Determinants of euro-area bank CDS spreads

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Abstract

This study relies on a structural approach model (Merton, 1974) to investigate the determinants of CDS spread changes for Euro-zone's financial institutions over the period January 2005 to December 2014. Going beyond the structural model, this study incorporates features such as the role of systemic risk factors, bank specific characteristics and credit rating. The novelty of this paper is that the empirical investigation is conducted by means of panel Vector Autoregressive Models. The main findings are that structural models seem to be oversensitive during high volatile periods and that the relation between the CDS and its theoretical determinants is not constant over time. Also, the importance of the systemic factor emerges during the Euro-zone debt crisis. All in all, the empirical results suggest that structural models perform well in explaining bank credit risk, but determinants of CDS also rely on the underlying economic situation and monetary policy makers have to take this into account in order to reach safe decisions.

1. Introduction

This study empirically investigates the determinants of Credit Default Swap (CDS) spread changes for Euro-zone's financial institutions over the period January 2005 to December 2014, covering both tranquil times, the subprime mortgage crisis and the Euro area sovereign debt crisis. The distress that many banks have experienced since the outbreak of the global financial crisis and the Eurozone sovereign debt crisis highlight the importance of modeling bank default risk. As a starting point, the theoretical determinants of Merton's structural model of default are important to explain the fluctuation of CDS spreads. However, CDS spread changes may signal systemic risk issues, the impact of monetary policy decisions or even the spillover/contagion effects of other financial institutions (see Acharya et al., 2012). The movement of CDS spreads reflects the market's point of view for banks' viability and their behavior is important for the authorities that supervise Euro-zone's financial stability, i.e. the knowledge of the banks' CDS main drivers allows the authorities to take the necessary measures; implicit or explicit ones. Also, it is of high interest to examine the impact that the guarantees and the unconventional monetary policy measures had had on the Euro-zone banking system.

We rely on a structural approach model to investigate the influence of theoretical determinants on the quarterly changes in bank CDS spreads during a ten-year period between January 2005 and December 2014. The literature suggests that the impact of variables from structural models seem to be strongly time varying (see Alexander and Kaeck, 2008; González-Hermosillo, 2008). Also, we investigate the assumption that theoretical determinants that have been found to affect CDS spreads of non-financial institutions lose their explanatory power when applied to financial institutions' CDS spreads (see Raunig and Scheicher, 2009; Grammatikos and Vermeulen, 2012). Going beyond the structural model, this study incorporates features such as the role of common risk factors. More precisely, we control for (i) the general market wide climate, (ii) the market wide volatility as a proxy for the business climate and (iii) the liquidity conditions. Also, we go the analysis one step further by taking into account the influence of bank characteristics, the role of the main unconventional monetary policy measures, the ability of sovereigns to support their banks and the too-big-to-fail issue. We also break the sample into three periods that gives us the opportunity to see how a structural model works during both 'tranquil' and 'turbulent' periods. The interventions made to the initial structural model aim towards having a more realistic approach.

The empirical investigation is conducted by means of Panel Vector Autoregressive (PVAR) models that allow the efficient estimation of parameters in systems with endogenous variables and a limited number of observations while at the same time they make possible the use of dynamic models. The conclusions we derive are based on coefficients of determination, Forecast Error Variance Decomposition (FEVD) analyses and Impulse Response Functions (IRF).

The main conclusion is that the structural model variables affect bank CDS spreads but their performance mostly depends on the market conditions. The role of the structural model determinants is intensified during volatile periods, i.e. the global financial crisis and the European sovereign debt crisis. However, it is important to mention that despite the intensified role of the "theoretical determinants" during debt crisis, they cannot explain alone the banks' CDS spreads. Our results are also in line with those from Benkert (2004), Eriksson et al. (2004), Bystrom (2006) and Alexander and Kaeck (2008), that CDS spreads seem to be exposed to the market circumstances during more volatile periods and that they exhibit a different behavior when market volatility is high or fluctuates intensely. We also find evidence for the existence of a systemic factor effect for periphery banks CDS during the European sovereign debt crisis. Most of bank characteristics seem to play a minor role during the global financial crisis period, except for the retail orientation and the capital adequacy ratio. Important evidence is that the too-big-to-fail issue does not affect the pricing of risk of the financial institutions in Euro-zone. The results are of great importance for bank supervisors and monetary policy makers, in the sense that they have to customize their decisions and their policy in relevance to the market conditions and take account of the systemic risk strength.

Our results make a contribution to the literature on the determinants of European bank credit risk. We deviate from previous studies first, by choosing to work with a panel Vector Autoregressive Model methodology which relies on both the time and the cross sectional dimension of the variables in order to explain the underlying processes. Second, we are the first to compare the results of the two most recent crisis periods; both financial crisis and debt crisis are examined, to those of a 'tranquil' one. Third, we compare the structural model and its effectiveness in financial institutions.

