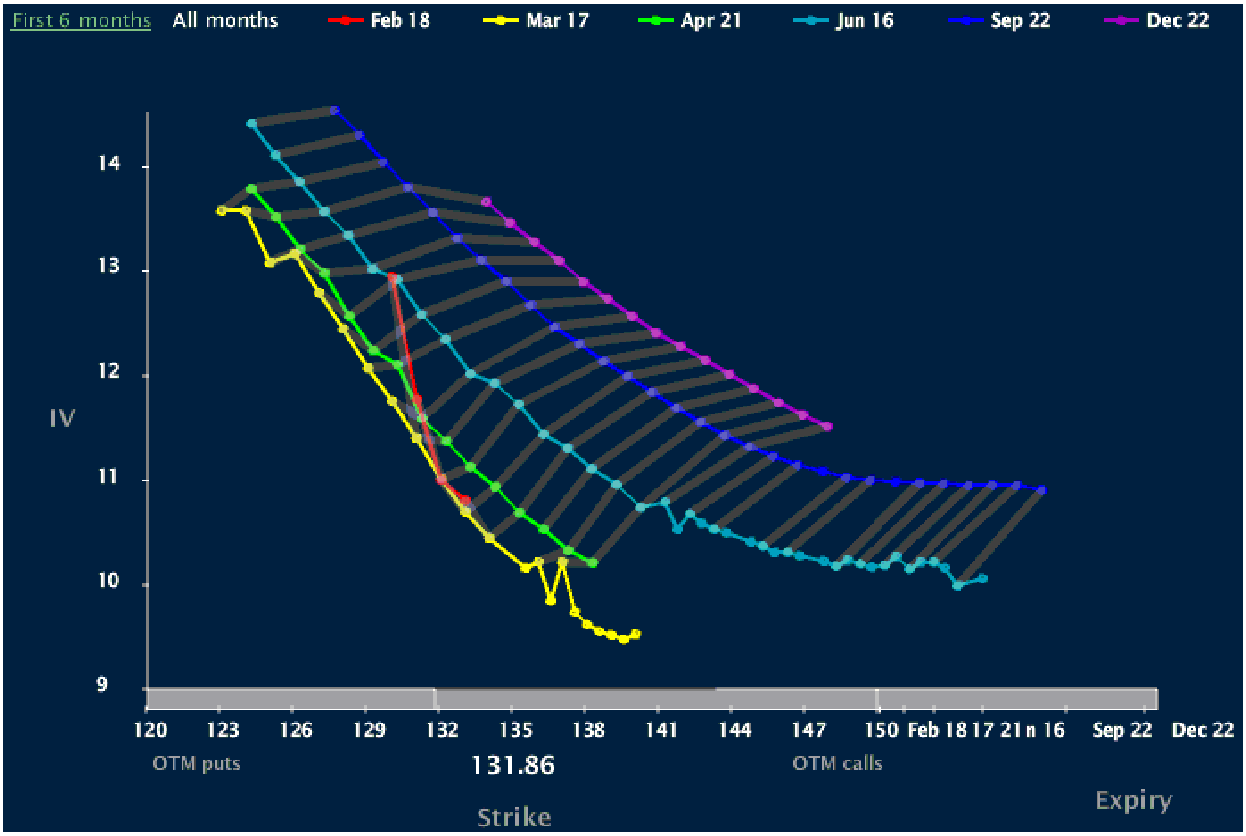


Figure 3:
Dollar-euro exchange rate and annualized volatility of the 3-months risk-neutral distribution of options on the dollar-euro exchange rate

Figure 4 :
Skewness and kurtosis of the 3-months risk-neutral distribution of options on the dollar-euro exchange rate

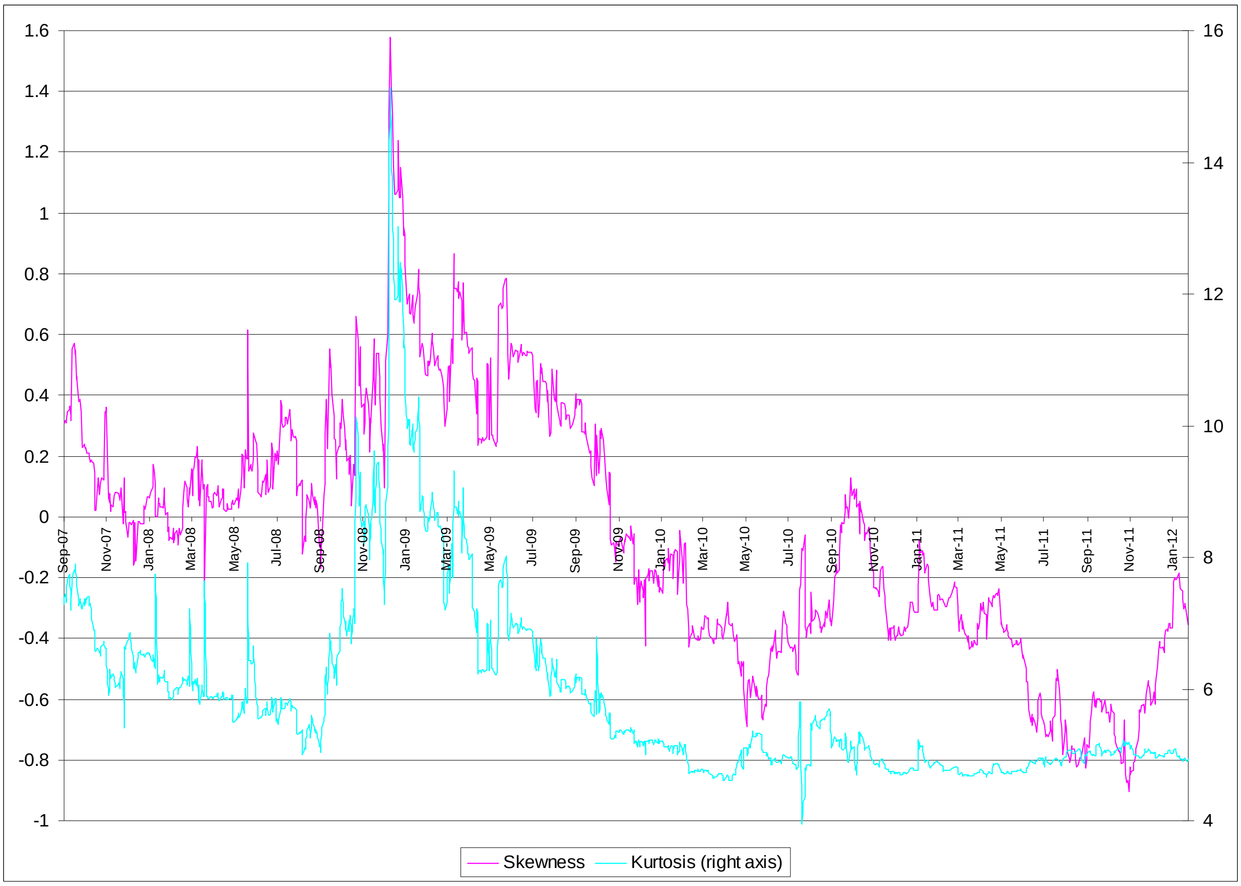
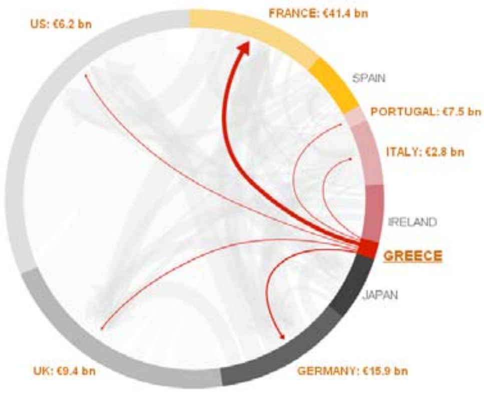


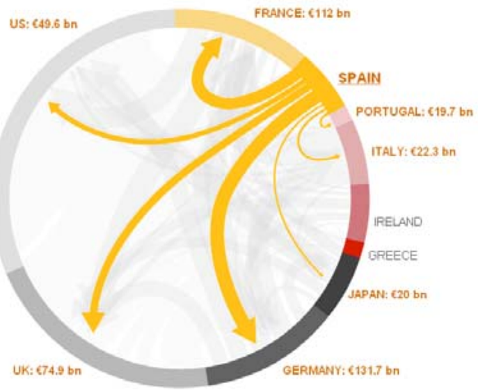
Figure 5 : BBC Eurozone debt web: Who owes what to whom?

The circles below summarize data from the Bank for International Settlements and show the gross external, or foreign, debt of some of the main players in the eurozone as well as other big world economies. The arrows point from the debtor to the creditor and are proportional to the money owed as of the end of June 2011. The exposures, represented by the proportional arrows, shows what banks in one country are owed by debtors - both government and private - in another country. (Source: BBC website, http://www.bbc.co.uk/news/business-15748696)

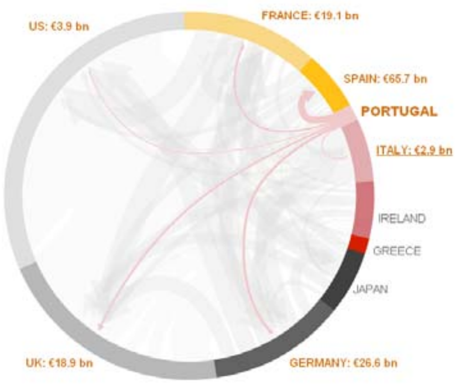
Greece



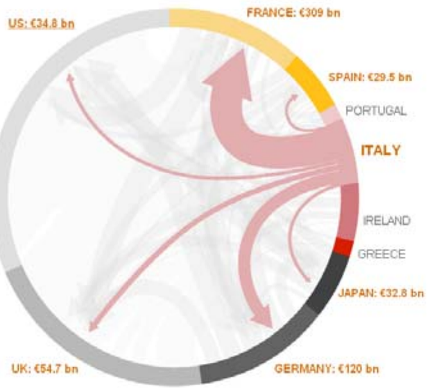
Spain



Portugal



Italy



Ireland

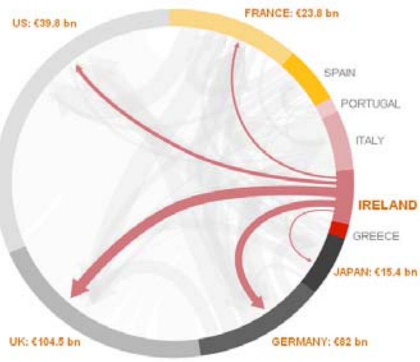


Figure 6 : Euro stability indicators

Euro stability indicators based on the 3-months risk-neutral distribution of options on the dollar-euro exchange rate. VaR ratio refers to the indicator based on the Value-at-Risks measure and ES ratio refers to the indicator based on the expected shortfall measure.

Table 1 : Summary Statistics: CDS spreads per country

	BE	FR	DE	NL	FL	A	IR	ES	PT	GR	IT
Overall sample period *from 05/09/2008 to 31/01/2012*											
Mean	127	79	47	56	40	99	366	198	384	970	191
Median	115	69	41	46	33	85	255	188	266	688	162
Maximum	406	250	119	140	91	269	1192	491	1527	5047	592
Minimum	21	12	8	11	11	11	11	39	39	52	41
Std.Dev	84	54	24	29	19	48	270	115	366	1086	128
Skewness	0.99	1.35	1.10	1.04	1.03	1.27	0.46	0.55	1.03	1.54	1.54
Kurtosis	0.15	1.18	0.49	0.02	-0.07	1.40	-1.03	-0.83	-0.19	1.27	1.46
Q1	56	40	32	35	28	69	150	94	82	172	106
Q3	161	91	56	68	50	119	615	266	548	1040	199
Subprime crisis *from 05/09/2008 to 13/10/2009*											
Mean	67	42	38	59	41	107	140	89	81	160	113
Median	61	39	35	48	37	100	151	87	75	147	104
Maximum	157	98	91	129	90	269	386	169	161	298	199
Minimum	21	12	8	11	11	11	11	39	39	52	41
Std.Dev	33	20	19	31	20	56	111	29	29	62	45
Skewness	0.97	0.85	1.09	0.58	0.63	0.80	0.23	0.69	0.70	0.38	0.36
Kurtosis	0.21	0.34	1.12	-0.75	-0.32	0.92	-0.95	0.09	-0.34	-0.77	-1.11
Q1	39	26	24	34	25	72	11	68	57	118	75
Q3	80	55	46	86	58	138	219	100	97	212	158
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*											
Mean	156	96	52	55	39	95	474	250	529	1359	229
Median	139	79	44	46	31	82	555	242	445	925	180
Maximum	406	250	119	140	91	241	1192	491	1527	5047	592
Minimum	33	20	19	24	17	48	111	66	51	123	68
Std.Dev	86	56	24	28	18	43	256	105	364	1131	137
Skewness	0.61	1.03	1.03	1.33	1.25	1.58	0.01	0.12	0.57	1.12	1.16
Kurtosis	-0.51	0.13	-0.02	0.63	0.14	1.50	-1.24	-0.80	-0.90	-0.02	0.07
Q1	93	64	37	35	28	68	199	180	245	677	138
Q3	213	108	59	60	39	98	688	342	837	1751	248

Note: Entries correspond to Q1 (first quantile), Q3 (third quantile), BE (Belgium), FR (France), DE (Germany), NL (Netherlands), FL (Finland), A (Austria), IR (Ireland), ES (Spain), PT (Portugal), GR (Greece), IT(Italy). Statistics are computed based on daily data and are expressed in basis points except for Skewness and Kurtosis. The total number of observations is 882 for the whole sample period , 288 for the first sub-period and 594 for the second.

Table 2 : Summary Statistics: Implied Volatilities of Put Options

PUT	10 Delta				25 Delta				At the Money			
	1M	**3M**	**6M**	**9M**	**1M**	**3M**	**6M**	**9M**	**1M**	**3M**	**6M**	**9M**
Overall sample period *from 05/09/2008 to 31/01/2012*												
Mean	15.42	16.44	17.00	17.24	14.23	14.78	15.04	15.16	13.40	13.67	13.82	13.88
Median	14.34	15.35	16.19	16.53	13.45	14.01	14.47	14.62	12.55	12.93	13.25	13.35
Maximum	33.60	28.65	25.55	24.33	31.05	25.70	22.49	20.95	29.00	24.25	21.70	20.15
Minimum	9.75	6.10	6.40	12.59	9.10	5.28	5.35	11.41	8.95	5.00	5.00	10.63
Std.Dev	4.15	3.46	2.93	2.66	3.64	2.94	2.39	2.12	3.48	2.79	2.23	1.94
Skewness	1.27	1.02	0.67	0.60	1.36	1.12	0.74	0.73	1.48	1.37	1.07	1.11
Kurtosis	1.36	0.48	-0.19	-0.67	1.91	1.03	0.41	-0.31	2.18	1.74	1.30	0.67
Q1	12.20	13.80	14.80	15.26	11.45	12.58	13.25	13.55	10.80	11.70	12.25	12.49
Q3	17.56	18.43	18.93	19.25	15.93	16.28	16.53	16.56	14.80	14.80	14.70	14.72
Subprime crisis *from 05/09/2008 to 13/10/2009*												
Mean	17.49	17.74	17.65	17.70	16.34	16.18	15.88	15.80	15.95	15.66	15.22	15.11
Median	15.76	16.06	16.34	16.54	14.88	15.05	15.03	15.00	14.85	14.80	14.68	14.53
Maximum	33.60	28.65	25.55	24.33	31.05	25.70	22.49	20.95	29.00	24.25	21.70	20.15
Minimum	9.75	6.10	6.40	12.59	9.10	5.28	5.35	11.41	9.00	5.00	5.00	10.63
Std.Dev	5.51	4.64	3.92	3.45	4.81	3.94	3.23	2.80	4.46	3.60	2.96	2.51
Skewness	0.56	0.44	0.22	0.21	0.57	0.42	0.13	0.22	0.51	0.37	0.05	0.19
Kurtosis	-0.72	-1.05	-1.15	-1.47	-0.54	-0.87	-0.79	-1.37	-0.61	-0.77	-0.54	-1.22
Q1	12.59	13.56	13.98	14.45	12.22	12.68	13.06	13.33	12.03	12.60	12.79	13.10
Q3	22.11	22.13	21.50	21.20	20.14	19.68	18.71	18.45	19.40	18.71	17.75	17.41
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*												
Mean	14.42	15.81	16.69	17.01	13.21	14.10	14.64	14.85	12.17	12.71	13.13	13.28
Median	13.83	15.23	16.16	16.50	12.95	13.73	14.27	14.48	11.85	12.38	12.90	13.06
Maximum	22.45	23.13	22.94	22.83	19.88	20.05	19.60	19.47	18.10	17.55	17.05	16.88
Minimum	10.23	11.49	12.19	12.62	9.50	10.83	11.75	12.15	8.95	9.95	10.70	11.07
Std.Dev	2.80	2.49	2.24	2.15	2.29	1.97	1.72	1.62	1.91	1.56	1.30	1.20
Skewness	0.85	0.77	0.78	0.78	0.71	0.65	0.72	0.75	0.65	0.61	0.62	0.69
Kurtosis	-0.13	-0.28	-0.24	-0.21	-0.22	-0.29	-0.19	-0.09	-0.28	-0.33	-0.16	0.00
Q1	12.89	14.48	15.64	16.03	11.30	12.52	13.30	13.61	10.60	11.50	12.10	12.34
Q3	15.78	17.19	17.87	18.11	14.45	15.24	15.58	15.72	13.34	13.79	13.95	13.99

Note: OTC European quotes at fixed maturities 1, 3 , 6 , 9 months of out-of-the-money put (10-20-delta) and at-the-money-options (50-delta). The quotes are in terms of delta-implied-volatilities of Black-Scholes. Statistics are computed based on daily data. The overall sample period spans from 05/09/2008 to 31/01/2012. The first sub-period (subprime crisis) is from 05/09/2008 to 13/10/2009 and the second sub-period (sovereign debt crisis) is from 14/10/2009 to 31/01/2012.