The remainder of this paper is organized as follows. In section 2 we present a short review of the relevant literature. Section 3 presents the data and the testing methodology. Section 4 reports our results and some empirical robustness checks. Section 5 summarizes the conclusions.

2. Relevant Literature

Merton (1974) suggested a credit risk model that explains how the probability of company default can be inferred from the market valuation of companies under some assumptions on assets and loans evolvement. More specifically, the event of default is determined by the market value of the firm's assets jointly with the firm's liability structure. If the value of the assets falls below a threshold, then the firm is considered to be in default. Many authors such as Black and Cox (1976), Geske (1977), Longstaff and Schwartz (1995a), Leland and Toft (1996), and Collin-Dufresne and Goldstein (2001) have expanded Merton's model. Also, there exist a number of studies, comparing the performance of alternative models by using bond spreads, however none of these modifications has been suggested as better than Merton model (see Eom et al, 2002; Gemmill, 2002).

Merton's model uses a formula for credit spread which is based on asset growth, asset volatility and leverage as the key economic drivers for bankruptcy. The best measure to capture a firm's asset value is through the firm's equity value. The firm issues a zero coupon bond and equity shares to finance its assets. The leverage shows the bounds of default. When the assets' value falls below the default boundary then the firm defaults. According to Christie (1982), the changes in the degree of financial leverage are related to the bank's stock return (also see Alexander and Kaeck, 2008). If stock returns are positive, leverage will decrease, leading to lower credit spreads and hence a negative relationship between stocks returns and credit risk is expected.

A firm's probability of default may be influenced by the firm value volatility. Benkert (2004) testifies different volatility measures on CDS spreads and concludes that option implied volatility is the most appropriate one. Theory suggests that the higher the asset volatility is, the higher credit spreads will be because the probability of default is greater. Chen et al. (2007) use historical volatilities. On the contrary, Cao et al. (2010) shows that the implied volatility of individual stock options has significant explanatory power for CDS spreads. Finally, Alexander and Kaeck (2008), test both historical volatility and implied volatility (volatiliy of Eurostoxx 50) and conclude that implied volatility performs better.

In Merton (1974), the risk free interest rate constitutes the drift in the risk neutral world. Theory suggests that the risk free interest rate should decrease the probability of default as the higher the rate is, the higher the risk neutral drift will be. Interest rates are positively linked to economic growth and higher growth should, ceteris paribus, imply lower default risk (see Tang and Yan, 2006). However, the interest rates movement is vulnerable to changes in the slope of the yield curve. Theory supports that the steeper the yield curve the higher future short term interest rates will be, so it is expected a negative relationship between the risk-free interest rates and the CDS spreads. Fama (1974) and Estrella and Hardouvelis (1991) add one more reason why the relationship between CDS and interest rates is negative by explaining that through the low interest rates which are observed during periods of recession. The excess bank risk taking is among the top lines of the financial markets; especially after the 2000s. The literature suggests a negative relationship between interest rates levels and the bank risk exposure. Many researchers have blamed the low interest rate environment for the global financial crisis and the euro-area sovereign debt crisis. The combination of low interest rates and the abundant liquidity led financial institutions to take excessive risks and promote leverage. This theory touched the role of the loose monetary policy; observers argue that a more aggressive policy about interest rates would have eliminated the crisis effect. Rajan (2006) investigates whether a low-interest rates period may drive banks to search for higher yield and adopt a riskier behavior. A low volatile period of interest rates may have the same results. Delis and Kouretas (2011) use various interest rates to investigate the relationship between interest rates and bank risk-taking and conclude that the short-term rates are negatively and strongly related to the bank risk-taking. Houweling and Vorst (2005), Hull et al. (2004) support that short-term rates have stronger impact on bank risk taking than longer term interest rates since they are very liquid, they have no short-sale constraints and they are not influenced by special tax regulations. On the contrary, long-term rates do not affect bank risk taking and even more government bonds are no longer considered by the markets to be the reference default-free instrument (see Clarida et al. 2001).

There is also a literature which investigates whether the financial institutions that are characterized as too-big-to-fail by the market benefit from better financing terms than other financial institutions or not. Acharya et al. (2013) investigates whether the implicit subsidy[1] to large financial institutions play a crucial role to bank aggregate risk or not. They find that expectations of government support are embedded in the credit spreads of bonds issued by large U.S. financial institutions. Schweikhard, Tsesmelidakis and Merton (2014) apply a set of bond characteristics and prices on a structural model to estimate the value of implicit guarantees to the U.S. financial sector. There is not much research on the too-big-to-fail issue in Euro area.

De Bruyckere et al. (2013) investigate the impact of bank-specific factors to CDS spreads and focus on indicators of retail orientation, funding structure, revenue diversification and the banks' capital adequacy (also see Altunbas et al.,2011). Angeloni and Wolff (2012) fail to find strong evidence of correlation between Eurozone banks' asset holdings on peripheral sovereign debt and their stock market returns. Rather, bank stock prices appear to be more associated to the risk of the country these banks are located in. Correa et al. (2012) provide indirect evidence that European banks didn't have easy access to the U.S. money markets due to the reduction of the value of collateral, in the form of sovereign debt, they could provide. Arezki et al. (2011) find that downgrades of sovereigns have implications not only for the country involved but that they spillover to other markets and countries as well. Finally, a number of authors studied the "transfer of risk" between banks and sovereigns and found that the implicit guarantee offered by the governments had produced causality, before bail-outs, running from banks' CDS spreads to sovereign risk spreads (Ejsing and Lemke, 2011). De Santis (2012) examined through a structural vector error correction model the spillover effects from rating changes and concluded that a downgrade of Greek sovereign bonds was associated with an increase in the spreads of other countries with weak fiscal fundamentals.

[1] The expectation of large financial institutions and their investors that the government will back their debt by providing a bailout package.

Finally, many studies suggest that adding variables describing market conditions improves the explanatory power of CDS movement. The main reason is that the default probabilities depend on the business cycle (also see Pesaran et al., 2006; Altman et al., 2006).

3. Data and Methodology

3.1 Data Description

In this analysis, we use data on nine EMU (European Monetary Union) countries. We split the sample into two sub-groups. The first one consists of Italian, Spanish, Greek and Portuguese banks and stand for the Eurozone's periphery. Irish banks are not included in the sample due to the lack of data. The second one consists of German, Austrian, Netherlands and French banks that form the "core" group. The data cover the period from 1/1/2005 to 31/12/2014 and have a quarterly frequency since we make use, among others, of bank balance sheet variables, which are available on quarterly basis only. Furthermore thin trading of CDS contracts, for most of the testing period, renders the analysis at a higher frequency as misleading since the revealed information from CDS prices does not reflect the market's perception of risk. Finally, we focus here on identifying the factors that determine CDS spreads on a medium term basis rather than their dynamic behavior at a higher frequency.

We break the sample into three sub-samples. Our intention is to measure the lasting effects of the chosen variables during the global financial crisis and the Euro-area sovereign debt crisis and compare them to those found during a pre-crisis period. The first period, which represents the tranquil period in the financial markets, is from 1/1/2005 to 31/12/2007. There are not available bank CDS data prior to 2005 and this is why the period begins then. The second period covers 2008 and 2009 and captures the global financial crisis, while the last one is from 1/1/2010 to 31/12/2014 and captures the euro-area sovereign debt crisis. The starting date of the last period has been chosen after taking into consideration the events that have marked the beginning of the European sovereign debt crisis, most of which are related to Greece[2].

In Table 1 we present the banks used per country. The choice of these banks is the outcome of the following selection procedure. Firstly, we collect the stress test data from the websites of national bank regulators in Europe. We use the European Union-wide banking stress tests of 2010, 2011 and 2014 that were conducted by the European Banking Authority. A total of 90 banks participated in the bank stress tests. These banks represent about 70 percent of bank assets in Europe. We select banks that are headquartered in Austria, Belgium, France, Germany, Netherlands, Spain, Greece, Italy, Portugal and Ireland, with more than €50 billion assets. We set this threshold since smaller banks and banks that are not headquartered in these countries usually do not have traded CDS. For all banks, we search for CDS prices in the database of Datastream. Using bank names, we match 37 banks to CDS prices that meet the requirements. Unmatched banks are mostly smaller banks that do not have publicly quoted CDS prices.

Credit risk Variables

Swap rates of three months are used as a proxy for risk-free interest rates. Results are robust when replacing the 3-month swaps with Eonia or the 3-month Euribor. The equity value variable is represented by each bank's stock returns. Stock prices for each bank have been obtained from Datastream- Thomson Reuters. In order to measure each bank's asset volatility we compute quarterly historical standard deviations based on intra-quarter daily stock returns. Banks' stock returns, and historical volatility therefore, are expressed as arithmetic returns, while swap rates appear in first differences.

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[2] On January 9th, 2009, S&P published a negative watch announcement and shortly after that, on January 15th, it downgraded Greece from A to A$^-$ (Baum et al., 2014).

Systemic risk factors

As it concerns the systemic factors, the European default risk conditions are represented by the *iTraxx*[3] index Europe, which contains the 125 most liquid single firm investment grade CDSs. The European capital markets "fear" condition is captured by the *Vstoxx*[4] volatility index and the European liquidity conditions by the *KfW* that is defined as the yield spread between the German *KFW* agency bonds and the German federal government bonds. The *iTraxx* and *Vstoxx* variables have been transformed into arithmetic returns while the liquidity variable is treated in first differences.