Table 3 : Summary Statistics: Implied Volatilities of Call Options

Call	10 Delta				25 Delta			
	1M	3M	6M	9M	1M	3M	6M	9M
Overall sample period *from 05/09/2008 to 31/01/2012*								
Mean	13.22	13.76	14.16	14.39	13.01	13.28	13.46	13.57
Median	11.95	12.80	13.38	13.62	12.03	12.50	12.89	13.06
Maximum	28.68	27.55	24.83	23.95	28.05	25.08	22.35	21.00
Minimum	8.38	6.30	6.70	10.74	8.43	5.13	5.45	10.64
Std.Dev	3.96	3.44	2.99	2.76	3.58	2.95	2.43	2.14
Skewness	1.61	1.61	1.44	1.42	1.57	1.54	1.37	1.41
Kurtosis	2.18	2.09	1.44	1.31	2.33	2.17	1.69	1.47
Q1	10.60	11.63	12.16	12.46	10.50	11.40	11.85	12.14
Q3	14.20	14.30	14.78	15.25	14.06	13.95	14.03	14.07
Subprime crisis *from 05/09/2008 to 13/10/2009*								
Mean	16.98	17.24	17.26	17.38	16.06	15.89	15.64	15.57
Median	16.24	16.50	16.64	16.89	15.19	15.21	15.15	15.01
Maximum	28.68	27.55	24.83	23.95	28.05	25.08	22.35	21.00
Minimum	9.65	6.30	6.70	11.43	9.10	5.13	5.45	10.64
Std.Dev	4.69	3.92	3.30	2.88	4.43	3.62	2.97	2.50
Skewness	0.41	0.38	0.08	0.21	0.47	0.36	0.04	0.22
Kurtosis	-0.80	-0.73	-0.62	-0.82	-0.69	-0.71	-0.46	-1.00
Q1	12.75	14.07	14.68	15.25	12.10	12.98	13.23	13.74
Q3	20.34	20.39	20.05	19.83	19.38	18.76	18.13	17.72
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*								
Mean	11.40	12.08	12.65	12.95	11.52	12.02	12.41	12.60
Median	11.20	12.08	12.65	12.91	11.43	11.90	12.35	12.52
Maximum	16.75	15.63	15.41	15.24	16.88	15.95	15.55	15.36
Minimum	8.38	9.63	10.41	10.74	8.43	9.43	10.25	10.68
Std.Dev	1.57	1.20	1.02	0.94	1.67	1.30	1.04	0.93
Skewness	0.47	0.10	0.05	0.11	0.44	0.27	0.27	0.29
Kurtosis	-0.27	-0.55	-0.86	-0.86	-0.38	-0.50	-0.47	-0.40
Q1	10.62	11.15	11.81	12.08	10.18	11.03	11.58	11.86
Q3	12.46	12.98	13.50	13.71	12.52	13.00	13.22	13.30

Note: OTC European quotes at fixed maturities 1, 3, 6 and, 9 months of out-of-the-money call (10-20-delta) options. The quotes are in terms of delta-implied-volatilities of Black-Scholes.

Table 4: Summary statistics of risk-neutral moments and the dollar-euro exchange rate

	Exchange rate	risk-neutral Skewness	risk-neutral Kurtosis	risk-neutral Volatility
Overall sample period *from 05/09/2008 to 31/01/2012*				
Mean	1.37	-0.10	5.85	0.15
Median	1.37	-0.24	5.12	0.14
Maximum	1.51	1.58	15.12	0.27
Minimum	1.19	-0.91	3.90	0.06
Std.Dev	0.07	0.46	1.61	0.03
Skewness	-0.13	0.60	2.16	1.41
Kurtosis	-0.75	-0.34	5.22	1.75
Q1	1.31	-0.41	4.88	0.12
Q3	1.42	0.29	6.25	0.16
Subprime crisis *from 05/09/2008 to 13/10/2009*				
Mean	1.36	0.47	7.64	0.17
Median	1.36	0.45	7.06	0.16
Maximum	1.49	1.58	15.12	0.27
Minimum	1.25	-0.17	5.04	0.06
Std.Dev	0.07	0.25	1.75	0.04
Skewness	-0.07	1.06	1.34	0.41
Kurtosis	-1.22	2.57	2.05	-0.90
Q1	1.30	0.30	6.28	0.13
Q3	1.42	0.56	8.61	0.20
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*				
Mean	1.37	-0.37	4.99	0.14
Median	1.37	-0.36	4.96	0.13
Maximum	1.51	0.29	5.94	0.19
Minimum	1.19	-0.91	3.90	0.10
Std.Dev	0.07	0.23	0.25	0.02
Skewness	-0.16	-0.01	0.75	0.66
Kurtosis	-0.59	-0.22	1.62	-0.18
Q1	1.32	-0.54	4.78	0.12
Q3	1.42	-0.23	5.12	0.15

Note: Statistics are computed based on daily data. The overall sample period spans from 05/09/2008 to 31/01/2012. The first sub-period (subprime crisis) is from 05/09/2008 to 13/10/2009 and the second sub-period (sovereign debt crisis) is from 14/10/2009 to 31/01/2012.Skew, Kurt and IV, respectively: Skewness, kurtosis and implied volatility are the independent variables.

Table 5 : Regression Results: Risk-Neutral Moments

	Skewness		**Kurtosis**		**Volatility**	
	Betas	T-stat	Betas	T-stat	Betas	T-stat
	Overall sample period *from 05/09/2008 to 31/12/2012*					
Belgium	0.008	0.09	0.529	1.48	0.022***	2.37
France	-0.010	-0.11	0.634	1.69	0.029***	2.94
Germany	0.047	0.05	0.858**	2.20	0.024***	2.34
Netherlands	-0.020	-0.19	0.567	1.40	0.027***	2.64
Finland	-0.044	-0.39	0.423	0.94	0.024**	2.09
Austria	-0.001	-0.01	0.311	1.02	0.017**	2.14
Ireland	-0.082*	-1.84	-0.331*	-1.87	-0.003	-0.69
Spain	-0.074	-0.77	0.339	0.89	0.028***	2.82
Portugal	-0.049	-0.51	0.596	1.56	0.026***	2.66
Greece	-0.137	-1.45	0.135	0.36	0.013	1.37
Italy	-0.075	-0.75	0.608	1.53	0.033***	3.13
	Subprime crisis *from 05/09/2008 to 13/10/2009*					
Belgium	0.089	0.54	0.569	0.76	0.016	0.93
France	0.082	0.43	0.774	0.89	0.034*	1.73
Germany	0.138	0.75	0.917	1.10	0.023	1.20
Netherlands	-0.005	-0.03	0.439	0.51	0.030	1.50
Finland	0.007	0.03	0.398	0.38	0.025	1.09
Austria	0.017	0.13	0.260	0.43	0.020	1.47
Ireland	-0.058	-0.86	-0.382	-1.26	-0.004	-0.63
Spain	-0.005	-0.02	0.272	0.26	0.028	1.16
Portugal	0.130	0.59	0.968	0.98	0.036	1.61
Greece	-0.100	-0.48	-0.120	-0.13	0.024	1.10
Italy	0.010	0.04	0.595	0.56	0.035	1.41
	Sovereign debt crisis *from 14/10/2009* to *31/01/2012*					
Belgium	-0.128	-1.26	0.538**	2.16	0.031***	2.81
France	-0.090	-0.99	0.420*	1.86	0.019*	1.94
Germany	-0.097	-0.92	0.698***	2.66	0.021*	1.80
Netherlands	-0.092	-0.85	0.657***	2.45	0.022*	1.84
Finland	-0.150	-1.37	0.481*	1.78	0.022*	1.89
Austria	-0.004	-0.04	0.421*	1.76	0.010	0.97
Ireland	-0.223**	-2.14	0.627***	2.43	0.016	1.40
Spain	-0.145*	-1.77	0.383*	1.89	0.024***	2.71
Portugal	-0.203**	-2.25	0.467**	2.10	0.018*	1.78
Greece	-0.105	-1.41	0.419**	2.31	0.004	0.57
Italy	-0.174**	-2.00	0.540***	2.51	0.030***	3.05
PCA_H	-0.045	-0.87	0.292**	2.25	0.011*	1.87
PCA_V	-0.099**	-2.14	0.275***	2.42	0.012***	2.34

Note: For each country, the dependent variables are the daily moments of the 3-months risk-neutral distribution of dollar-euro exchange rate options (the second moment is expressed in terms of annualized volatility). T-stats are computed based on the Wald test. . (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level.

Table 6 : Regression Results: Value-at-Risk and Expected Shortfall ratios

	VaR ratio		**ES ratio**	
	Betas	T-stat	Betas	T-stat
Overall sample period *from 05/09/2008 to 31/12/2012*				
Belgium	-0.01	-0.315	-0.03	-0.585
France	-0.05	-1.114	-0.06	-1.000
Germany	-0.01	-0.282	-0.02	-0.392
Netherlands	-0.04	-0.771	-0.06	-0.853
Finland	-0.07	-1.202	-0.09	-1.264
Austria	-0.02	-0.621	-0.04	-0.876
Ireland	-0.04	-1.925	-0.04	-1.411
Spain	-0.07	-1.404	-0.08	-1.290
Portugal	-0.05	-1.100	-0.06	-1.010
Greece	-0.06	-1.123	-0.06	-1.292
Italy	-0.09*	-1.750	-0.10	-1.503
Subprime crisis *from 05/09/2008 to 13/10/2009*				
Belgium	0.03	0.365	0.00	-0.014
France	-0.02	-0.192	-0.02	-0.159
Germany	0.02	0.199	0.02	0.156
Netherlands	-0.03	-0.374	-0.05	-0.442
Finland	-0.05	-0.478	-0.08	-0.517
Austria	-0.02	-0.251	-0.04	-0.500
Ireland	-0.03	-0.864	-0.02	-0.462
Spain	-0.05	-0.416	-0.04	-0.272
Portugal	0.02	0.220	0.03	0.191
Greece	-0.01	-1.151	-0.03	-0.951
Italy	-0.08	-0.740	-0.07	-0.445
Sovereign debt crisis *from 14/10/2009* to *31/01/2012*				
Belgium	-0.08	-1.518	-0.09	-1.359
France	-0.08	-1.573	-0.09	-1.423
Germany	-0.07	-1.298	-0.10	-1.404
Netherlands	-0.06	-1.078	-0.08	-1.119
Finland	-0.09	-1.554	-0.12	-1.674
Austria	-0.01	-0.274	-0.02	-0.269
Ireland	-0.12**	-2.195	-0.14**	-2.007
Spain	-0.08*	-1.925	-0.11**	-1.991
Portugal	-0.10**	-2.024	-0.12**	-2.006
Greece	-0.07	-1.371	-0.10	-1.364
Italy	-0.12***	-2.495	-0.15***	-2.530
PCA_H	-0.034	-1.21	-0.043	-1.23
PCA_V	-0.055**	-2.26	-0.069**	-2.27

Note: For each country, the dependent variables are the Value-at-Risk ratios and Expected Shortfall ratios of the daily moments of the 3-months risk-neutral distribution of dollar-euro exchange rate options (the variance is expressed in terms of annualized volatility). T-stats are computed based on the Wald test. . (***) indicates statistical significance at the 1 percent level, (**) at the 5 percent level and (*) at the 10 percent level.

Chapter Three :

European Banks and their Sovereigns: The View from the Credit Rating Agencies***

3.1 Motivation

The recent financial turmoil has sparked debate relating to the ability of credit rating agencies to assess credit quality, and how this might have contributed to the financial and sovereign debt crises. The primary role of these institutions is to estimate the risk attached to a bond, thereby providing information relative to its creditworthiness to investors. Therefore, they are thought to influence price movements of not only bonds but various financial assets and market indices. Furthermore, the recent financial crises have raised awareness of the complex relationship between governments and their domestic banking sector. Indeed, governments endorse banks and would go great lengths to prevent them from going bust. In turn, banks are major buyers of governments bonds. Hence, it seems relevant to analyse the extent to which investors grasp the relationship between governments and the banking sector.

Using event study methodology and panel data analysis, along with a comprehensive dataset of credit ratings from the three major rating agencies (Moody's, S&P and Fitch), this paper examines the impact of both sovereign and bank rating actions on a spectrum of variables and market indicators which are of relevance to the banking sector. The aim is to determine, in view of the recent financial turmoil, the type of news which elicits more reaction in the financial markets , when it comes to bank-related variables. A further contribution is to analyse the joint effect of banks' and sovereigns' credit announcements to see if, jointly, these two types of news exert a more powerful effect on financial markets. The study should help ascertain whether investors observing banks' credit risk and macro-financial indicators believe credit rating agencies' actions on sovereigns are more powerful than those actions endured by the bank itself. Ultimately, it sheds light on whether investors view governments and banks as inextricably connected (i.e. investors are able to grasp the close link between governments and banks).

Altogether, our findings indicate that the measures of banks' credit risk react more to changes in the sovereign credit ratings than those endured by the bank itself. Similarly, changes in sovereign rating spur greater reaction of macro-financial indicators. These effects are accentuated over the sovereign debt crisis period and by the occurrence of multiple-notch downgrades. When looking at the joint effect of sovereign and bank ratings, results show that the higher the distance between the rating of the sovereign and the bank, the stronger the effect on the bank's credit risk measures as well as on the bank-related macro-financial indicators. Thus, we find evidence that markets grasp the strong connection between banks and their sovereigns.

A large body of literature has addressed the role rating agencies play in driving prices in the financial markets prior to and following their announcements. The literature can be pinned down into two categories: the first deals with corporate credit announcements and the second looks at sovereign ratings. On the corporate ratings front, the bulk of the early literature has focused on the response of stock and bond markets[21].Dichev and Piotroski (2001) document significant negative returns during the first month following a downgrade by Moody's. Vassalou and Xing (2003) take the stance that the result whereby abnormal returns occur following a downgrade can be altered if these returns are adjusted for default risk. The rational argument being that firms with higher default risk are deemed to earn more returns. Analysing the response of the bond market to credit rating announcements has also been the

[21] Weber and Norden (2004) provide a comprehensive summary of early literature dealing with the impact of rating events on bonds and stocks.

aim of many studies. Katz (1974) finds no evidence for anticipation but sees abnormal performance 6-10 weeks after downgrade news. A more recent paper by Milidonis (2013) investigating the lead–lag relationship for changes in bond ratings (BRs) and financial strength ratings documents an economically significant lead effect of investor-paid downgrades.

In more recent work, attention has shifted towards the impact of rating events on the derivatives market. Weber and Norden (2004) compare the response of stocks along with the CDS spreads of the same firms to announcements by three rating agencies. The study concludes that overall, while both markets do not exhibit significant response to positive rating events, they anticipate downgrades and reviews for downgrades. In addition, reviews for downgrades appear to be associated with abnormal performance following reviews for downgrades by Standard & Poor's and Moody's but this does not happen following an actual downgrade. Similarly, Hull et al. (2004) explore the extent to which credit rating announcements by Moody's are anticipated by participants in the credit default swap market, and find that significant positive adjusted CDS spread changes occur before negative announcements. On the hand, Finnerty et al. (2013) use an extensive database of ratings and CDS spreads ((14,248 corporations over the period of 2001-2009) and show that corporate upgrades are actually anticipated by the CDS market, albeit not to the same degree as downgrades. Positive CARs[22] are also observed at the time of positive watch and outlook news. Focusing on the banking sector, we have a larger sample of banks and bank rating news compared to prior work.

The other strand of literature relevant to our work deals with the impact of sovereign announcements on different types of assets**.** Examples include: Azerti et al. (2011) and Alfonso et al. (2012). The former paper studies the spillover effects across countries using sovereign CDS spreads, a banking stock index, an insurance stock index and country stock indices. The latter focuses on the response of government yield spreads. More work in the area includes: Alsakka and ap Gwilym (2012); Brooks et al., (2004); Hill and Faff, (2010); Gande and Parsley, 2005; Ferreira and Gama, 2007. From a non-European perspective. Kaminsky and Schmukler (2002) assess the impact of sovereign rating changes on stock indices. Ismaeliciu & Kazemi (2010) examine the effect of sovereign CR on the CDS spreads of the country of announcement along with the spillover effects on the CDS premium of the economies. Kraussel (2005) uses a financial stability index to assess the role of sovereign ratings change in the financial markets of emerging economies.

Perhaps the work most related to our study is that of Correa,et al.(2014). The authors analyse the joint impact of expected government support to banks and changes in sovereign credit ratings across 37 countries. They show that banks which are expected to benefit from government support suffer most from the impact of a downgrade through their stock returns. This result is interesting because it suggests that stock market investors view sovereigns and domestic banks as interconnected. While this work is similar to ours (in the way that it relates sovereign rating news to banks' assets in an attempt to understand how the financial condition of a sovereign influences the health of the banking sector) we differ from it in many ways. First, we examine a different and larger array of bank-related variables. Second, our ratings dataset emanates from the three major agencies S&P, Moody's and Fitch. Most importantly, they use a measure of 'expected government support', defined as the difference between Moody's standalone rating for a given bank and the assigned rating embedding 'possible' external support for the same bank. While this is an innovative empirical approach, gauging government support remains a difficult task because of the opaque nature of the information. Hence, we believe our approach is more suitable when it comes to shedding light on the ties between governments and the banking sector. Indeed, our approach is to compare the impact of sovereign ratings to that of bank-specific ratings on bank-related indicators, and then to look at the joint effect of the two types of rating events. Given that both sovereign ratings and bank-specific ratings are quantifiable, discrete events, drawing conclusions about the perception of financial markets regarding the relationship between sovereigns and the banking sector would prove more accurate and straightforward.

In short, none of these studies seems to investigate the response of the set of bank-related variables of interest to our study to bank-specific and sovereign announcements. Rather than looking separately at how sovereign and bank credit rating actions influence asset prices, we place the focus on confronting the impact of sovereign rating actions against bank-specific rating actions on an array of bank-related indicators. In addition, we investigate the extent to which investors grasp the relationship between sovereigns and their domestic banks. We do this by looking at the joint effect of sovereign and bank-specific ratings.

3.1.1 Why would a change in sovereign's rating impinge on a bank-related asset?

In this section we elaborate upon a transmission channel through which changes in the credit rating could potentially have an impact on bank-related assets.

In view of the complexity of the relationship between governments and banks, several channels exist, the most obvious being the fiscal one. For example, Demirguc-Kunt and Huizinga (2013) relate government indebtedness and deficit to bank stock prices and CDS spreads. The study documents a drop in market capitalisation of banks along with soaring CDS spreads when the country is fiscally troubled. From a purely credit rating perspective, Alsakka, Ap Gwylim &Vu (2013) explore the link between bank ratings and sovereign ratings and find evidence that, in the context of the sovereign debt crisis, bank downgrades are strongly affected by sovereign downgrades and negative watch signals.

Our explanation relies on a contingent claim framework by Gray 2002; Gray et al., 2002; Draghi et al.,2003. The underpinning idea of the framework is that sectors of an economy are entwined throughout their balance sheets and that the same principles of Merton's contingent claim model relevant for a single firm can be applied to sectors. This is because sectors can be treated as an aggregation of individual firms.