Bank-specific factors

The first bank specific variable we use is each bank's size. It is measured as the ratio of each bank's total assets over its home country GDP. As a robustness check we replace the home country GDP with the EU's GDP (28 countries). According to BIS (2011a) the larger a bank is, the more likely it is for this bank to receive a bailout package. In this sense, we also take into consideration the too-big-to-fail (TBTF) issue and we expect therefore that the larger this variable is the smaller the CDS changes are going to be. We also focus on capital regulation, since the higher the capital buffer is, the less risky a bank is. Tier 1 capital ratio is used for this purpose and as a robustness check we apply the equity ratio as well; the total shareholders' equity over each bank's total assets. The third bank specific variable is the loan-to-asset ratio as it gives a picture of the bank's retail orientation. Ayadi et al. (2011) and Köhler (2013) suggest that retail orientated banks appeared to be less risky than other banks during the recent financial crisis. The fourth bank specific variable used is the non-interest income over each bank's total revenue. According to Altunbas et al. (2011) this is considered to be a measure of each bank's diversification, since the less a bank relies on interest income, the less exposed the bank is to a negative shock. All bank specific

[3] Source Bloomberg: ITRXTX5I

[4] Vstoxx is an implied volatility based on options on the DJ Eurostoxx 50. Source Datastream.

variables are introduced in levels and therefore they allow, effectively, for the fixed effect term to be time depended.

Monetary policy measures

We also control for the effects that monetary policy decisions might have had on the results we have presented. We have introduced dummies for the following events: the Securities Market Program (SMP) (May, 2010)[5], the creation of the European Financial Stability Mechanism (EFSF) in June 2010, the Outright Monetary Transactions (OMT) (September, 2012)[6], the Greek Debt restructuring (GDR) (February, 2012), and "*The whatever it takes*" speech by M. Draghi (WIT) (July, 2012).

Sovereign Credit ratings

Finally, we introduce the S&P sovereign credit rating as a discrete variable that has been constructed by transforming the alphabetic rating scale of S&P to a numerical one. Following the practice of other authors in the literature the values of the relevant series range from 1, assigned to the highest AAA group, to 22, assigned to the state of default (Afonso et al., 2011; De Santis, 2012; Aizenman et al., 2013). We have also taken into account announcements on changes in the credit outlook and credit watch where the first negative (positive) news -either outlook or watch- is set equal to +0.5 (-0.5) while the second negative (positive) news is set equal to +0.25 (-0.25) (see De Santis, 2012).[7] As a robustness check we also check the results when using credit ratings by Moody's and Fitch. We expect that a downgrading of sovereign debt will decrease the reliability of the explicit

[5] ECB announced direct purchases of government bonds in secondary markets under the SMP. In May 2010, bond purchases were limited to Portuguese, Irish and Greek bonds. In August 2011, purchases expanded to Spanish and Italian bonds.
[6] OMT gives the possibility of unlimited purchases of government bonds issued by countries under the umbrella of European Stability Mechanism (ESM)
[7] Some authors claim that the empirical finding that credit rating changes lag the market is the outcome of the expected nature of these changes. On their hand, credit watch and credit outlook changes usually lead the markets because they are often unexpected and act as a portent of future rating events.

or implicit guarantees offered by a government to support its banking system. Therefore we would expect that the ratings variable will be positively related to the bank CDS spread changes.

3.2 Methodology

We employ a PVAR methodology. In PVAR models all variables in the system are treated as endogenous, as in a traditional VAR model, and unobserved individual heterogeneity is being allowed for, as in panel-data estimations. Consider that Y_t is a stacked version of a Gx1 vector of endogenous variables y_t, each one of which corresponds to N units, i.e. $Y_t = (y_{1t}^{'}, y_{2t}^{'}, \ldots y_{Nt}^{'})$. Then a first order PVAR is given by:

$$Y_{it} = A_1 Y_{it-1} + A_2 Y_{it-2} + \cdots + A_{p-1} Y_{it-p+1} + A_p Y_{it-p} + BX_{it} + u_i + e_{it} \quad (1)$$

$$i \in \{1,2,\ldots,N\}, t \in \{1,2,\ldots,T_i\}$$

where Y_{it} is a $(1xk)$ vector of dependent variables; X_{it} is a $(1xl)$ vector of exogenous covariates; u_i and e_{it} are $(1xk)$ vectors of dependent variable-specific panel fixed-effects and idiosyncratic errors, respectively. The (kxk) matrices $A_1, A_2, \ldots, A_{p-1}, A_p$ and the (lxk) matrix B are parameters to be estimated. We assume that the innovations have the following characteristics: $E[e_{it}] = 0, E[e_{it}' e_{it}] = \Sigma$ and $E[e_{it}' e_{is}] = 0$ for all $t > s$.

The PVAR shown in (1) does not allow for dynamic interdependencies in the sense that the lags of the endogenous variables of the same unit only appear. Also, it does not allow either for cross sectional heterogeneities, since As are the same across all units, or for static interdependencies since we assume that $\text{cov}(\varepsilon_{it}, \varepsilon_{jt}) = 0$, for $i \neq j$ (see Love and Zicchino, 2006, Canova and Ciccarelli, 2013, Grossmann et al., 2014). Therefore the heterogeneity between different units (banks) is captured exclusively by the fixed effects variable, u_i.

In our case we have estimated five versions of the PVAR model in (1); in the first one we employ G=4 variables, the banks' stock returns, the 3-month swap rates, the statistical volatility based on historical stock return data and the bank CDS spreads. In the second version we add the systemic factor as contemporaneous exogenous variables, i.e. the three systemic variables; *iTraxx*, *Vstoxx* and *KfW*. In the third version we add the bank specific balance sheet data as exogenous variables. These variables are each bank's total assets/ home country's GDP, the loan-to-asset ratio, the non-interest income over total revenue and the Tier 1 capital ratio. In the fourth version, we use as exogenous variables the unconventional monetary policy measures of ECB. In the last one, we add each bank's home country sovereign credit rating.

For the estimation of the PVAR model we used the Stata program of Love and Ziccino (2006). The estimation method is the Generalized Method of Moments (GMM) where the individual bank fixed effects have been removed through the Helmert transformation by applying forward mean-differencing. This is a necessary procedure since the usually applied mean-differencing technique does not address the problem of lack of orthogonality between lagged regressors that are used as instruments and transformed variables, in the presence of lags of the dependent variables and fixed effects. Arellano and Bover (1995) have suggested that we remove the mean of all future observations available for each unit and period and then to estimate model (1) by GMM.[8]

[8] Binder et al. (2005) show that the quality of GMM estimators in PVAR models depend on the ratio of the variance of the individual effects relative to the variance of the errors in (1). The higher from one the value of this ratio is the worse the performance, both asymptotically and in finite samples, of the GMM estimator gets. Also, the GMM estimator is not appropriate for datasets with a large number of time periods and few cross-section units, which is not the case in our model.

We calculate impulse response functions and Forecast Error Variance Decompositions[9] for both the "small" and the "extended" models. For the latter two cases a Cholesky decomposition of the variance-covariance matrix of residuals is implemented for identification purposes. This procedure demands a specific ordering of the variables through which the variables that come first affect all the others contemporaneously, as well as with a lag, while the latter ones affect those coming before them only with a lag. In our case we treat the bank's stock return as the most exogenous one while on the other end the bank CDS variable is the most endogenous one. Ordering may be sensitive in case there exist high residual correlations. In table 5, we present residuals correlation matrices and there is no evidence that residual correlation issue may affect ordering. Impulse responses are presented along with their 5% and 95% percentile bounds that have been produced by Monte Carlo simulations with 200 and 1000 replications. Therefore, whenever the zero line lies outside the confidence bands there is evidence of a statistically significant response to the shock inflicted.

4. Empirical Results

At the beginning we present three alternative panel-data unit-root tests for all the variables in our model. We have applied a batch of different tests that gave us similar, qualitatively, results. First, we applied the Levin et al. (2002) test, which is an Augmented Dickey-Fuller (ADF) type test on panel data where the autoregressive coefficient is restricted to be homogenous across all units. Then, we applied the Im et al. (2003) test, which allows for heterogeneity across units in the coefficient of the autoregressive component as well as for different serial correlation properties, across different units, of the error term. The testing procedure relies on separate ADF test statistics for each unit that are

[9]The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t+h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t

combined to a final test statistic that follows the normalized standard distribution. Finally, we applied a Fisher-type test proposed by Choi (2001), according to which the probability values of unit root tests for each cross section unit are combined in a test statistic that follows the χ^2 distribution. Table 3 presents the results from the Im et al. (2003) unit-root test which shows that in the case of K*f*W, in the last period, and in the cases of CDS and iTraxx, in the last period we were not able to reject the null hypothesis for the existence of a unit root (similar results have been obtained from the other two test statistics). However, since the CDS appears in the estimation in 1st differences we address this problem.