Take the case of the sovereign and the banking sector. Governments endorse banks and would go to great lengths to prevent them from going bust. In turn, banks are major buyers of governments bonds. This 'controversial' relationship materialises in the balance sheet in the following way. A major item on the liabilities side of a sovereign's balance sheet represents the financial guarantees endorsing the banking system. The same item is found on the assets side of the balance sheet of the banking system (Figure 1 and 2). These guarantees can be viewed as a contingent claim, and so, based on contingent claim analysis, they can be modelled as a put option. Hence, they are a key transmission factor of credit risk. The put option in the Merton model corresponds to the expected loss (which amounts to a default probability multiplied by a loss given default). A deteriorating risk profile of a sovereign is likely to drive up its implicit guarantee, and this mirrors a deteriorating credit risk profile. The more these guarantees rise, the more difficult it becomes for a sovereign to provide for or honour its guarantees. Ultimately, this could cause serious damage to the banking system which holds the guarantees as an asset. A more harmful scenario is when banks hold government bonds it worsens the quality of their assets as the value of government bonds plunges. The ripple effect of that is a need for more implicit financial guarantees which would inevitably lead to a further deterioration in the value of government bonds. This feeds back onto bank assets, and has the potential to hit any related assets or indicators. It is then straightforward to introduce credit rating into this reasoning. The event of a sovereign bond downgrade is the result of change in perception of its credit quality, and its negative impact on the value of the bond has been documented in the literature. Accordingly, the value of the sovereign's guarantee might increase, thus inducing the compound effects explained above.

A recent work by Acharya and al. (2013) shows how a deterioration in sovereign credit risk (due to a financial sector bail-out based on the dilution of the value of bond holdings) feeds back into the financial sector. The effect is an erosion in the value of guarantees and bonds held by financial institutions. Over the period of 2007-10, they show that bank CDS spreads and sovereign CDS spreads co-move significantly after announcements of financial sector bails-out in the Eurozone. This result underlines the importance of the quality of sovereign guarantees in determining the credit risk of financial institutions.

3.2 Data description & statistics

3.2.1 Credit rating data

We examine the reactions of a set of bank-related indicators to changes in bank and sovereign ratings from Fitch, Moody's and S&P from 01/01/2007 through 30/08/2013. So, our dataset encompasses two categories of rating actions: bank ratings (obtained from InteractiveData Credit Ratings International Database) and sovereign bond ratings on long-term foreign-currency denominated debt (collected from the publications of the rating agencies). For the bank rating actions, we identify a total of 433 bank-specific rating changes, while we find a total of 631 sovereign rating changes. The bank ratings data we possess relate to either downgrades or upgrades, whereas we have information about outlook and watch reviews for the sovereign ratings category in addition to the downgrades and upgrades. Another important point is that sovereign ratings are daily data whereas bank ratings are on monthly basis. In matching sovereign rating data to bank rating data we have transformed the latter to daily basis, assuming that no changes occurred in the course of a month for the banks in our sample. Specifically, we are interested in matching the rating change of a given bank to the change in rating of its corresponding sovereign to facilitate the examination of the joint effect of sovereign and bank rating changes on variables which are relevant to the bank.

It is common practice in the literature dealing with rating actions to use a numerical scale to translate rating actions into numerical values. For instance, a rating of AAA/Aaa is assigned the value 20, and a rating of SD/C is assigned the value 1 (see Table 3). However, we are interested in the actual changes of the ratings, so we use the numerical scale to construct a time-series of daily changes expressed in terms of notches.

As previously mentioned, we also collect watch reviews and outlook reports. Watch data are reviews issued by rating agencies to reflect concerns about a given rated entity, with on-going scrutiny to assess whether a change in rating should take place. Outlook reports on the other hand, are forecasts about the evolution of the credit rating given by an agency, and these can be an outlook suggesting a potential future upgrade, downgrade, or a stable outlook. With a view to constructing a time series for the changes in rating signals, we follow Sy (2004), Alsakka et al.(2014) and use a 58-point-numerical-scale which enables us to integrate watch and outlook signals to actual ratings. The scale starts with AAA/Aaa = 58 and finishes with SD/C=1. We add or subtract '2' in the event of positive/negative watch signal and '1' in the event of a positive/negative outlook. In the case of stable outlook or the absence of watch signals, the value of the numerical adjustment is '0'. Hence, a sovereign with a negative watch or/and outlook will escalade down the scale compared to a sovereign whose rating is subject to a positive watch or/and outlook.

Overall, and for all types of rating events, we attribute the absolute value of an increase on the numerical scale to positive events, and the absolute value of a decrease to negative events. Once we differentiate between positive and negative events, we assign the value '1' to the occurrence of a change in rating and '0' otherwise regardless the level of the increase or decrease on the numerical scale. Put another way, we do not differentiate between the various notches of rating changes. But, since we are also interested in capturing the difference in the impact of the various notches, we isolate changes in ratings with the same numerical value, then similarly assign the value '1' to the occurrence of a change in rating and '0' otherwise.

Tables 1 and 2 report the statistics of the ratings events considered in this study.

3.2.2 Variables of interest to the study:

Credit risk variables

We compute default probabilities (DP) à la Merton for a sample of 41 European banks over a sample period spanning from January 2007 to August 2013. We choose to work on specific banks that were subject to the stress test conducted by the ECB in 2012. Initially, the ECB sample includes 91 banks. We narrow it down to 41 due to a lack of availability and matching issues of the variables needed to estimate default probabilities. For the estimation of banks' default probabilities we retrieve daily data from Bloomberg about equity prices, the number of shares outstanding, government bond yields, and the S&P 500 index. From the same database we obtain quarterly book values of short and long-term debt. In addition, we download monthly implied equity risk premiums from Damodaran's website (http://pages.stern.nyu.edu/~adamodar/) available on a monthly basis. To ensure meaningful comparison, the stock prices are euro-denominated. Details of the estimation procedure can be found in section 3.1

We retrieve historical five-year maturity CDS spreads for a sample of 35 European banks whose CDS data is reliable. The sample size decreases further to 21 banks whose CDS data is available throughout the sample period. To a certain extent, looking at the reaction of Banks'

CDS spreads in addition to default probabilities allows for comparison of two credit risk measures: one which is observed in the markets, and the other implied through a model.

Macro-financial indicators

Our dataset encompasses a set of macro-financial indicators, namely :

The EURIBOR-OIS[23] (respectively UKLIBOR-OIS SwissLibor-OIS) a proxy for liquidity and credit risk premia in the European (respectively the UK and Swiss) interbank market, and thus it is used as an indicator of financial distress. The Euribor (respectively UKLIBOR and SwissLibor) encompass the expected risk-free interest rate over a specific term, the term premium, the credit risk premium of unsecured trading, and the liquidity risk premium. Whereas the OIS measures the expected risk-free interest rate of secured transactions over a specific term. In tranquil times, the EURIBOR-OIS , UK LIBOR-OIS , Swiss Libor-OIS spreads are close to zero. The stronger the liquidity strain on the markets, the higher the spreads. A positive spread reflects an opportunity cost for term funding, but more importantly it indicates a reluctance of banks to lend to each other. We use three different spreads to account for differences in the liquidity and credit risk features in European countries with different currencies.

The VSTOXX index : It is the European equivalent of the VIX (Chicago Board Volatility Index), and is computed based on EURO STOXX 50 real-time options prices. It reflects market expectations about volatility by taking the square root of the implied variance across

[23] EURIBOR-OIS (Euro interbank offered rate – overnight index swaps for the euro) 3 Month Spread/ UK LIBOR-OIS 3 Month Spread (London interbank offered rate – overnight index swaps for the pound)/ Swiss Libor-OIS 3 Month Spread (London interbank offered rate – overnight index swaps for the Swiss franc): Ait Sahalia and al. (2010) (NBER WP) use the LIBOR-OIS as an indicator of financial distress in the US. It is a measure of the liquidity and credit premia in the interbank markets. In our study, an identical measure is constructed for the European context.

all options of a given time to expiration. Hence, it is used to gauge the risk appetite of the market. The higher the index, the greater the fear of investors about the prospects of the financial markets

European and UK Bank CDS Indices which are financial sector CDS indices tracking senior debt of a number of banks in Europe and the UK respectively.

3.2.3 Statistics

The time-series plots in Figure 3 display the daily observations of Euribor-OIS , UKlibor-OIS , Swiss Libor-OIS spreads in terms of the level and changes. A general pattern emerges over the period spanning from January 2007 to the beginning of 2010 (beginning of 2009 for the Swiss Libor-OIS). The spreads moved in a similar fashion despite differences in scale. This is particularly true for the Euribor-OIS and the UKlibor-OIS. The first sharp increase occurred towards mid 2007. This coincides with two sizable events in the European Banking system: BNP Paribas declaring its exposure to sub-prime mortgage markets, and Northern Rock being on the brink of bankruptcy because of its mortgage-loan portfolio and spurring the first bank run in Britain in 150 years. A more pronounced increase is observed in the wake of the collapse of Lehman Brothers in September 2008, a collapse that sparked off financial panic worldwide, and placed tremendous liquidity strain on the interbank lending markets. After a relatively stable phase (essentially due to various interventions from governments and central banks meant to boost markets recovery and prevent financial instability) spreads spiked upwards again towards the beginning of 2011 (mid 2011 in the case of Swiss interbank market) and continued to soar until the end of 2012. This coincides with the European sovereign debt crisis which inevitably affected the interbank markets.

Looking at the summary statistics reveals that the Swiss interbank markets experienced less financial distress with a mean spread of (0.22) compared to the Eurozone and UK interbank markets, respectively 0.44 and 0.47. The Swiss interbank market was also relatively less volatile than the two other markets, with a volatility of 0.26 compared to 0.34 and 0.46 for the Eurozone and UK.

The plots of the European and UK bank CDS indices display largely similar patterns and reflect the behaviour of the CDS spreads for European and UK banks (figure 2). The CDS spreads widened shortly after the collapse of Lehman Brothers, and registered an even larger increase around October 2010 which marked the burst of the sovereign debt crisis in Europe. Overall, the spreads of the European bank CDS index were higher and more volatile compared to the UK index, with a mean value of 220bp versus 135.22bp , and a standard deviation value of 140.40 versus 59.35.

3.3 Research Design

Our research purpose is to gauge the response of financial measures relevant to the banking sector to rating events, therefore we employ standard event study methodology (Campbell et al. 1997 and McKinlay 1997). More precisely, our approach is to compare the impact exerted by sovereign ratings to that of bank-specific ratings on bank-related variables. We then look at the joint effect of the two types of ratings. Ultimately, the objective is to draw conclusions about how financial markets perceive the relationship between banks and their sovereigns.

We have rating actions and news emanating from three different rating agencies. We conduct the analysis separately on the effect of the news from each rating agency on the set of bank-related variables and macro-financial variables of our sample. We start off by defining

τ a count variable taking the value 0 on the event day , 1 prior to the event day and -1 and the day. We carry out our analysis with estimation windows of $\tau<-10$, $\tau>=-70$ and $2\tau<-10$, τ>=-210 (windows of 60 and 200 trading days respectively). The event windows used contain 3 and 11 trading days such that for the first window τ>=-5and τ<=5 and τ>=-5 and τ<=5

Then we test the statistical significance of the events on a pooled sample as follows:

$$\begin{cases} \delta AbCDS_{it} = \alpha + \beta Ev_{it}^{-} + \varepsilon_{it} \\ \\ \delta AbCDS_{it} = \alpha + \beta Ev_{it}^{+} + \varepsilon_{it} \end{cases}$$

$$\begin{cases} \delta AbPD_{it} = \alpha + \beta Ev_{it}^{-} + \varepsilon_{it} \\ \\ \delta AbPD_{it} = \alpha + \beta Ev_{it}^{+} + \varepsilon_{it} \end{cases}$$

Where:

$\delta AbCDS$ and $\delta AbPD$ are measures for the abnormal performance of the CDS spreads and the Default probabilities.

Ev_{it}^{-} are negative events representing either bank-specific downgrades, sovereign downgrades or sovereign downgrades corrected for watch and outlook news.

Ev_{it}^{+} are positive events representing either bank-specific upgrades or sovereign upgrades.

Given that we are not dealing with stock returns , the abnormal measure, necessary to capture the impact of the event cannot be derived using the market model, we are required to find alternative measurements to define abnormal performance. We compute the abnormal performance of default probabilities $(\delta AbPD)$ as the difference between daily changes of the default probability of bank *i* and the daily changes in the default probability of SvenskaBank.

The underpinning argument is that most Swedish bank have not experienced a deterioration in their credit profile in the aftermath of the financial crisis. Having the lowest default probabilities across the sample period, SvenskaBank is used as a benchmark against which the credit risk performance of banks in our sample is measured. Similarly, The abnormal performance of the bank CDS spreads (δAbCDS) is computed as the difference between the daily changes of CDS spreads of bank i and the daily changes of a CDX index tracking banks in Europe or UK depending on whether bank i is located in Europe or in the UK. As an alternative measure of abnormal performance we also perform the analysis using simply the daily changes in the default probabilities and CDS spreads.

The next set of statistical tests is related to the response of macro-financial variables to credit ratings events :

$$\begin{cases} \delta AbMV_{it} = \alpha + \beta Ev_{it}^{-} + \varepsilon_{it} \\ \delta AbMV_{it} = \alpha + \beta Ev_{it}^{+} + \varepsilon_{it} \end{cases}$$

Where:

δAbMV is the abnormal performance of our set of macro-financial indicators, namely :

-EURIBOR-OIS 3 Month Spread, UK LIBOR-OIS 3 Month Spread, Swiss Libor-OIS 3 Month Spread which is a financial distress indicator since it measures of the liquidity and credit risk premia in the interbank markets.

- European and UK bank CDS Indices tracking senior debt of major European and UK banks.

-VSTOXX Index which is an estimate of the market risk appetite (market volatility & investors sentiment).It is the European equivalent of the VIX (Chicago Board Volatility Index)

The calculation of abnormal performance for these indicators following Ait Sahalia and al. (2010): abnormal differences are simply defined as actual daily changes. Then cumulative abnormal measures are computed by averaging out the daily changes of each measure. The condition is that the day to day changes are not statistically different from zero. (see figure 3).

As a robustness check[24], abnormal differences are also computed as the difference between the expected daily change of the market indicator and its actual daily change. The expected daily change is computed as the average daily change over the last 20 trading days.

There are a couple of identification issues which are inherent to event study methodology which should be addressed. The issue of contamination effects between announcements in event windows is addressed by using a narrow event window of 10 and 3 days, respectively [-5,5] and [-1,1]. Also, the classification of rating actions per agency, along with the classification of ratings announcements by type (downgrade or upgrades of 1, 2 or 3 notches, watch and outlook news) proves useful. More importantly, we define estimation and event windows such that there is no overlap between the two. In effect, this ensures that the estimation of the abnormal measure is not affected by the occurrence of an event during the estimation window. In practice, we temporarily exclude any event that is included in the estimation window to ensure abnormal performance is not contaminated.

Furthermore, it is crucial to verify that there is no clustering of events (i.e no overlap of events in the event window) to ensure correct identification of our event study models. Indeed, the

[24] Should the assumption of zero mean reversion not be valid.

results rely on the assumption of the absence of correlation across the abnormal measures comprised in the sample.

For each of the variables, we opt for the abnormal measure that we think will best reflect the abnormal component of the variable. But, we check for the robustness of our results by using alternative measures to make sure that they are not sensitive to our choice of a particular abnormal measure.

The perception by financial markets of credit rating actions is likely to differ according to the condition of the wider economy. As such, factors other than rating news might contribute to spurring market response. Breaking down the sample into two periods helps account for differences in market conditions. Hence it controls for the economic factors that may produce the response of our variables of interest. The two periods are the financial crisis (from 01/01/2007 to 14/10/2009) and the Eurozone debt crisis (from 14/09/2009 to end of sample period). Mid-October 2009 marks the outbreak of the Eurozone debt crisis with the newly elected Greek prime minister revealing that the hole in the finances of the country is larger than initially thought

In a second stage of the analysis, we run a fixed effect panel regression instead of testing for the significance of the impact of the event as it is done with standard event study[25] .The advantage of the new specification is that is enable us to control for fixed effects and other market factors which might affect our variables of interest.

$$\delta AbM_{it} = \alpha + \beta_1 Ev_{it} + \beta_2 X_{i(t-1)} + \alpha_{it} + e_{it} (model2)$$

[25] In effect, we lose a significant number of observations because we run the regressions after computing the abnormal measures around to the event and estimation windows conditions.

AbM_{it} is the abnormal measure for our variables of interest as described above.

Ev_{it} is the change in the credit rating event be it bank-specific or sovereign-related.

$X_{i(t-1)}$ is a vector of control variables which might affect market expectations ,namely: sovereign CDS spreads, liquidity and risk premia spreads, and market risk appetite.

a_{it} is the time-invariant component the error composite representing unobserved bank-specific and country-specific effects of the cross section of banks and sovereigns observed over time.

Finally and with a view to examining the joint effect of sovereign credit ratings and bank-specific ratings, the following fixed effect regression is estimated.

Finally and with a view to examining the joint effect of sovereign credit ratings and bank-specific ratings, the following fixed effect regression is estimated.

$$AbM_{it} = \alpha + \beta\delta(Sov - Bank)_{it} + X_{i(t-1)} + a_{it} + e_{it}$$

Where:

AbM_{it} is the abnormal measure for our variables of interest as described above.

$\delta(Sov - Bank)_{it}$ is the difference in levels between the rating of the sovereign and the bank in absolute value. The distance between both type of ratings is a proxy to gauge their joint effect.

$X_{i(t-1)}$ is a vector of control variables which might affect market expectations ,namely: sovereign CDS spreads, liquidity and risk premia spreads, and market risk appetite.

ait is the time-invariant component the error composite representing unobserved bank-specific and country-specific effects of the cross section of banks and sovereigns observed over time.

3.3.1 Estimating Default probabilities

A necessary step to calculating theoretical CDS is the estimation of the Risk Neutral Probabilities, henceforth DPs. These are estimated using the structural model of Merton (1973). The appeal of structural models stems from their ability to combine information from the balance sheet together with market data, and that they exploit option pricing theory to provide reliable indicators for credit risk. The distinctive point about this type of model is that liabilities are modelled as claims on stochastic assets such that the equity of a firm is viewed as a call option on the asset of the firm[26]. Default occurs when the value of the firm's asset escalates below the level of promised payments on debt.

Formally, the model relies on the Black-Scholes equation of the value of a call as given by

$$V_E = V_A\, N(d_1) - Be^{-rT} N(d_2) \qquad (1)$$

Where :

$$d_1 = \frac{\ln\frac{V_A}{B} + (r + \frac{\sigma_A^2}{2})}{\sigma_A\sqrt{T}} \quad \text{and} \quad d_2 = d_1 - \sigma_A\sqrt{T} \qquad (2), (3)$$

V(E) is the value of the bank's equity

V(A) is the value of the bank's asset

[26] Assuming that the capital structure of a firm is composed of equity and debt, and that equity holders are junior claimants compared to debt holders. In the event of a default, equity holders either receive the difference between the value of assets and debt or nothing.

B is the book value of debt maturing at time T. It is also referred to as the 'distress barrier' and constitutes the strike price of the call option. When V(A)< B, (i.e. the asset value hits the distress barrier) default occurs.

r is the risk free rate

N is the cumulative function of the standard normal distribution

In addition, applying Ito's Lemma to equation (1) leads to the following expression of σ_E the volatility of equity:

$$\sigma_E = N(d_1)\frac{V_A}{V_E}\,\sigma_A \qquad (4)$$

The model can be implemented by simultaneously solving $for\ V_A\ and\ \sigma_A$ in equations (1) and (4).Given that the system of equations includes two unobserved variables an iterative approach proves necessary to imply the values of $V_A\ and\ \sigma_A$ .We opt for the same procedure as in Vassalou and Xing (2004) which is similar – albeit less complex- to the procedure used by KMV-Moody's and described in Crosbie (1999). For each bank in the sample, the volatility of equity σ_E is calculated based on daily data over the previous year, this estimate is set an initial value for the estimation of σ_A. Also, the Black and Scholes formula allows us to compute V_A values for each trading day over the previous year by setting V_E as the market value of equity on that particular day. Hence, we end up with a time series of V_A and we are able to compute the standard deviation, which, in turn, is set as the value of σ_A for the next iteration. It is necessary to repeat this performance until the values of σ_A stemming from both iterations converge. Once convergence is reached with σ_A it becomes possible to imply V_A from equation (1).

We obtain monthly values of σ_A because the procedure is repeated at the end of each month. Subsequently, it becomes straightforward to recover the monthly probability of default for each bank as given by N(-*d*2) using equation (2) and (3). It is, however, worth noting that unlike the KMV-Moody's model which generates actual default probabilities based on an empirical distribution of default, the DPs generated through the implementation of the Merton model are risk-neutral.

3.4 Empirical results

In this section we report and discuss the results of the response of the variables of interest to this study to changes in bank-specific ratings, changes sovereign ratings and to an additional measure capturing the joint effect of bank-specific and sovereign ratings. We start by presenting the results induced, then present the results of various robustness checks.

3.4.1 Effect of changes in bank-specific ratings

Credit risk measures: Default probabilities and Credit default swaps

Panel A and B of table 5 report the findings relating to the effect of bank-specific ratings on the default probabilities and on CDS spreads of our sample banks over event windows of [-5,5] (an 11 days window, 5 days before the event and 5 days after) and [-1,1](a 3 day window, 1 day before and one after) .

Abnomal performance is displayed by the default probabilities as a reaction to downgrade news issued by the three rating agencies statistical significance. The positive sign of the coefficients indicates that downgrade news drive up default probabilities, hence deteriorating the credit profile of banks. The same is observed for the CDS spreads of these banks. However, default probabilities respond more strongly (from a statistical significance viewpoint) to negative news compared to CDS spreads. A plausible explanation is that CDS markets have an opaque nature, while default probabilities are likely to reflect banks' fundamentals better because they combine information from the market (equity values) with information from the balance sheet (book values of debt).

Opting for a narrow event window[27] in an attempt to address endogeneity issues , (i.e. ensuring that the abnormal measure of default probability or CDS spread is not induced by changes in other market factors or the occurrence of other event) makes a difference in the magnitude of the abnormal performance, but the statistical significance obtained with the 11 days event window remains intact.

In tune with the work of Weber and Norden (2004) & Hull et al. (2004) who find that the CDS market does not exhibit response to positive rating news. Upgrade news of the banks in our sample do not lead to statistically significant abnormal performance of their CDS spreads, nor do they elicit reaction of their default probabilities. Markets appear to be more receptive of bad news in general and, more specifically those which mirror a deteriorating credit profile of the banks.

While no differences were noted across the rating agencies in terms of the impact on the banks' CDS spreads , their impact varies when it comes to the default probabilities. The abnormal performance caused by announcements by Moody's displays stronger statistical significance. This nuanced result across agencies, observed with probability of default and not with the CDS spreads, possibly supports our previous argument of the former being a more informative measure of credit risk than the latter.

[27] Opting for a narrow event window also serves as a means to prevent events clustering in an event window. But, our data sample does not suffer from the issue with the 11 days windows.

Macro-financial variables

The question we are concerned with here is: How do indicators reflecting macro-financial conditions which are highly relevant to the banking sector react to changes in banks' ratings. The results are reported in Panels C1, C2 and C3.

The credit and liquidity risk premia measures (Eurlibor-OIS and UKlibor spreads) are indicators of financial distress. The higher spread, the more strain is placed on the interbank market. This is in stark contrast to bank-specific credit measures, which respond to downgrades but not upgrades. The Eurlibor-OIS measure reacts to upgrades issued by S&P and Fitch, but not to downgrades (with the exception of Moody's whose downgrades induce a reaction in the 11 day window). The UKlibor-OIS is largely not influenced by any type of news except for a significant abnormal reaction due to upgrade news by S&P. For both financial distress indicators, the negative and significant coefficients observed-albeit not highly significant- for upgrades suggest that positive news lessen spreads and thus help ease liquidity strain in the interbank market. The lack of impact of downgrades could arguably be attributed to the fact that both interbank markets believe that governments are likely to endorse these systemically important institutions in times of liquidity strain through various actions (government guarantees, quantitative easing, recapitalisations), and so they expect an amelioration in the liquidity and credit positions of the banks.

The interbank premia index (which is a system indicator)is not affected by bad news about bank specific ratings.

Panel C2 shows the reactions of CDS indicesex tracking the senior debt of banks in mainland Europe and the UK. The spreads on bank CDS indices react massively to downgrade actions. Downgrades for the systemically important banks in our sample which are of systemic importance cause the spreads of the European and UK CDS indices to soar. Interestingly, and unlike bank-specific CDS spreads, bank CDS Indices spreads respond to upgrade actions as well, albeit to a lesser extent. A small reaction is registered by the European CDS index following news issued by S&P. A much more statistically significant reaction is exhibited by the UK CDS index following upgrade news by Moody's. The positive news is associated with lower spreads.

Possibly, the reason why upgrade news provoke reactions in interbank markets and the CDS indexes is that amid the global financial and the sovereign debt crisis, markets are 'desperate' to see signs of recovery. Hence, the aggregate change in positive ratings of all banks is better appreciated by a system-wide indicator as opposed to a bank-specific measure.

Panel C3 displays the response of the VSTOXX index which reflects investors' expectations about market volatility, and hence the aggregate risk appetite of the market. The higher the index, the greater the investors' fear of investors about the prospects of the financial markets. The table shows that (unlike the interbank premia indicators and the bank CDS indices), bank rating news do not elicit a particularly strong reaction. Moreover, the results are ambiguous. Downgrade news by Moody's over the 11-day event window are associated with positive and significant coefficients, suggesting that more negative news induces higher volatility expectations. The reaction is more statistically significant in the case of Moody's over the 3 day event window. In effect, downgrading banks of systemic importance spreads fear and uncertainty to the market. News of the same nature by S&P provoke a decline in the level of the market volatility index, rather than an increase. When it comes to the effect of upgrade news, the sign of the coefficient associated with the -significant- reaction of the index to upgrade news from Fitch is negative. This entails, as one would expect, that upgrade news lessen investors' 'fear'. Yet again, we observe the opposite reaction to news from S&P.

The discrepancies in the reactions in the case of the VSTOXX index, the small significance of its abnormal performance compared to the other macro-financial variables, and the differences across agencies, might well be a reflection of the different nature of this indicator which is tied to financial market volatility rather than credit risk.

Not only does our analysis of macro-financial indicators capture differences in the impact exerted by the three ratings agencies, but it also differentiates between the reactions of systems in Europe and the UK.

3.4.2 Effect of changes in sovereign ratings

Credit risk measures: Default probabilities and Credit default swaps

Panels A and B of Table 6 show the responses of banks' credit risk measures to changes in sovereign ratings. Altogether, it appears that the default probabilities and the CDS spreads of the banks in our sample suffer more from changes in sovereigns' ratings[28] experienced by sovereigns than those changes their own ratings endure. Sovereigns experiencing a downgrade affect the perception of markets about the credit and liquidity risk profile of systemically important banks. Presumably, this is due the strong ties governing the relationship between banks and their sovereigns and European sovereigns to which they are exposed through government bonds purchases. Markets are anxious that sovereigns with parlous fiscal and credit situation are likely to fail bailing out troubled banks. Hence the stronger response of banks' credit measures to sovereign rating changes compared to changes in bank-specific ratings.

[28] We discard upgrade news and focus on downgrade news and outlook/watch news embedded to downgrade news in the sovereign analysis because the limited number of upgrade observations seems to lead to spurious results.

By and large, the patterns previously noted with respect to the effect of bank-specific ratings on the credit risk measures hold true: the stronger statistical significance of the response of default probabilities compared to that of CDS spreads; and the effect of narrowing the event window further which only slightly affects the magnitude of the abnormal performance.

Our sovereign ratings data also features outlook and watch news which we incorporate to downgrade news, as explained in the data section. The results emerging from changes in this type of news are fairly akin to those of downgrade news. However, the higher statistical significance of the abnormal performance observed in Panel B possibly reflects that the prospect of bad news as opposed to bad news materialisation in the form of a downgrade makes up for more anxiety in the CDS market and hence causes a more significant response.

Macro-financial variables

The results discussed in this section are reported in Table 6 Panel C.

Sovereign ratings spur a greater reaction amongst financial distress indicators. While the UK and the Eurozone interbank credit and liquidity premia do not respond to negative changes in bank-specific rating, they experience an increase following sovereign ratings downgrades and downgrades which account for outlook and watch news. A change in the creditworthiness of a sovereign is a marco-economic event, and so it is likely to exert an impact on variables indicators which are of a macro-financial nature. In view of the strong ties sovereigns maintain with banking systems, interbank markets expect a sovereign enduring a downgrade to cause more harm in terms of widening credit and liquidity spreads than a downgrade systemically important bank would.

When it comes to bank CDS indices tracking European and UK banks, the response is largely similar in magnitude and significance to that produced by bank-specific downgrades. Negative rating news (be they downgrades or downgrades corrected for outlook and watch news) are associated with high spreads, indicating the anxiety of the derivative markets about the deteriorating credit profile of European sovereigns.

Lastly, the negative sovereign rating news not only elicit a stronger reaction in the market risk appetite indicator. Negative sovereign news from all agencies cause the Vstoxx index to increase, thus reflecting more fear in the market. Not only is the reaction stronger, but it is also more coherent than that observed following bank-specific news. Despite the fact that the Vstoxx is unrelated to credit and liquidity risk, and is concerned with volatility expectations of the market, the downgrade (or the prospect of downgrade) of a sovereign appears to exert an effect on the market risk appetite index.

Model 2 (whose specifications are explained in the methodology section) generates outcomes that lend further credence to our previous results. (See previous tables)

3.4.3 Joint effect of sovereign and bank-specific ratings

Sovereign ratings have, typically, been higher than bank ratings. But, the recent sovereign debt crisis altered the credit rating landscape, and some sovereigns with weak economic and fiscal fundamentals saw their ratings severely downgraded, reaching similar or lower rating levels as troubled banks.

The aim of this section is to assess the perception of the financial market of the widening gap between the rating of a bank and that of its sovereign. Hence, this will provide insight into the grasp of the market about the connection between banks and sovereigns. To this end, we look at the impact of the difference in levels between sovereign and bank-specific ratings on our set of variables. The advantage of this approach is that sovereigns which could not be taken into account in the previous analysis because their credit ratings did not experience a change (e.g Germany, Denmark) can be included.

As one would predict, the results reported in table 7 show that the higher the distance between the sovereign and the bank, the stronger the effect on the credit risk measures of the banks, as well as on the bank-related macro-financial variables. This is so because of the interconnectedness between the risk profile of a given bank and its sovereign. A deterioration in sovereign credit risk (due to a financial sector bail-out based or the dilution of the value of bond holdings) feeds back into the financial sector. Inversely a deterioration in bank sovereign credit risk makes the credit profile of a sovereign worse off as it necessitates more guarantees and interventions by the latter. The documented effect is ostensible for the variables of interest and is largely similar in magnitude across the three ratings.

3.5 Robustness checks

We test the robustness of our results by using alternative abnormal performance measures, disentangling multiple-notch downgrades (2 and above) from one-notch downgrades and finally by splitting the sample to cover two crises: the financial crisis (from 01/01/2007 to 14/10/2009) and the Eurozone debt crisis (from 14/09/2009 to the end of the sample period). Mid-October 2009 marks the outbreak of the Eurozone debt crisis with the newly elected Greek prime minister revealing that the hole in the finances of the country is larger than initially thought. Our results[29] are robust to using alternative measures of the abnormal performance of our bank credit risk measures and macro-financial variables**.** Overall, we observe similar magnitudes and statistical significance levels of the previous abnormal performance measures. As one would expect, the effect of downgrades is accentuated by the occurrence of higher-notch ratings. The more a bank or a sovereign is reprimanded relating to its creditworthiness, the stronger the abnormal performance associated with the credit risk

[29] Table of results available upon request.

measure or the macro-financial indicator. The effect of downgrades is also accentuated over the Eurozone debt crisis. Plausibly, markets in Europe were more sensitive over this period.

3.6 Conclusions

In this analysis we examine the reaction of bank-specific changes in credit ratings versus those in sovereign ratings (and news) on a set of market variables highly relevant for a sample of major European financial institutions. Rather than looking separately at how sovereign and bank credit rating actions influence asset prices, we place the focus on confronting the impact of sovereign rating actions against bank-specific rating actions on an array of bank-related variables. Ultimately, we cast light over the close ties between banks and their sovereigns.

The response of bank CDS spreads to bank-downgrades is akin to that of default probabilities. By this we mean that negative news about banks' ratings cause deterioration in banks' credit risk profile. However, the statistical significance of the reaction is stronger for default probabilities. The latter credit risk measure default probabilities is likely to reflect banks' fundamentals more because it combines information from the market with balance sheet information.

As one would expect, macro-financial measures are not responsive to bank-specific negative rating news. Interestingly, bank-specific positive ratings exert an (albeit small) influence on the financial distress indicators (the UK and the Euro interbank credit and liquidity premia) and bank-CDS indices. Positive downgrades are associated with a decline in spreads. Possibly, amid the global financial and the sovereign debt crisis, interbank markets and the CDS markets are particularly anxious in their search for signs of recovery.

While macro-financial measures do not respond to negative changes in bank-specific rating, they experience abnormal performance following sovereign rating downgrades, and downgrades which account for outlook and watch news. Interbank markets along with bank-CDS (indices) markets expect a sovereign enduring a downgrade to cause more harm in terms of widening credit and liquidity spreads than a systemically important downgraded bank would. Moreover, we find evidence that the default probabilities and the CDS spreads of the banks in our sample suffer more from changes in ratings experienced by sovereigns than those changes their own ratings endure. This is due to the close ties sovereigns maintain with their sovereigns. In effect, markets are anxious that sovereigns with parlous fiscal and credit situation are likely to fail bailing out troubled banks.

The results emerging from changes in downgrades which are corrected for watch and outlook news are fairly akin to those of downgrade news. The observed differences could be explained by the fact that the prospect of bad news as opposed to bad news materialisation in the form of a downgrade makes up for more anxiety in the markets. Despite the fact that the Vstoxx is unrelated to credit risk and concerned with volatility expectations of the market the downgrade (or the prospect of downgrade) of a sovereign appears to exert an effect on the market risk appetite index.

Performing robustness checks not only supports our results but unveils additional aspects. Namely, the effect of downgrades is accentuated over the sovereign debt crisis, and similarly with the occurrence of higher-notch ratings.

When looking at the joint effect of actual sovereign and bank ratings, results show that the higher the distance between the sovereign and the bank rating, the stronger the effect, on the banks' credit risk measures as well as on the bank-related macro-financial variables.

In an era marked by recurrent government intervention to bolster the banking system be they bails out or other liquidity-boosting operations, the credit and liquidity risk of a bank hinges largely on the ability of its sovereign to intervene in times of financial trouble. Unequivocally**,** we find evidence that markets grasp the strong connection between banks and their sovereigns.

Table 1 : Number of bank rating events (changes) per agency

	Moody's	**S&P**	**Fitch**
Overall upgrades	63	11	8
1-notch upgrades	17	11	4
2-notches upgrades	8	0	4
3-notches or above	38	0	0
Overall downgrades	124	117	110
1-notch downgrades	67	93	76
2-notches downgrades	36	15	28
3-notches or above	21	9	6

Table 2 : Number of changes in sovereign ratings actions per agency

	Moody's	**S&P**	**Fitch**
Upgrades	4	7	10
1-notch upgrades	0	1	0
2-notches upgrades	2	3	5
3-notches or above	2	3	5
Downgrades	66	86	102
1-notch downgrades	31	42	48
2-notches downgrades	23	38	34
3-notches or above	12	6	20
Positive W/O News	4	7	17
1-notch downgrades	3	0	12
2-notches downgrades	0	0	0
3-notches or above	0	7	5
Negative W/O News	101	86	141
1-notch downgrades	21	0	45
2-notches downgrades	37	0	16
3-notches or above	43	86	80

Note: the sovereign rating events are included in the count each time a given bank is from a particular country, which means that they can be included as many times as the number of banks having the same country.