In order to select the appropriate number of lags we use the MMSC-Akaike's information criterion (MMSC-AIC) from the Moment and Model selection criteria (MMSC) developed by Andrews and Lu (2001)[10]. Additionally, we report the overall coefficient of determination (CD). Results are presented in table 4. The method is based on Hansen's (1982) J statistic of over identifying restrictions. The model requires that the number of moment conditions have to be larger than the number of endogenous variables. We focus on MMSC-AIC results, since Andrew and Lu (2001) have suggested that it has certain advantages over both the modified BIC (MBIC) and the modified QIC (MQIC. Then we check for the stability of the PVAR model. We are interested in the impact of exogenous changes in each endogenous variable to other variables in each modification that is under investigation. Prior to estimating impulse-response functions (IRF) and forecast-error variance decompositions (FEVD) we check each system's stability. The stability of the PVAR requires the moduli of the eigenvalues of the dynamic matrix to lie within the unit circle, which is the case in all estimated models. Stability implies that the panel VAR is invertible and has an infinite-order vector moving-average representation, providing thus a

[10] The criteria select the pair of (p,q) that minimizes the: $MMSC_{BIC,n}(k,p,q) = J_n(k^2p, k^2q) - (|q| - |p|)k^2 \ln n$, where $J_n(k,p,q)$ is the J statistic of over-identifying restriction for a k-variate panel VAR of order p and moment conditions based on q lags of the dependent variables with sample size n. It is available only when q>p.

reasonable interpretation to estimated impulse-response functions and forecast error variance decompositions. Granger causality for a first-order panel VAR may be inferred from the panel VAR coefficients so there is no reason for presenting separately the results.

In Table 6 we present the coefficients from the PVAR model for core and peripheral banks for the tranquil, the global financial crisis and the European sovereign debt crisis periods. In these models returns, the volatility index, short interest rates and CDS spreads, all in first differences, are treated as endogenous. Therefore, the equation for the CDS spreads takes the following form:

$$\Delta CDS_{i,t} = \alpha + \beta_1 \Delta CDS_{i,t-1} + \beta_1 \Delta R_{i,t-1} + \beta_3 \Delta Vol30_{i,t-1} + \beta_4 \Delta S.R._{i,t-1} + u_t + \varepsilon_t$$

The results for the tranquil period (Jan. 2005 to Dec. 2007) are presented in *Panel A.* In both cases bank stock returns affect negatively the bank's CDS (at the 5% significance level). The relationship between the risk-free interest rates and the bank credit risk is negative. In Merton (1974), an increase in the risk-free interest rate should decrease the probability of default, as a higher risk-free interest rate raises the risk neutral drift. In addition, there are further arguments to support this negative relationship in a macro-economic setting, in the sense that interest rates are associated with higher economic growth and lead to lower default risk (also see Fama, 1984; Estrella and Hardouvelis, 1991). Historical volatility does not affect the CDS in both cases. This evidence moves in tandem with Alexander and Kaeck (2008) who support that in tranquil periods CDS spreads are more sensitive to stock returns than they are to stock volatility. In *Panel B* we notice that the role of stock markets is eliminated while historical volatility, congruent with theory, affects positively and strongly the CDS. Finally, during the euro area sovereign debt crisis period all three variables of the structural model affect strongly the CDS, for the peripheral banks at the 1% significance level, with a sign that is in agreement with the theoretical suggestions.

In Table 7, we present the coefficients for the first modified structural model where the systemic factors are exogenously added. For instance, the equation for the CDS now takes the following form:

$$\Delta CDS_{i,t} = \alpha + \beta_1 \Delta CDS_{i,t-1} + \beta_1 \Delta R_{i,t-1} + \beta_3 \Delta Vol30_{i,t-1} + \beta_4 dS.R._{i,t-1} + \beta_5 \Delta iTraxx_t + \beta_6 \Delta Vstoxx_t + \beta_6 KfW_t + u_t + \varepsilon_t$$

In the current analysis we expand the previous analysis by controlling for systemic risk factors. Firstly, we are interested in testing whether the results presented in the previous analysis are still valid if we control for the Euro-zone's risk. Longstaff et al. (2011), for instance, argued that sovereign credit risk appears related to global rather than country-specific factors while Aizenman et al. (2013) have established the importance of domestic and international economic factors in the pricing of sovereign risk, in addition to credit risk ratings. Second, most of the variables that are used in structural models are firm-specific and focus on leverage and asset volatility while the relevant literature suggests taking into account variables that capture the overall market situation as well (see Jarrow and Turnbull, 2000). The systemic factors are assumed to affect the endogenous variables contemporaneously. The results suggest that market wide variables influenced strongly the banks' CDS spreads during the Euro-zone debt crisis, this result holds for the "core" banks during the financial turmoil period as well. Finally, it is worth mentioning that the systemic variables had no effect in the pricing of CDSs during the first period.