Table 3 : Summary statistics of macro-financial variables used in the analysis (January 2007 to August 2013)

	mean	max	min	sd	skewness	kurtosis	p25	p50	p75
EURIBOR-OIS	0.44	1.95	0.041	0.34	1.47	5.77	0.19	0.34	0.64
UKLIBOR-OIS	0.47	2.98	-0.07	0.46	1.97	7.16	0.16	0.28	0.59
SwLibor-OIS	0.22	1.74	-.004	0.26	2.23	9.50	0.04	0.09	0.31
CDSINDEX_EU	220	606	7.37	140.42	0.31	2.23	109.01	216.15	314.75
CDSINDEX_UK	135.22	295.35	4.7	59.35	-0.36	3.30	110.4	137.02	168.51
VSTOXX	27.09	87.51	13.41	9.95	1.82	7.47		24.42	30.05

Note: EURIBOR-OIS (respectively UKLIBOR-OIS SwissLibor-OIS) a proxy for liquidity and credit risk premia in the European (respectively the UK and Swiss) interbank market and is thus used as an indicator of financial distress. The Euribor (respectively UKLIBOR and SwissLibor) encompass the expected risk-free interest rate over a specific term, the term premium, the credit risk premium of unsecured trading and the liquidity risk premium. Whereas the OIS measures the expected risk-free interest rate of secured transactions over a specific term. The VSTOXX Index is based on EURO STOXX 50 real-time options prices. It reflects the market expectations of near-term up to long-term volatility by measuring the square root of the implied variance across all options of a given time to expiration. Hence it is a measure of the risk appetite of the market. CDSINDEX_EU and CDSINDEX_UK are financial sector CDS Index tracking senior debt of a number of banks in Europe and the UK respectively.

Table 4: Numerically-scaled ratings

Actual Rating	Numerical equivalent
AAA/Aaa	20
AA+/Aa1	19
AA/Aa2	18
AA-/Aa3	17
A+/A1	16
A/A2	15
A-/A3	14
BBB+/Baa1	13
BBB/Baa2	12
BBB-/Baa3	11
BB+/Ba1	10
BB/Ba2	9
BB-/Ba3	8
B+/B1	7
B/B2	6
B-/B3	5
CCC+/Caa1	4
CCC/Caa2	3
CCC-/Caa3	2
SD/C	1

Note: Fitch and S&P use the same notation system (AAA to SD) while the equivalent rating system of Moody's goes from Aaa to C.

Table 5 : Bank-specific ratings: Statistical tests for two event windows

Panel A: Reaction of Default probabilities (DP) to Bank-specific rating changes by agency

Dependent variable: DP	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]**
	Model (1)					
Upgrades	0.03	0.01	-0.04	-0.11	0.2	0.07
	(0.32)	(0.62)	(-1.37)	(-1.38)	(1.29)	(1.30)
Downgrades	1.7**	0.44**	3.21***	0.88***	3.45**	0.94**
	(3.07)	(3.04)	(3.54)	(3.47)	(2.74)	(2.73)
	Model(2)					
Upgrades	-0.0047	-0.0049	-0.007	-0.009	-0.004	-0.003
	(-1.79)	(-1.77)	(-1.03)	(-1.38)	(-1.44)	(-1.47)
Downgrades	0.093**	0.093**	0.05***	0.05***	0.04***	0.043***
	(5.12)	(5.12)	(8.05)	(8.2)	(13.5)	(13.7)

Panel B: Reaction of CDS spreads to Bank-specific rating changes by agency

Dependent variable: CDS spreads	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
	Model (1)					
Upgrades	-	-	0.92	0.72	0.96	0.86
			(1.02)	(1.01)	(1.00)	0.98
Downgrades	8.62*	5.87*	10.78*	6.56*	9.41*	7.08*
	(2.03)	(1.98)	(1.98)	(1.97)	(2.61)	(2.63)
	Model (2)					
Upgrades	-	-	-0.071	-0.063	-0.065	-0.061
			(-1.81)	(-1.83)	(-0.97)	(-0.98)
Downgrades	0.062**	0.061**	0.087*	0.085*	0.093*	0.1*
	(3.24)	(3.24)	(2.09)	(2.1)	(2.17)	(2.3)

Panel C: Reaction of bank-relevant maco-financial indicators to Bank-specific rating changes by agency

C.1 Financial Distress indicators

Dependent variable: EURLIBOR-OIS	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Upgrades	-1.6*	-1.5*	0.7	1.1	-2.5*	-2.0*
	(-2.82)	(-2.72)	(0.89)	(1.24)	(-2.82)	(-2.47)
Downgrades	0.4	0.9	3.1*	0.53	0.74	0.18
	(0.62)	(1.41)	(2.63)	(1.09)	(1.46)	(1.79)
			Model (2)			
Upgrades	-0.022*	-0.035*	-0.018	0.015	-0.038*	-0.027*
	(-2.13)	(-2.15)	(1.69)	(1.69)	(-2.31)	(-2.34)
Downgrades	0.07	0.09	0.053	0.057	0.092	0.094
	(0.32)	(0.54)	(0.61)	(1.09)	(1.75)	(1.77)
Dependent variable: UKLIBOR-OIS	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Upgrades	-5.51	-1.1	1.7	2.07	-1.7*	1.3
	(-0.21)	(-0.66)	(1.60)	(1.48)	(-2.39)	(1.79)
Downgrades	0.5	0.1	-0.12	-0.9	0.4	0.14
	(0.77)	(1.42)	(-1.76)	(-1.41)	(0.60)	(1.69)
			Model (2)			
Upgrades	-0.062	-0.063	-0.024	-0.022	-0.003	-0.003
	(-0.87)	(-0.90)	(-1.80)	(-1.71)	(-1.46)	(-1.48)
Downgrades	0.04	0.03	0.015	0.014	0.067	0.069
	(0.34)	(0.45)	(1.56)	(1.56)	(0.72)	(0.76)

C.2 Bank CDS index for Europe and the UK

Dependent variable: CDS spreads	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Upgrades	-2.44 (-0.05)	-5.44 (-0.1)	-8.98 (-1.22)	-17.83* (-2.34)	-16.2* (-2.31)	17.79 (1.73)
Downgrades	29.13*** (9.49)	26.65*** (10.23)	38.52*** (14.76)	25.43*** (14.13)	19.58*** (6.42)	10.35*** (8.65)
			Model (2)			
Upgrades	-0.0043 (-0.76)	-0.0041 (-0.77)	-0.0065 (-1.13)	-0.0063 (-1.13)	-0.0086 (-0.4)	-0.0088 (-0.76)
Downgrades	0.059*** (6.45)	0.057*** (4.77)	0.095*** (8.63)	0.085*** (9.22)	0.103*** (5.68)	0.109*** (5.79)
Dependent variable: CDS spreads	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Upgrades	-1.03 (-0.67)	-1.37 (-0.48)	-12.9*** (-7.81)	-25.05*** (-7.05)	28.70 (1.75)	22.08 (1.29)
Downgrades	19.89*** (8.20)	16.31*** (7.02)	26.78*** (4.73)	17.62*** (8.97)	15.40 (1.62)	11.34** (3.07)
			Model (2)			
Upgrades	-0.0083 (-1.57)	-0.0081 (-1.55)	-0.027** (-3.28)	0.034** (-3.22)	0.039 (1.08)	0.035 (1.08)
Downgrades	0.17*** (10.67)	0.179*** (10.03)	0.206*** (9.87)	0.209*** (10.10)	0.092* (1.98)	0.097* (1.98)

C.2 Market risk appetite

Dependent variable: VSTOXX	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
	Model (1)					
Upgrades	3.52	-7.44*	1.55	-0.33	9.99**	-1.05
	(0.80)	(-2.2)	(1.21)	(-0.23)	(3.61)	(-0.49)
Downgrades	0.01	0.69	5.75**	8.35***	-7.36*	-3.96
	(0.01)	(0.53)	(3.07)	(7.37)	(-2.45)	(-1.15)
	Model (2)					
Upgrades	0.0056	0.0063	0.0027	0.0059	0.0078	0.0065
	(1.23)	(1.44)	(0.76)	(1.76)	(0.38)	(0.33)
Downgrades	0.0078	0.0068	0.054	0.055	0.081*	0.085*
	(0.38)	(0.73)	(0.73)	(1.08)	(2.37)	(0.97)

Note: The dependent variable is indicated in each panel of table 5. Model (1) is the standard event study methodology testing for statistical significance of the cumulative abnormal performance due to the event occurence; the reported figures are cumulative abnormal performance and not coefficients. The t statistics reported in parenthesis give the statistical significance of the cumulative abnormal performance across all banks. Model (2) is a modified specification of model (1) that introduces a vector of controls X and is run as a panel fixed effect regression over the event windows. The figures reported are coefficients of the relationship between the abnormal performance of the default probabilities and the changes in bank rating .. In panel C1 the swisslibor-ois (a financial distress indicator of thr swiss interbank market) is used as a robustness check measure. No statistical significance is found since the sample does not include Swiss banks. Downgrades O/W refer to downgrade actions which are corrected for watch and outlook news. Standard errors are robust.***, ** and * denote significance at the 1%,5% and 10% levels respectively

Table 6 : Sovereign ratings: Statistical tests for two event windows

Panel A: Reaction of Default probabilities (DP) to sovereign rating changes by agency

Dependent variable: DP	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]**
	Model (1)					
Downgrades	5.62***	5.14***	8.4***	7.28***	6.81***	6.29***
	(10.29)	(10.25)	(7.07)	(7.04)	(7.90)	(7.88)
Downgrades O/W	7.24***	7.02***	7.43***	6.37***	6.81***	6.29***
	(10.71)	(10.59)	(6.30)	(6.15)	(7.90)	(7.88)
	Model(2)					
Downgrades	0.065***	0.059***	0.078***	0.073***	0.058***	0.048***
	(11.32)	(11.30)	(9.14)	(9.19)	(12.45)	(12.06)
Downgrades O/W	0.077***	0.070***	0.061***	0.057***	0.058***	0.048***
	(11.19)	(11.14)	(10.40)	(10.33)	(12.45)	(12.06)

Panel B: Reaction of CDS spreads to sovereign rating changes by agency

Dependent variable: CDS spreads	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
	Model (1)					
Downgrades	9.55*	6.26*	14.22*	12.60*	7.72***	8.33
	(2.18)	(2.07)	(2.23)	(2.14)	(5.14)	(1.74)
Downgrades O/W	8.43**	8.09**	17.28**	13.51**	5.48***	6.94***
	(2.63)	(2.63)	(3.32)	(3.18)	(4.27)	(5.14)
	Model (2)					
Downgrades	0.11***	0.04***	0.0155	0.0151*	0.0895**	0.0892**
	(5.40)	(5.28)	(1.42)	(2.42)	(3.37)	(3.34)
Downgrades O/W	0.092**	0.088**	0.149**	0.149**	0.043***	0.046***
	(3.07)	(3.16)	(3.74)	(3.74)	(6.78)	(6.24)

Panel C: Reaction of bank-relevant maco-financial indicators to sovereign rating changes by agency

C.1 Financial Distress indicators

Dependent variable: EURLIBOR-OIS	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
	Model (1)					
Downgrades	2.77***	2.4***	2.3***	1.9	9.01	2.7***
	(6.14)	(5.40)	(5.51)	(4.54)	(1.84)	(6.21)
Downgrades O/W	2.79***	1.8***	5.1*	-4.2	9.01	2.7***
	(6.19)	(4.31)	(2.08)	(1.60)	(1.84)	(6.21)
	Model (2)					
Downgrades	0.031***	0.038**	0.026***	0.022***	0.028	0.028***
	(8.29)	(3.20)	(4.67)	(4.73)	(0.90)	(5.93)
Downgrades O/W	0.033***	0.033**	0.08**	0.09**	0.05	0.04**
	(8.37)	(3.54)	(2.44)	(2.41)	(1.46)	(2.65)
Dependent variable: UKLIBOR-OIS	**Fitch**		**Moody's**		**S&P**	
	[-5,5]	**[-1,1]**	**[-5,5]**	**[-1,1]**	**[-5,5]**	**[-1,1]**
	Model (1)					
Downgrades	5.34***	5.35***	3.57***	3.56***	2.04***	2.8***
	(10.15)	(10.77)	(6.02)	(5.65)	(8.06)	(10.06)
Downgrades O/W	2.8***	3.1***	-0.6	-0.2	2.0***	2.8***
	(6.4)	(7.85)	(-1.66)	(-0.56)	(8.06)	(10.06)
	Model (2)					
Downgrades	0.07***	0.07***	0.06**	0.04**	0.05***	0.03***
	(8.20)	(8.16)	(3.14)	(3.17)	(7.30)	(5.34)
Downgrades O/W	0.05***	0.04***	0.018	0.012	0.03**	0.02**
	(7.30)	(7.30)	(1.14)	(1.14)	(3.44)	(3.47)

C.2 Bank CDS index for Europe and the UK

Dependent variable: EU CDS INDEX	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Downgrades	23.51***	21.42***	25.44***	22.06***	17.73***	12.34***
	(13.40)	(12.30)	(8.56)	(9.22)	(12.56)	(8.79)
Downgrades O/W	26.19***	24.77***	27.70***	28.47***	17.73***	12.34***
	(14.54)	(13.57)	(10.67)	(10.19)	(12.56)	(8.79)
			Model (2)			
Downgrades	0.19 ***	0.105 ***	0.13***	0.12***	0.14***	0.106***
	(8.45)	(8.44)	(7.06)	(7.12)	(8.52)	(8.17)
Downgrades O/W	0.21***	0.22***	0.25***	0.25***	0.13***	0.108***
	(10.29)	(9.67)	(12.07)	(11.9)	(9.64)	(9.23)
Dependent variable: UK CDS INDEX	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Downgrades	15.46***	14.68***	25.41***	19.49***	10.85	19.27***
	(9.14)	(7.18)	(5.30)	(7.21)	(1.00)	(4.11)
Downgrades O/W	18.20***	15.87***	24.55***	19.81***	10.85	19.27***
	(11.45)	(11.04)	(11.98)	(12.54)	(1.00)	(4.11)
			Model (2)			
Downgrades	0.17***	0.14***	0.19***	0.17***	0.12**	0.16***
	(5.42)	(5.70)	(4.89)	(4.84)	(3.15)	(5.23)
Downgrades O/W	0.19***	0.16***	0.18***	0.17***	0.12**	0.16***
	(4.27)	(4.49)	(9.04)	(8.98)	(3.15)	(5.23)

C.2 Market risk appetite

Dependent variable: VSTOXX	Fitch		Moody's		S&P	
	[-5,5]	[-1,1]	[-5,5]	[-1,1]	[-5,5]	[-1,1]
			Model (1)			
Downgrades	3.19*	12.53***	2.49	10.23***	1.10	13.44***
	(2.13)	(12.32)	(1.39)	(7.72)	(0.93)	(5.77)
Downgrades O/W	5.17***	14.55***	12.41***	8.05***	1.10	13.44***
	(4.10)	(8.64)	(5.64)	(10.00)	(0.93)	(5.77)
			Model (2)			
Downgrades	0.06**	0.076**	0.03*	0.05**	0.026	0.07***
	(2.64)	(2.60)	(2.19)	(6.42)	(0.83)	(5.44)
Downgrades O/W	0.07***	0.079***	0.068***	0.066***	0.026	0.07***
	(6.12)	(6.04)	(9.24)	(9.20)	(0.83)	(5.44)

Note: The dependent variable is indicated in each panel of table 6. Model (1) is the standard event study methodology testing for statistical significance of the cumulative abnormal performance due to the event occurence; the reported figures are cumulative abnormal performance and not coefficients. The t statistics reported in parenthesis give the statistical significance of the cumulative abnormal performance across all banks. Model (2) is a modified specification of model (1) that introduces a vector of controls X and is run as a panel fixed effect regression over the event windows. The figures reported are coefficients of the relationship between the abnormal performance of the default probabilities and the changes in bank rating .. In panel C1 the swisslibor-ois (a financial distress indicator of thr swiss interbank market) is used as a robustness check measure. No statistical significance is found since the sample does not include Swiss banks. Downgrades O/W refer to downgrade actions which are corrected for watch and outlook news. Standard errors are robust.***, ** and * denote significance at the 1%,5% and 10% levels respectively

Table 7 : Results of regression analysis of the joint effect of sovereign and bank ratings

	Fitch	**Moody's**	**S&P**
DP	0.19***	0.12**	0.06***
	(5.62)	(3.35)	(7.45)
CDS	0.03*	0.066**	0.089*
	(1.99)	(2.87)	(2.08)
EURLIBOR-OIS	0.04**	0.07***	0.009**
	(2.73)	(5.62)	(3.08)
UKLIBOR-OIS	0.03***	0.11*	0.04**
	(4.77)	(2.03)	(2.65)
EU CDS INDEX	0.21**	0.43*	0.19***
	(3.08)	(1.99)	(6.25)
UK CDS INDEX	0.45**	0.31***	0.17**
	(2.67)	(8.67)	(2.67)
VSTOXX	0.04**	0.08*	0.17
	(3.18)	(2.07)	(1.76)

Note: The first column features the dependent variables. The independent variable is the joint effect of sovereign and bank specific ratings proxied by the distance between both ratings. Standard errors are robust.***, ** and * denote significance at the 1%,5% and 10% levels respectively.

Figure1: Sovereign and Banking Sectors Balance Sheets

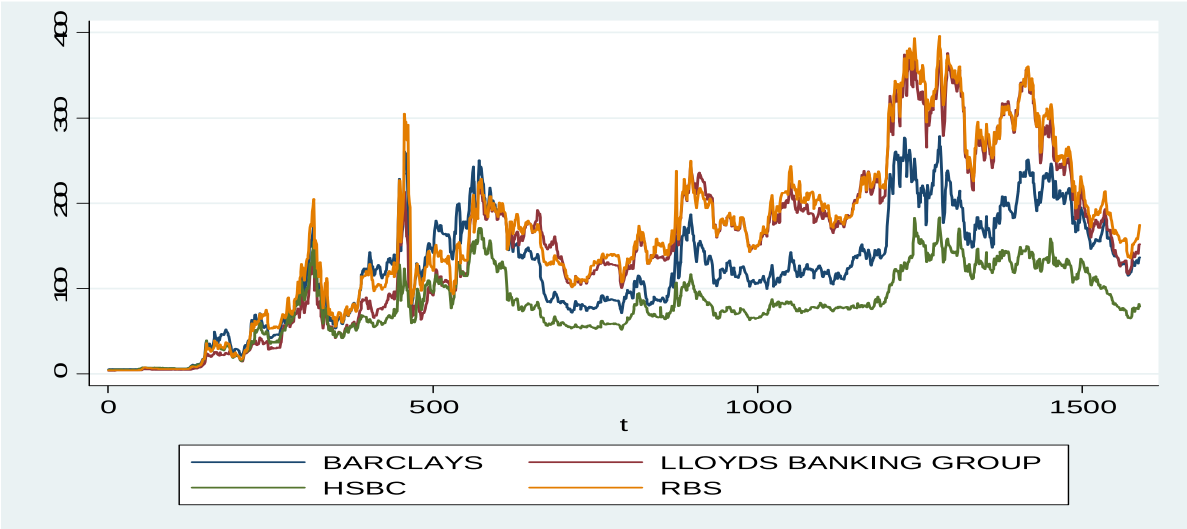
Banking Sector Balance Sheet

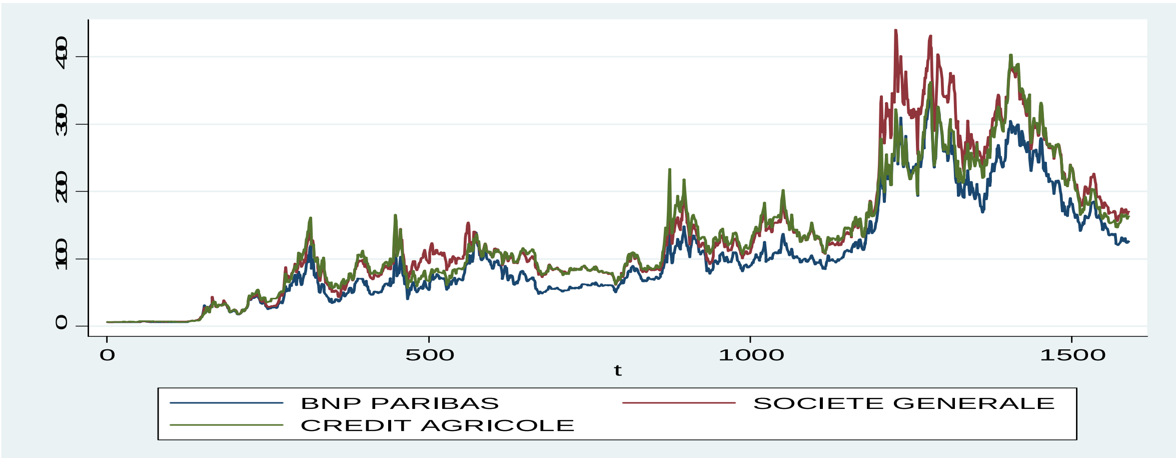
Assets	**Liabilities**
Loans (debt of corporate sector)	Debt
Other assets	Deposits
Financial guarantee (implicit put option)	Equity

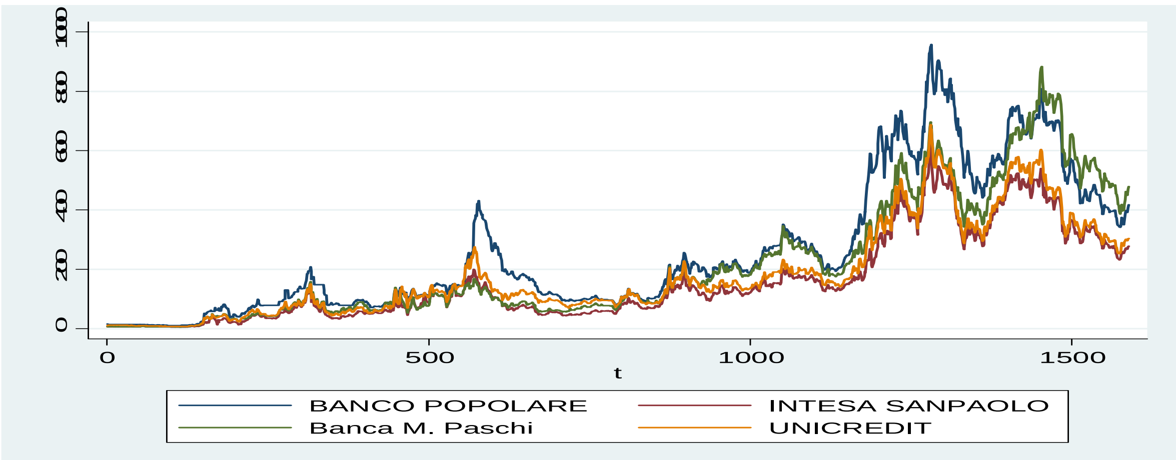
Public Sector Balance Sheet

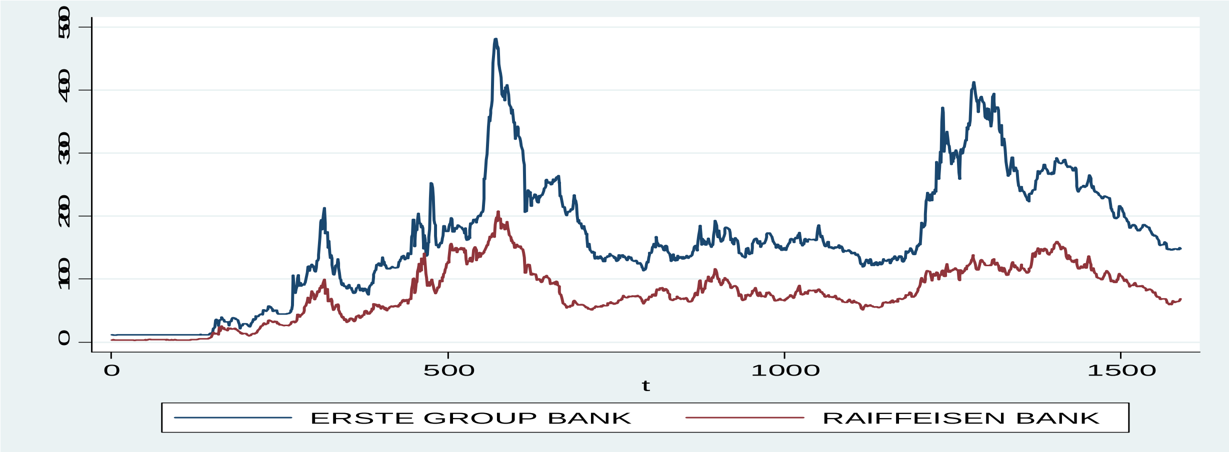
Assets	**Liabilities**
Foreign reserves	Financial guarantee (implicit put option)
Net fiscal asset and other Assets	Foreign debt
Value of monopoly on issue of money	Base money and local currency debt

Figure2 : Time series plot of the banks CDS spreads per country









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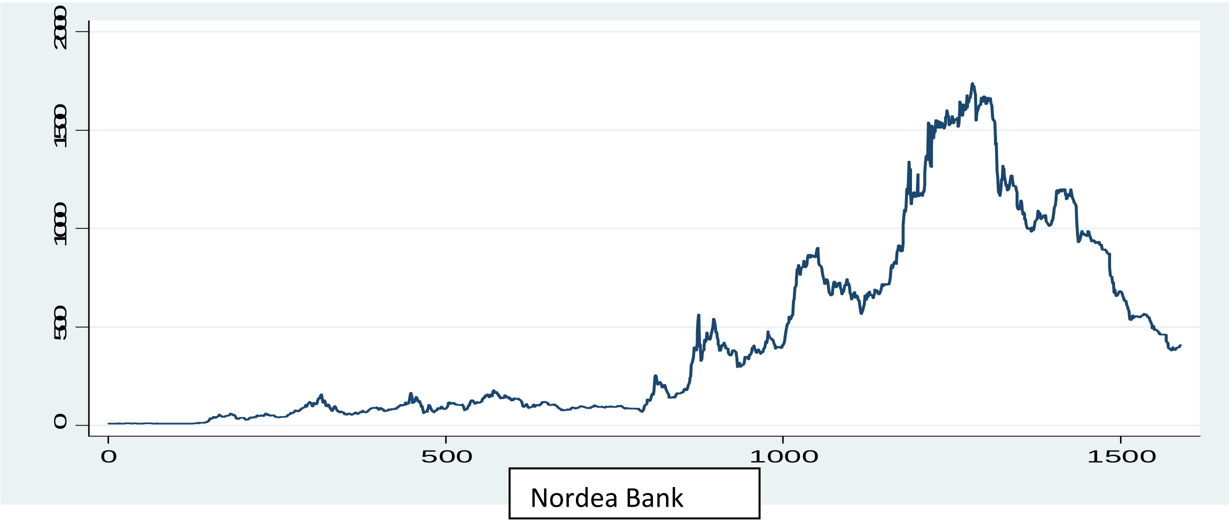
ERSTE GROUP BANK
RAIFFEISEN BANK



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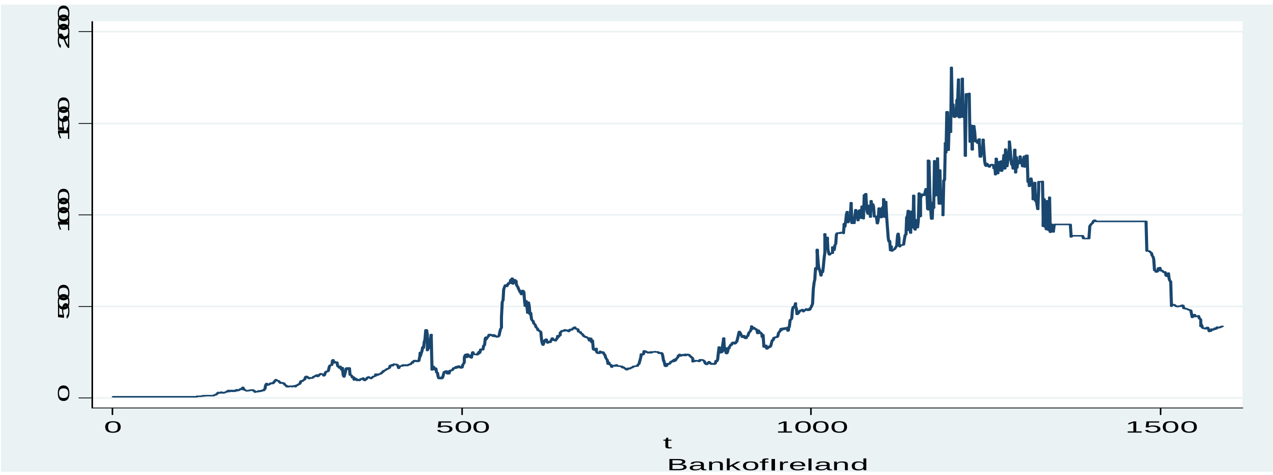
Nordea Bank



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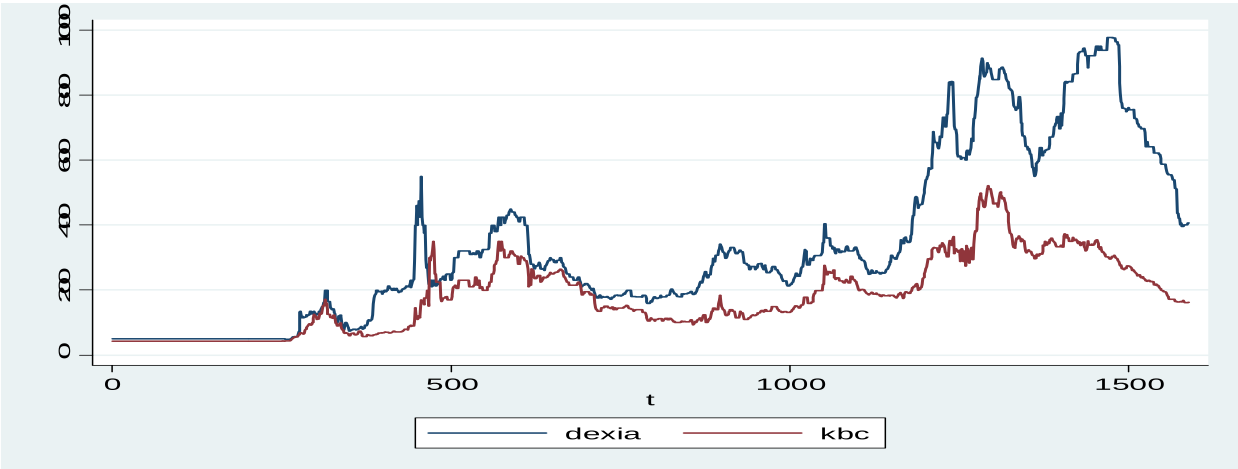
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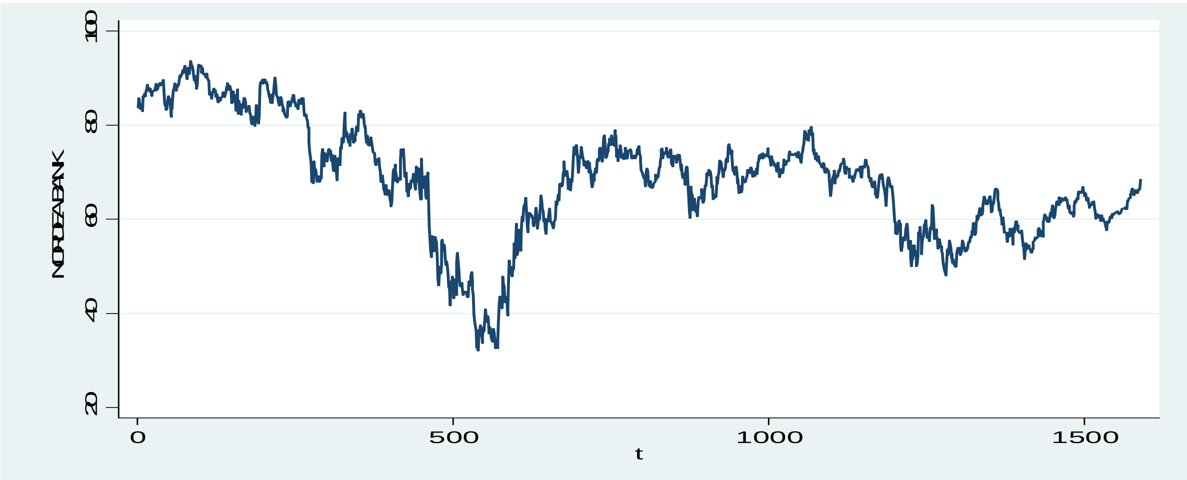
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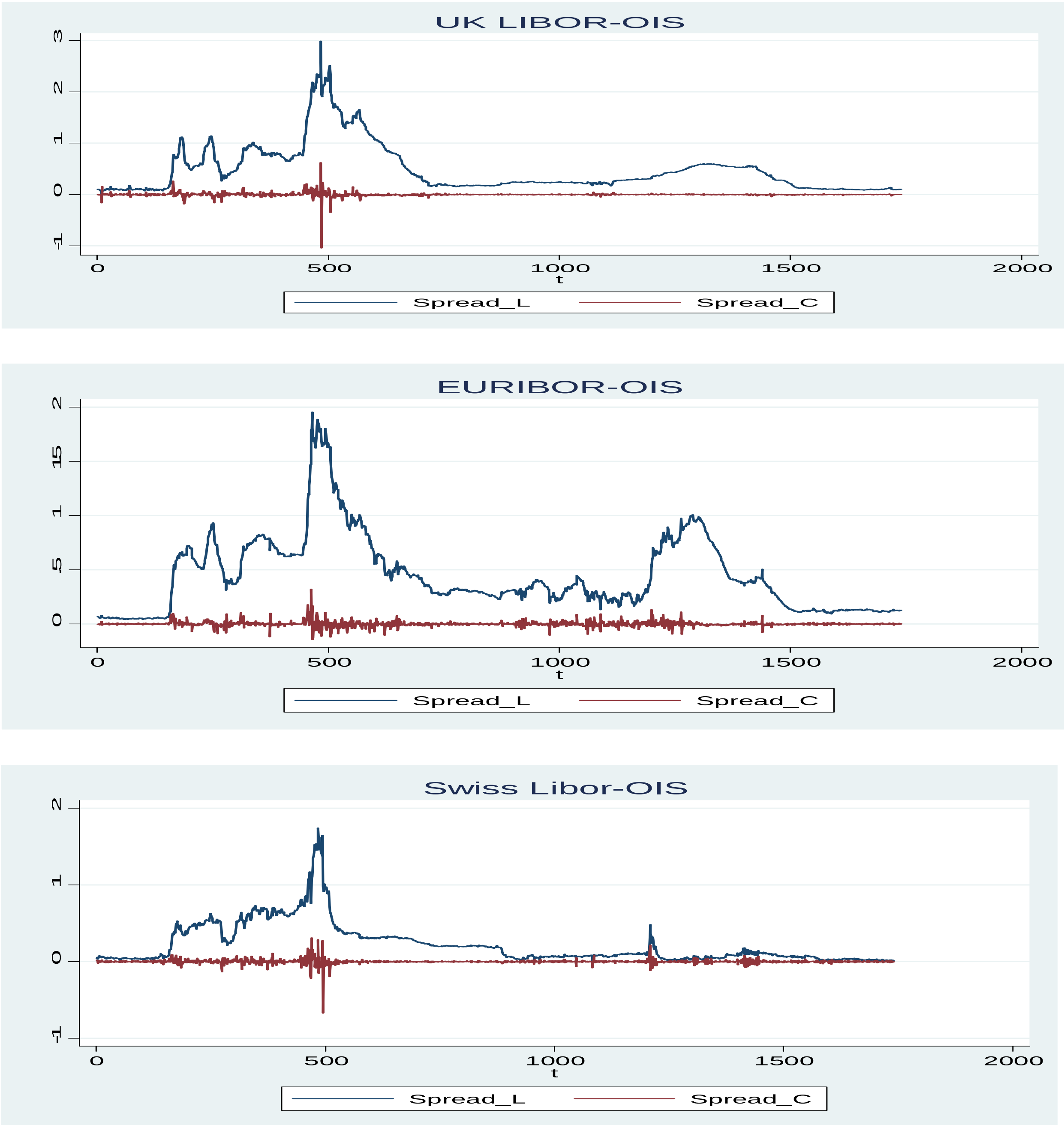
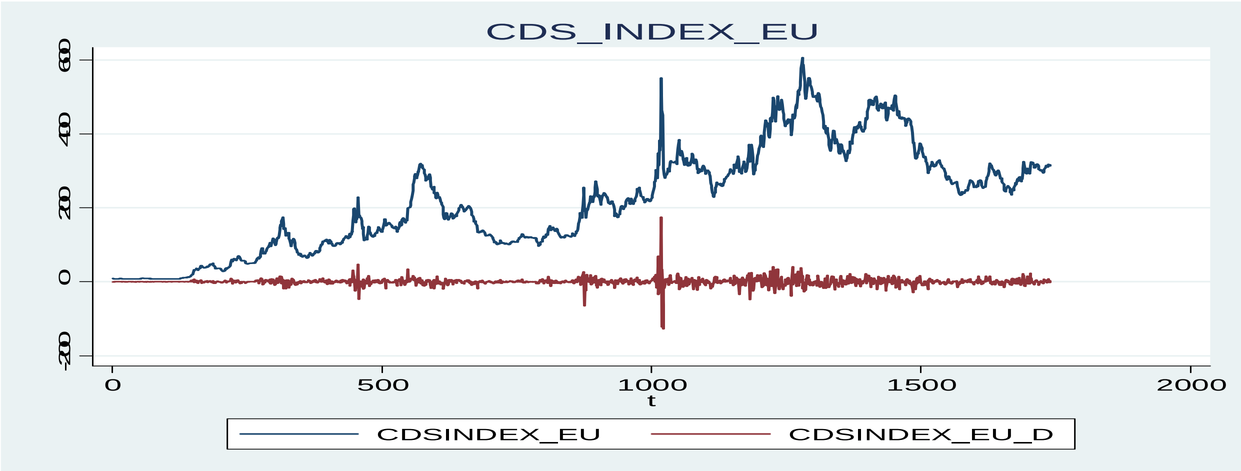
Figure 3: Time series plots of indicators of financial distress , EURIBOR-OIS UKLIBOR-OIS SwissLibor-OIS , European Banks CDS index and UK Banks CDS index in actual levels and daily changes over the period from January 2007 to August2013.