In table 8, we modify the basic structural model by allowing for the effect, contemporaneously, of bank-specific variables. The equation for the CDS variable is now:

$$\Delta CDS_{i,t} = \alpha + \beta_1 \Delta CDS_{i,t-1} + \beta_1 \Delta R_{i,t-1} + \beta_3 \Delta Vol30_{i,t-1} + \beta_4 dS.R._{i,t-1} + \beta_5 \Delta SMP_t$$
$$+ \beta_6 \Delta OMT_t + \beta_6 GDR_t + u_t + \varepsilon_t$$

We take the analysis one step further by investigating the impact of bank-specific characteristics on the pricing of their credit risk. Bank credit risk in euro zone seems to be immune to changes in bank specific characteristics. We do not support the result of Schepens and Vander Vennet (2009) that retail banks are less risky (especially during financial crisis) since they have lower market betas and generate more profits and capital. Also, core banks that performed well in capital adequacy ratios reduced their exposure to credit risk; this result is expected if we take under consideration that between 2008 and 2009 were under severe stress. Of course, for actual bank default prediction, one must also consider the presence of explicit and implicit government guarantees, including too-big-to-fail (TBTF) subsidies. According to BIS (2011a) large banks are more likely to be systemic institutions that may need a public bailout in case of distress and a large bank bailout will affect confidence in the financial system. As a result, we expect that bank size would be negatively and significantly connected to CDS; however there was no empirical support for this case. We do some robustness checks towards that direction by breaking the bank sample into two groups by means of their total assets and we take similar results with no crucial difference. So, we conclude that the too-big-to-fail issue plays a minor role in the explanation of bank CDS. However, we have to mention that the sample used includes the largest banks in Euro-zone (based on stress tests) and for this reason results may need further investigation.

In table 9, we take a look at the impact of ECB unconventional monetary policy measures on CDS. We control for a number of shocks, using dummies to capture the announcements effects of policies. This approach measures the impact of Outright Monetary Transactions, the Securities Market Programme, the announcements of the set up of EFSF and the Greek debt restructuring. The fact that we use quarterly data means that we may lose information or that some monetary policy measures maybe fall within the same quarter. Therefore it comes as no surprise that unconventional measures seem not to influence the banks' CDS spreads.

In table 10, we analyze the relationship between sovereign credit rating agencies and peripheral bank CDS by adding each bank's home-country sovereign credit rating by S&P. As a robust check we replace S&P credit ratings with those of Moody's and Fitch. We investigate this relationship only for the peripheral banks since core sovereign credit ratings for core countries do not fluctuate. The main result is that sovereign credit ratings do not influence the CDS. However, when Greek banks are excluded from the sample, credit ratings are related with CDS in a negative way and according to Ghysels et al. (2014) this result might be due to endogeneity problems, i.e., the purchases of bonds are triggered when yields are high or when the CDS are rising.

In table 11, we report results from forecast error variance decomposition analysis for the structural model. It seems that during periods of crisis, structural model explains more of CDS variations in core banks, while during calm periods the banks sector credit risk seems to be more "idiosyncratic" (see Table 11a). Results are similar, to a less extent though, for peripheral banks (see table 11b). The evidence suggests that the impact of variables related to structural models seem to be strongly time varying (also see Alexander and Kaeck, 2008; González- Hermosillo, 2008). During turbulent times, both peripheral and core banks' credit risk is substantially affected by banks' stock returns. Table 12 presents results from forecast error variance decomposition for the structural model, when the systemic factor is exogenously added. It is of high interest to investigate whether the obtained results are still valid if we add factors that incorporate euro-zone risks. We observe that core and peripheral banks' credit risk become more idiosyncratic during Euro-area sovereign debt crisis (see Tables 12a and 12b). Going beyond the structural model, we exogenously add the bank characteristics and present the relevant forecast error variance decomposition for both core and peripheral banks (see Tables 13a and table 13b). We derive the result that during Euro-area sovereign debt crisis, peripheral banks' credit risk remains more idiosyncratic. On the contrary, the modified structural model explains more of core banks; CDS variation and that core banks' credit risk is better explained when bank-specific characteristics are added. It is worth notice that reactions of banks' CDS must have been very fast since we calculated forecast errors 10 step ahead, and the percentages explained by the models were almost the same. This is clearer from the impulse response functions (IRFs) that concern the initial structural model.[11] It seems that the reactions of banks' CDS spread changes are never significantly different than zero but they are significantly different in the first 1-3 steps, as these reactions can be attributed to unexpected shocks.