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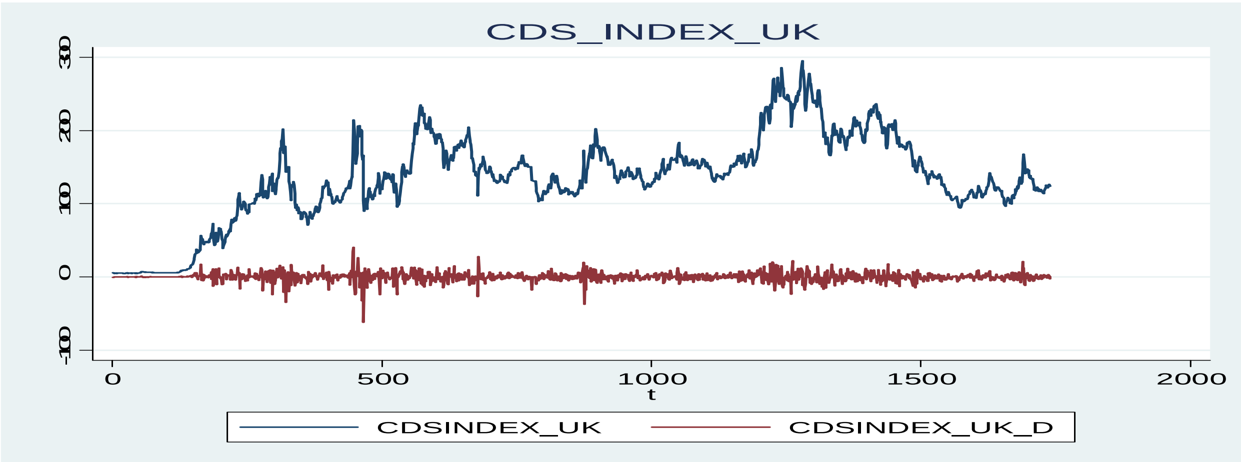
CDSINDEX_EU
CDSINDEX_EU_D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Chapter Four:

Healing through Liquidity Injections? ****

4.1 Motivation

The recent banking crisis has deeply changed the economic and financial landscape. One change worth noting is related to the borrowing ability of banks. Before 2007, European banks were able to borrow at a lower cost than other corporations. Since the banking crisis in 2007/8, the bond yield spreads of financial corporations (which reflect their borrowing costs) have been higher than those of non-financial corporations; an unprecedented occurrence. Clearly, investors are not optimistic about the outlook of these institutions. In order to compensate for expected loss[30], they demand higher risk premium for holding banks bonds, which translates into higher bond yields and, in turn, higher credit spreads.

Figure 1 illustrates how for the first time since borrowing costs of banks (proxied by bond yields on the graph) reached unprecedentedly higher levels than those of industrial firms. The world's biggest institutions are paying more than industrial companies to borrow in the corporate bond markets. Banks have less access to funding from financial markets and turn to governments. In effect, investors are demanding higher risk premiums for holding banks bonds, which translates into higher bond yields.

Longstaff et al. (2005) exploit the information contained in the CDS premia to derive default and non-default components from corporate spreads. They find that the bulk of corporate spread is due to default risk. On the other hand, the non-default component is liquidity-related. Based on the argument that part of the default risk is explained by liquidity, this paper

[30] Which is defined as the probability of default times the loss given default. EL=RNPD*LGD*B e(-rt)

re-visits the connection between default probabilities *à la Merton* and their borrowing costs for a sample of large European banks in view of new market conditions : unprecedentedly high borrowing costs of banks along with the armada of interventions by the ECB and kin institutions to prevent a financial haemorrhage as the banking crisis and then the Eurozone crisis has left the liquidity position in a frail state. Hence, the objective of this paper is twofold. First, it analyses the question of whether policy interventions alters the relationship between borrowing costs and default. Second, it investigates whether the ECB measures, particularly those which are liquidity related, have succeeded in curing the European banking system. To this end, it studies a sample composed of 21 large European banks, using data on their borrowing costs (as proxied by CDS spreads) and default indicators (Merton-type default probabilities and distances to default). The sample period spans from 01/01/2007 to 30/01/2013. In addition, the paper uses a compilation of policy events found on the ECB website and classified into four categories namely: *banking liquidity interventions, sovereign liquidity interventions, interest rates interventions***,** *economy-wide news*. In addition, the paper makes a theoretical contribution to the literature linking credit spreads to default probabilities. It does this by building on Merton's model to propose a simple measure of credit spreads that accounts for the nature of the credit risk profile of large financial institutions. The empirical findings with respect to the relationship between borrowing costs and default probabilities during the banking and debt crisis are unequivocal, and suggest that higher default probabilities significantly explain the deteriorating ability of banks to borrow from the financial markets. More importantly, the degree to which default probabilities explain borrowing costs increases when incorporating the various policy measures undertaken by the ECB. Conversely, the effect of the liquidity interventions is ambivalent: While liquidity measures directed towards the banking system have a curing effect on the borrowing costs of banks, those related to sovereigns seemingly have an impeding effect.

4.2 Literature Review

The link between default probabilities and credit spreads has been addressed in a significant body of literature. From a theoretical standpoint, Merton's model (1974) lays the foundation for the link between corporate bond spreads and default probabilities. Drawing on Merton's model, Longstaff and Schwarz (1995) propose a new structural model whose outcome predicts that the relationship between actual default rates and credit spreads is positive while it is negative for risk neutral default rates and credit spreads. Hull, Nelken and White (2004), propose a link between CDS spreads and stock option prices through a modification in the estimation of Merton's framework.

The empirical work conducted with a view to testing the ability of credit risk structural models to price corporate bonds accurately, offers mixed evidence. A comparative study of various credit risk models by Anderson and Sundaresan (2000) documents that these models perform fairly well. Variations in leverage and asset volatility (which are the main constituents of the default probabilities generated by these models) account for the bulk of the variation in observed aggregate corporate yields. The default probabilities are consistent with the historical measures reported by Moody's. In order to address the question about the portion of corporate yields which is attributable to default risk, Longstaff et al.(2005) exploit the information contained in the CDS premia to derive default and non-default components from corporate spreads. They find that the bulk of corporate spread is due to default risk. On the other hand, the non-default component is liquidity-related

Collin-Dufresne et al. (2001) investigate the drivers of credit spreads. Their results suggest that changes in variables generated by structural models (namely default probabilities and recovery rates) barely explain 25% of the observed credit spreads. In an attempt to capture a common-risk factor which would explain the changes in credit spreads, the authors test another set of financial, macroeconomic and liquidity variables. None of the different proxies proves successful in explaining the common factor. It is thus concluded that the changes in credit spreads are rather driven by demand/supply shocks.

Eom et al. (2004) implement five different structural models of corporate bond pricing and conclude that none of these models accurately predicts spreads. Some models are found to underpredict spreads, others overestimate them, and a third category overstates spreads for high yield bonds, while it understates spreads for safe bonds. Huang and Huang (2003) follow a calibration method, and show that if credit risk explains only a small share of spreads for investment grade bonds, it accounts for a more important share when it comes to high-yield bonds.

Maning (2004) relies on Merton-type default probabilities (generated by a model of the Bank of England along with a sample of investment grade bonds issued by UK companies) to explore this relationship. His findings are in line with previous empirical evidence in that default probabilities are found to explain only little of credit spread variations experienced by issuers with high credit quality. However, default probabilities' explanatory power rises considerably with respect to the variability of credit spreads of lower-investment grade bonds.

While the relationship between default probabilities and credit spreads has been addressed by the literature, it seems meaningful to re-visit this relationship in view of new market conditions: the unprecedentedly high borrowing costs of banks, along with the armada of interventions by the ECB and kin institutions. These were aimed at preventing a financial haemorrhage as the banking crisis, followed by the Eurozone crisis, has left the liquidity position of the banking system in a frail condition.

4.3 Data & Statistics

I opt for CDS spreads as an alternative proxy for bond yield borrowing costs to bond yields for a number of widely acknowledged reasons. Unlike bonds, the problem of choice of a risk-free rate in order to obtain a credit spread is not posed. Also, and given the standardised nature of CDS contracts, especially in terms of quotations and maturities, comparison across the borrowing costs of banks is rendered more straightforward. The corresponding default probabilities are estimated using the Merton model (1974). The sample is composed of 21 large European banks and data spans from 01/01/2007 to 30/01/2013.

I collect key events relating to the interventions embarked upon by the ECB and other institutions to forestall financial turmoil on the banking sector and stabilize the economy. The ECB website offers access to a compilation of ECB press releases. The timeline of events spans from 29/01/2007 to 20/07/2012, and encompasses dates where conventional and unconventional measures were taken, along with major crisis-related news (as opposed to actions) .While liquidity-related events directed towards banks are the primary focus of the study , other events also receive attention as they enable good comparisons to be made with liquidity-related events.

The final dataset encompasses 117 events. I group the events into four categories :

Banking Liquidity intervention: This category encompasses all actions and announcements whose ultimate objective is to bolster the liquidity of the euro area banking system. These can take the form of:

-*Direct capital injections* into the banking system to remedy the slowdown in interbank market lending and lending to the sectors of the economy

- *Quantitative easing and covered bond programs:* The first consists of buying government bonds from banks to boost their liquidity position and lending capacity. In effect, the ECB takes over loans by banks to the governments. The rising price of bonds should incentivize banks to sell them and lend to the economy. The latter measure aims at supporting specific market segments relevant to banks funding through the purchase of private sector assets on the primary and secondary markets.

- *Securities market programme:* an asset purchase programme involving the purchase of risky assets from banks, and consequently, the removal from their balance sheets of the credit risk inherent to those assets.

-*Refinancing operations:* The ECB facilitates access to refinancing through various measures. These include the following measures: the ECB teaming up with the Fed to ease pressure on short-term funding markets by offering US dollar funding to Eurosystem counterparties; extending maturities; other special term refinancing operations (with a view to enhancing the overall liquidity position of the euro area banking system) such as making it possible for banks to bid for unlimited funds for a period of one year

-*Words rather than actions:* This category includes important news related to bank liquidity. For instance, on 08/10/2008, the ECB issues a press release where it announces to the markets that it has decided on extraordinary liquidity measures whereby it provides as much liquidity as banks needs provided they have enough collaterals. On 27/12/2009, the ECB declares the end of dollar/euro swaps, as financial markets showed signs of recovery. Another example is the ECB announcing stricter rules on bank collaterals on 28/07/2010.

Interest rates interventions : The most conventional monetary policy to manage credit cycles and stimulate the economy. Over the period of our study, interest rates are cut aggressively to encourage more borrowing. However, the dataset also includes decisions about interest rates increases.

***Sovereign liquidity interventions*:** Country specific actions and news relating to the European debt crisis. These encompass:financial aid requests and approvals, loan attributions, statements by financial authorities (the European Central Bank, the European Commission, and the International Monetary Fund) giving an assessment of the creditworthiness of the financially-struggling countries alongside the validation of those countries' economic adjustment programmes.

Economy-wide news: News related to the financial sector and the economy. This type of news should have an impact of a macro-financial nature. It ranges from announcements about the stress tests of selected banks, to decisions and statements regarding financial stability. This category excludes news which are debt crisis-related and aimed at a specific country.

4.4 Methodology

To investigate the relationship between banks' borrowing costs and their default probabilities along with the ramifications of policy interventions to rescue the banking system I use the following identification:

$$CDS_{it} = \alpha_{it} + \beta_{1it}.PD_{it}.PolicyIn + \beta_{2it}.PD_{it} + \beta_{3it}.PolicyIn \quad (1)$$

First, I run the model without making a distinction between the name of the various interventions and news from the ECB to gauge the aggregate joint effect of all actions and news. In this case, PolicyIn is a dummy variable that takes value 1 on the day the ECB carries out an action or makes news announcements and 0 otherwise. Second, I pin down the events into four categories so that *PolicyIn* refers to: *Banking liquidity interventions* , *interest rates interventions, sovereign liquidity interventions, financial stability interventions* where the dummy variable takes values 1, 2, 3 and 4 respectively and 0 otherwise. Then the model is run again. It is worth noting that on trading days where two events belonging to two different categories occur, one of the events is temporarily discarded and is considered subsequently in a second round of regressions. In addition, I accounted for a fifth category of events, where the dummy takes value 5 and denotes those days where two policy interventions occur on the same trading day. In doing so, I account for potential mixed effects arising from the potential confusion in bank credit markets.

The inferences are based on panel-robust standard errors. This allows errors to be correlated over time for a given bank, while allowing variances and co-variances to differ across banks. Panel-robust standard errors are chosen over the standard default standard errors because the latter relies on the assumption of i.i.d errors which leads to bias.

For the sake of comparison, I consider a number of alternative panel data estimators, namely pooled OLS, fixed effects (within) and random effects. Additionally, I run the same model substituting DD (distance to default) to PD (default probabilities). The substitution serves as a robustness check since DD is derived from the same model and is supposed to lead to results implying an opposite relationship to PD. In other words, the higher the default probability (PD) the lower the distance to default (DD), and hence the closer a bank is to hitting the distress barrier as defined in (Merton 1974).

I do not lose sight of the potential for contamination between the various events. Therefore, if two events of different or kin category occur on the same day, the one believed to have the biggest impact is considered. The decision to favour an event over the other is based on how much coverage it received in the media, but also on the intensity of the search for keywords contained in the event statement as estimated by Google trend search. The issue of overlapping events is of more concern in the instance of two events of different categories. Markets could react more strongly due to the occurrence of two events of different nature, but this could more likely cause markets to be confused and display meaningless reactions. We address this issue by examining the effect of each event separately.

4.5 Simple Extension of the Merton model (1973)

In this section I depart from the Merton Model (1973) which lays the foundation for the relationship between default risk and bond spreads and propose a simple modification of this relationship that should accommodate for the nature of the credit profile of large financial institutions.

The formula for the credit spread is:

$$s = y - r \quad (2)$$

Such that $y = \frac{\ln\left(\frac{B}{D}\right)}{T}$

On the other hand, at time t=0 :

$$D = Be^{-rT} - P$$

With D is the risky , Be^{-rT} is the default-free debt and P is an implicit put option which represents the expected loss

Re-arranging:

$$\ln(D+P) = \ln Be^{-rt}$$

We obtain an expression for r is the risk-free-rate:

$$r = \frac{1}{T}.\ln\left(\frac{B}{D+P}\right)$$

So the formula (2) for the credit spread becomes :

$$s = \ln(\tfrac{B}{D})/T - \ln(\tfrac{B}{D+P})/T \qquad (3)$$

⇨ $Ts = \ln\left(\frac{B}{D}\right) - \ln\left(\frac{B}{D+P}\right)$

⇨ $Ts = \ln(B) - \ln(D) - \ln(B) + \ln(D+P)$

⇨ $Ts = \ln(D+P) - \ln(D)$

⇨ $s = \ln\left(\frac{D+P}{D}\right)/T$

⇨ $s = \frac{ln\left(1+\frac{P}{D}\right)}{T}$ (4)

According to Taylor series approximation of the function $ln(1+X)$ in 0 , $ln(1+X)$ is equal to X when X is close to 0

Given that P<<D, meaning that the value of the expected loss is very small compared to the risky debt, a case which applies well to large financial institutions, then P/D is close to 0.

Setting P/D =X we obtain a new formula for the credit spread:

$$s = \frac{1}{T} . \frac{P}{D} \qquad (5)$$

Hence if P<<D (10P=D) then we obtain (5) by applying Taylor approximation rule to (4)

4.6 Empirical findings

Table 4 reports the results for the responsiveness of banks' borrowing costs to changes in default probabilities in view of the ECB and kin institutions policy interventions undertaken with a view to preventing a financial haemorrhage in the banking system and the wider economy. Table 5 reports the results of the same relationship but with the difference that policy interventions are pinned down to four distinct categories and the impact of each category is investigated separately.

Altogether, the findings are unequivocal and suggest that higher default probabilities/lower distances to default considerably explain the deteriorating ability of banks to borrow from the financial markets (coefficients of over 20%). More interestingly, the degree to which default probabilities explain borrowing costs increases substantially (by at least 35%) when incorporating the policy measures undertaken during the sample period. Incorporating the effect of policy measures is done by interacting the credit risk estimators with a dummy variable for the occurrence/non-occurrence of a given policy intervention. Hence, accounting for government interventions permits a better grasp of the relationship between borrowing costs and default probabilities/distances to default of the European banks composing the sample.

Another key result is one related to the effect of policy interventions per se on the borrowing costs of European banks. While the aggregate effect of all policy interventions taken together is positive in the way that it drives the borrowing costs down (table 4), the results are nuanced regarding the separate effect of each distinct category of policy measures. *Banking liquidity interventions* most of which are unconventional measures as explained in the data section appear to have met the ECB's intended objective of helping to improve banks' liquidity. The relationship between the borrowing costs of banks and the dummy variable capturing this category of measures is negative and significant indicating that the interventions lessen the borrowing burden of banks during periods of financial trouble. In sharp contrast, *sovereign liquidity interventions* have had an impeding effect on the liquidity profile of banks. The relationship between borrowing costs and the dummy variable capturing this category of measures is positive and significant indicating widening borrowing costs. Possibly, markets react badly to these liquidity interventions because they view them as signals of weak economic fundamentals. The underlying idea is that given the strong ties between banks and governments, a sovereign with weak economic fundamentals is not in a position to rescue a troubled banking system.

With respect to *interest rates interventions,* the relationship is negative, which is the desired sign but it is not significant. Interest rates cuts which are conventionally used to manage credit cycles and stimulate the economy do not seem to receive a positive reaction in credit markets costs. A plausible explanation is one by which credit markets are not responsive to this category of measures because it sends signals about the ECB trying to contain a fledging recession. On the other hand, it could be argued that the impact could have been a detrimental one since the increased level of borrowings spurred by interest rate interventions increase banks' leverage and could inadvertently translate into higher borrowing costs.

As to the last category of interventions, *economy-wide news* , which encompasses news about decisions to foster financial stability excluding those that directly deal with the euro-debt crisis, the coefficients are negative and significant. This suggests that borrowing costs react positively to this category of interventions. A helpful example of why this category might elicit a positive reaction is that it includes, for instance, statements about results of banks stress tests. The banks surviving the test should have an increased ability to borrow at lower costs.

The ambivalent effects of the various policy interventions on borrowing costs raises a number of questions. The first question is that of activism versus a laissez-faire approach. In other words, is it beneficial for credit markets that policymakers counteract the liquidity strain and thus the looming downturn? While the reaction of banks' borrowing costs' to the bank-tailored liquidity intervention by the ECB during the crisis suggests so, the impeding effect of sovereign liquidity measures, together with the confused reaction of markets toward interest rates, suggest that borrowing costs of banks might have been better off without ECB intervention. To stretch the argument further, if the ECB is not to intervene, i.e., follows a laissez-faire approach, there should be a belief that markets are endowed with a self-stabilising ability and are hence able to face turbulence on their own and adjust prices. The underpinning argument here would be one that supports the efficient markets hypothesis. However, there is ample evidence against the efficient markets hypothesis. Therefore, a key implication of the findings of this paper is that, instead of being injected with the ECB liquidity syringes, banks should face more scrutiny from the regulators with regard to their liquidity and credit risk. Indeed, regulators should put more effort in reducing the risk of moral hazard for banks which takes root in the role of lender of last resort played by central banks. Ultimately, massive interventions come with the risk of banks becoming progressively more reliant on central banks and more prone to amass debt. The more debt is built up, the harder it gets for similar policies to offset crises.

4.7 Conclusions

The paper analyses the impact of policy interventions on the relationship between borrowing costs and default risk of a sample of large European banks. Second, it investigates whether those interventions, particularly those which are liquidity related, have succeeded in curing the European banking system . The policy measures were spurred by the banking and the sovereign debt crises, both of which left the banking system in a frail condition. Furthermore, the paper makes a theoretical contribution to the literature linking credit spreads to default probabilities (by building on Merton's model) to propose a simple measure of credit spreads that accounts for the nature of the credit risk profile of large financial institutions.

The empirical findings with respect to the relationship between borrowing costs and default probabilities during the banking and debt crisis are unequivocal. They suggest that higher default probabilities significantly explain the deteriorating ability of banks to borrow from the financial markets. More importantly, the degree to which default probabilities explain borrowing costs increases when incorporating the various policy measures undertaken by the ECB. Conversely, the effect of liquidity interventions is ambivalent: While liquidity measures directed towards the banking system have a curing effect on the borrowing costs of banks, it comes with the risk of banks becoming progressively more reliant on central banks and more prone to amass debt. The more debt is built up, the harder it gets for similar policies to offset crises. The negative reaction of credit markets to sovereign-liquidity measures is possibly linked to the view that a sovereign with weak economic fundamentals is not in a position to rescue a troubled banking system. Furthermore, the non-responsiveness of credit markets to cuts in interest rates potentially signals a confusion in those markets. The confusion could be due to the presence of the unconventional policy measures alongside interest rates cuts. The former policy measures contain a surprise component that is arguably no longer attached to the latter. Another plausible explanation is one by which credit markets are not responsive to the low and zero/bound nominal interest rates is that they are perceived as signals about the ECB trying to contain a fledging recession. On the other hand, it could be argued that the impact of interest rates cuts has been a detrimental one because interest rate interventions may increase banks' leverage levels and inadvertently translate into higher borrowing costs. Finally, The results of this study suggest the liquidity support provided by the ECB to European banks fosters an over reliance from banks and causes debt to amass. However, it is necessary to point out the trade-off facing the European Central Bank relating to their liquidity provision role. The difficulty of their role lies in striking a balance between reducing the default risk of banks while reducing the moral hazard risk, i.e., preventing a situation of excessive risk taking by banks.

Table 1: List of Banks

Bank	Country
BARCLAYS	UK
LLOYDS BANKING GROUP	UK
HSBC	UK
RBS	UK
BankofIreland	Ireland
BANCO POPOLARE	Italy
INTESA SANPAOLO	Italy
Banca M. Paschi	Italy
UNICREDIT	Italy
NORDEA BANK	Sweden
CREDIT AGRICOLE	France
BNPPARIBAS	France
SOCIETE GENERALE	France
Dexia	Belgium
KBC	Belgium
Erste Group	Austria
Deutsche Bank	Germany
Commerzbank	Germany
Banco de Sabadell	Spain

Table2 : Number of events per type of intervention

Type of intervention	Banking Liquidity	Interest rates	Sovereign Liquidity	Economy-wide News
	36	33	12	36

Note :The complication of events by category is available upon request.

Table3: Cross-sectional summary statistics for CDS spreads, default probabilities and distances to default

	CDS spreads	distances to default	default probabilities
mean	122,50	6,89	0,07
sd	86,85	4,34	0,08
min	21,80	2,68	0
max	365,38	17,89	0,3292

Note: Table3 reports the mean, the standard deviation (sd), the minimum (min), the maximum(max) of the cross section of a sample comprising 21 banks. The number of observation per bank is 1588. The CDS spreads are historical spreads expressed in basis points while the default probabilities together with the distances to default are implied from the Merton-model.

Table 4: Responsiveness of the borrowing costs to changes in credit risk measures in view of policy interventions- Linear Panel Model Estimators

	P-OLS	Within-FE	RE-GLS
	Aggregate effect of all policy interventions		
DP	0.234***	0.249***	0.244***
DP*PolicyIn	0.414***	0.457***	0.452***
PolicyIn	-0.135***	-0.172***	-0.172***
R-squared	0.29	0.36	0.32
DD	-0.154***	-0.183***	-0.181***
DD*PolicyIn	-0.253***	-0.297***	-0.265***
PolicyIn	-0.131***	-0.137***	-0.133***
R-squared	0.17	0.28	0.24
Observations	117	117	117

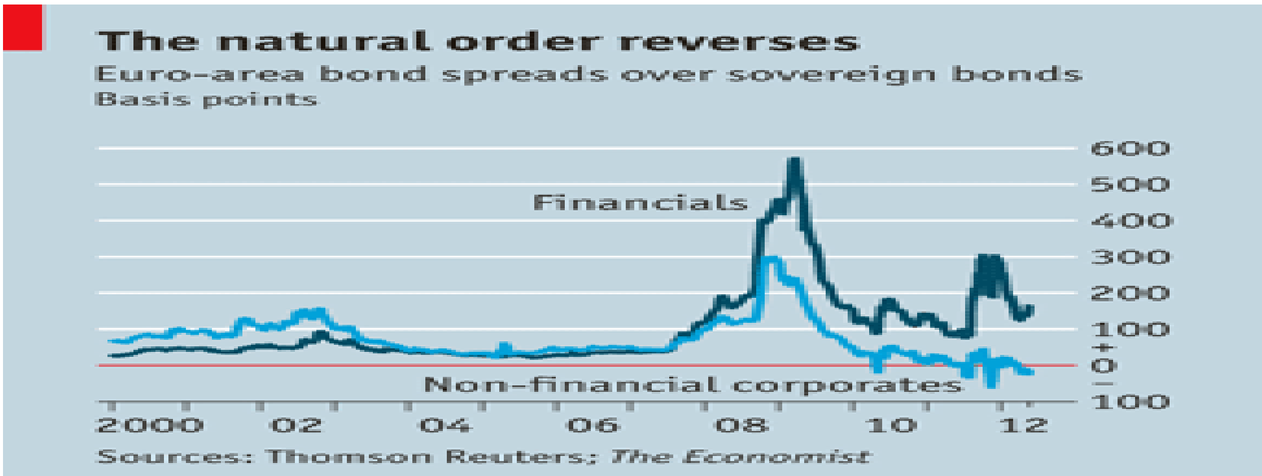
Note: The inferences are based on panel-robust standard errors. This allows errors to be correlated over time for a given bank while allowing variances and covariances to differ across banks. Observations refer to the number of policy events collected over the period from 29/01/2007 to20/07/2012. The dependent variable is the borrowing costs as proxied by the changes in CDS spreads. The independent variables are *DP* (default probabilities), *PolicyIn* (a dummy variable taking value 1 if a policy intervention –regardless of the category- took place and 0 otherwise), *DP*PolicyIn* (an interaction term between default probabilities and policy interventions confounded capturing the effect of the default probabilities when a policy event takes place). P-OLS, Within-FE, RE-GLS refer to pooled OLS estimators, within fixed effects estimators and random effects-Generalised least squared estimators. The figures reported are coefficients with '***' referring to a statistical significance at the 1% level. The Hausman test result is H=14> Chi^2=2.78 rejects the hypothesis that the random effects model is the true model.

Table 5: Responsiveness of the borrowing costs to changes in credit risk measures in view of policy interventions (per category)- Linear Panel Model Estimators

	P-OLS	Within-FE	RE-GLS
	PolicyIn : Banking Liquidity interventions		
DP	0.234***	0.249***	0.244***
DP*PolicyIn	0.402***	0.431***	0.418***
PolicyIn	-0.215***	-0.271***	-0.263***
R-squared	0.24	0.32	0.29
DD	-0.154***	-0.183***	-0.181***
DD*PolicyIn	-0.211***	-0.287***	0.273***
PolicyIn	-0.176***	-0.179***	-0.177**
R-squared	0.18	0.23	0.21
Observations	36	36	36
	PolicyIn : Interest rates interventions		
DP	0.234***	0.249***	0.244***
DP*PolicyIn	0.345***	0.363***	0.358***
PolicyIn	-0.193	-0.198	-0.197
R-squared	0.22	0.31	0.29
DD	-0.154***	-0.183***	-0.181***
DD*PolicyIn	-0.207***	-0.251***	-0.249***
PolicyIn	-0.182	-0.185	-0.184
R-squared	0.16	0.21	0.20
Observations	33	33	33
	PolicyIn : Sovereign liquidity interventions		
DP	0.234***	0.249***	0.244***
DP*PolicyIn	0.311***	0.334***	0.325***
PolicyIn	0.155**	0.161**	0.159**
R-squared	0.12	0.16	0.15
DD	-0.154***	-0.183***	-0.181***
DD*PolicyIn	-0.309***	-0.317***	-0.316***
PolicyIn	0.155**	0.161**	0.159**
R-squared	0.10	0.15	0.17
Observations	12	12	12
	PolicyIn : Economy-wide news		
DP	0.234***	0.249***	0.244***
DP*PolicyIn	0.432***	0.439***	0.435***
PolicyIn	-0.206***	-0.210***	-0.208***
R-squared	0.21	0.31	0.31
DD	-0.154***	-0.183***	-0.181***
DD*PolicyIn	-0.378***	-0.386***	-0.384***
PolicyIn	-0.206***	-0.210***	-0.208***
R-squared	0.19	0.27	0.23
Observations	36	36	36

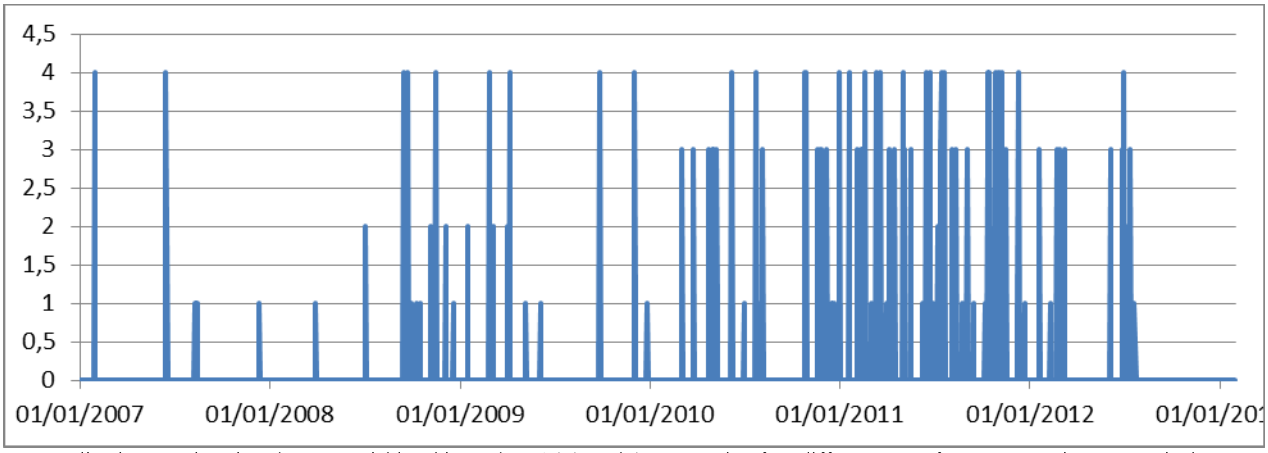
Note: The inferences are based on panel-robust standard errors. This allows errors to be correlated over time for a given bank while allowing variances and covariances to differ across banks. Observations refer to the number of policy events collected over the period from 29/01/2007 to20/07/2012. . The dependent variable is the borrowing costs as proxied by the changes in CDS spreads. The independent variables are *DP* (default probabilities), *PolicyIn* (a dummy variable taking values 1,2,3, and 4 representing four different type of event categories , respectively: *Banking liquidity interventions* , *Interest rates interventions, Sovereign liquidity interventions, Financial stability interventions* and 0 otherwise), *DP*PolicyIn* (an interaction term between default probabilities and policy interventions confounded capturing the effect of the default probabilities when a policy event takes place). P-OLS, Within-FE, RE-GLS refer to pooled OLS estimators, within fixed effects estimators and random effects-Generalised least squared estimators. The figures reported are coefficients with '***'and'**' referring to a statistical significance at the 1% and 5% levels respectively. The Hausman test result is H=12> Chi^2=3.84 rejects the hypothesis that the random effects model is the true model.

Figure 1: Borrowing costs of financial as opposed to non-financial firms, induced through bond yields



Source: Thomson Reuters; the Economist

Figure2: Time series plot of the various policy interventions of the ECB over the sample period



Note: Policy interventions is a dummy variable taking values 1,2,3, and 4 representing four different type of event categories , respectively: *Banking liquidity interventions* , *Interest rates interventions, Sovereign liquidity interventions, Financial stability interventions* . The dummy variable takes value 0 otherwise. I depart from an initial number of events of 128 which is reduced to 117 events due to the elimination of duplicate events of the same category occurring on the same trading day. Such a situation was encountered on the following trading days: 29/09/2008, 10/05/2010, 06/10/2011, 02/05/2010, 28/11/2010, 17/05/2011, 28/02/2012, 27/06/2012, 16/12/2010, 18/03/2011, 21/07/2011.

Conclusion

This thesis makes a number of contributions to the literature analysing credit risk. On the one hand, it exploits option pricing literature to provide new credit risk measures for the banking and the sovereign sectors. On the other hand, it casts light over the role of credit rating agencies and the ECB in shaping the landscape of the financial markets during turbulent times. The complex relationship banks maintain with their sovereigns is a recurring aspect in this work.

With the regard to the credit risk of European banks, we show that our measure of default arrival rates does not only reflect the angst of the financial markets with respect to the deteriorating credit risk profile of European banks but can serve, at times, as early warning signals. Furthermore, our findings suggest that higher sovereign financial guarantees make up for a lower default risk and thus a lower CDS spread along with a lower estimated default arrival rate. A major implication of the results is that combined information from the CDS spreads, put options could be used as an alternative indicator of credit deterioration instead of solely relying on CDS derivatives deemed to have an opaque nature.

As to the credit risk of the Eurozone member countries, the striking result is that the creditworthiness of countries with vulnerable fiscal positions is the main, but not the only risk-endangering factor of the euro-stability. While the creditworthiness 'vulnerable' countries has a significant impact on the skewness measure (i.e crash risk) and the stability indicators, healthier countries equally drive the relationship between the creditworthiness and the kurtosis (i.e tail risk). As one would expect, Ireland, Portugal, Spain and Italy are risk-endangering countries for the stability of the common currency. However, this does not seem to be the case for Greece. This can be partly explained by the marginal loan exposure of European banks to Greece.

Addressing the issue of the credit risk of banks and their relationship with their sovereigns from the perspective of rating agencies highlights crucial aspects. The credit risk measures of banks react more to changes in the sovereign credit ratings than those endured by the bank itself. Besides,when looking at the joint effect of actual sovereign and bank ratings, results show that the higher the distance between the sovereign and the bank rating, the stronger the effect, on the banks' credit risk measures as well as on the bank-related macro-financial variables. The fact that the credit and liquidity risk of a bank hinges largely on the ability of its sovereign to intervene in times of financial trouble emphasize the need for a better grasp and scrutiny of the strong connection between banks and their sovereigns.

Approaching the question of banks' credit in view of the massive interventions the ECB embarked on to prevent a collapse of the banking system leads to interesting results. The degree to which default probabilities explain borrowing costs increases when incorporating the various policy measures undertaken by the ECB. Notwithstanding, the effect of liquidity interventions is ambivalent: While liquidity measures directed towards the banking system have a curing effect on the borrowing costs of banks, it comes with the risk of banks becoming progressively more reliant on central banks and more prone to amass debt. Inevitably, this raises questions with respect to the impact of activism of central banks in neutralising downturn episodes as well as their role in driving moral hazard by being a lender of last resort to the financial institutions. The negative reaction of banks' credit measures to sovereign-liquidity measures is possibly linked to the view that a sovereign with weak economic fundamentals is not in a position to rescue a troubled banking system, which again underlines the necessity for further research to understand of the dynamics of the relationship: Bank/Sovereign

Ultimately, the results of this thesis could serve as good justification ground for the myriad regulatory and supervisory changes which took place since the outburst of the global financial crisis. A prominent regulatory change in Europe was the introduction of the Single Supervisory which endows the ECB and other national supervisory authorities with more power in their supervision role. Other important regulatory measures relating to banks' liquidity include the Counter Cyclical Capital Buffer, the Systemic Capital Buffer, the Liquidity Coverage Ratio, the Net Stable Funding Ratio. The regulator seeks to reduce the dependence of banks on public money. Hence, future research should take into account the dramatic regulatory changes which marked the financial landscape when addressing issues about market expectation and market behaviour.

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