5. Concluding Remarks

We rely on a structural approach model to investigate the influence of theoretical determinants on the quarterly changes of bank CDS spreads during a ten year period between January 2005 and December 2014. Going beyond the structural model, this study incorporates features such as the role of common risk factors, bank-specific characteristics, monetary policy (unconventional) measures and credit rating issues. The suggestion in this paper is based on the fact that the theoretical determinants of Eurozone banks' CDS do not perform the same in different market cycles (also see Alexander and Kaeck, 2008, and González- Hermosillo, 2008). As the period under investigation changes from the tranquil

[11] The IRF graphs are available upon request.

period (Jan. 2005 to Dec. 2007) to the global financial crisis (Jan. 2008 to Dec. 2009) and to the Euro-zone sovereign debt crisis, the influence of the structural model increases. More specifically, the evidence shows that in tranquil periods stock markets have strong effects on both core and peripheral banks' credit risk. Historical volatility plays a role only during global financial crisis. Finally, during Euro-zone debt crisis period all three theoretical determinants influence strongly the banking credit risk in Euro-zone. The evidence does not offer support to the argument that theoretical determinants that are found to affect CDS spreads of non-financial institutions lose their strength when applied to financial institutions CDS (see Raunig and Scheicher, 2008; Grammatikos and Vermeulen, 2012). The main conclusion is that the structural model variables affect the bank CDS spreads but their performance mostly depends on the market conditions, and that the role of the structural model determinants is intensified during volatile periods, i.e. the global financial crisis and the European sovereign debt crisis.

In addition, it is remarkable that there exist a strong effect that comes from the systemic factor. Also, bank credit risk in euro zone seems to be immune to changes in bank specific characteristics. We do not support the result of Schepens and Vander Vennet (2009) for the peripheral banks that retail banks are less risky (especially during financial crisis), since they have lower market betas and generate more profits and capital. Also, core banks only seem to be affected by the capital adequacy ratios and only for the turbulent 2008-09 period. Finally, we observe that the too-big-to-fail issue failed to affect the CDS spreads. However, we have to mention that the sample already includes the largest banks in Euro-zone and for this reason results may need further investigation.

The relation between the CDS and its determinants is not constant over time and the fact that it varies across the different phases of business cycle and across core and peripheral countries, highlights the need to approach it every time in a different way. It is of high importance for policy makers to take the right decisions, based on the “correct” factors that affect the CDS spreads.

Our results make a contribution to the modeling of European bank credit risk. We deviate from previous studies first, by choosing to work with a panel Vector Autoregressive Model methodology which relies on both the time and the cross sectional dimension of the variables in order to explain the underlying processes. Second, we are the first to compare the results of the two most recent crisis periods, to those obtained during a ‘tranquil’ period. Third, we compare the structural model and its effectiveness in financial institutions. Also, we control for the too-big-to-fail issue in Eurozone’s banks.

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Table 1: Banks per country

No	Country	Bank Name
1	Austria	Erste Group
2	Austria	Raiffeisen
3	Belgium	Dexia
4	Denmark	Danske Bank A/S
5	France	BNP Paribas
6	France	Credit Agricole SA
7	France	Societe Generale
8	France	Natixis
9	Germany	Commerzbank AG
10	Germany	Deutsche Bank AG
11	Germany	IKB Bank
12	Germany	DZ Bank
13	Germany	HSH Nordbank
14	Germany	WestLB
15	Greece	EFG Eurobank Ergas
16	Greece	National Bank
17	Greece	Alpha Bank
18	Ireland	Anglo Irish Bank

No	Country	Bank Name
19	Italy	Monte Paschi di Siena
20	Italy	Intesa Sanpaolo
21	Italy	MedioBanca
22	Italy	UBI (Unione di Banche)
23	Italy	Unicredit
24	Italy	Banca Popolare Italiana
25	Netherlands	ING Groep
26	Netherlands	SNS Bank
27	Netherlands	Rabobank
28	Portugal	Banco Comecial Portugues
39	Portugal	Espirito Santo
30	Portugal	Banco BPI
31	Portugal	Caixa Generale
32	Spain	BBVA
33	Spain	Banco Popolare
34	Spain	Sabadell
35	Spain	Santander
36	Spain	La Caixa
37	Spain	Banco Pastor

Note: We use the European Union-wide banking stress tests of 2010, 2011 and 2014 that were conducted by the European Banking Authority. A total of 90 banks participated in the bank stress tests. These banks represent about 70 percent of bank assets in Europe. We select banks that are headquartered in Austria, Belgium, France, Germany, Netherlands, Spain, Greece, Italy, Portugal and Ireland, with more than €50 billion assets. We set this threshold since smaller banks and banks that are not headquartered in these countries usually do not have traded CDS.

Table 2: Variables Description

Variable	Description
Endogenous Variables	
CDS_C	Core Banks CDS 5-year spread
CDS_P	Peripheral Banks CDS 5-year spread
R	Bank's stock return
S.R.	3 month Swap Rates
Vol30	Statistical volatility based on historical (30 days) stock return data
Exogenous Variables	
iTraxx	iTraxx Europe main index (125 investment grade companies, all sectors)
Vstoxx	The volatility index of EURO STOXX 50
KFW	The yield spread between German federal gov. bonds and German KfW agency bonds
Size	Bank's total assets / Home country's GDP
eu_size	Bank's total assets / EU's GDP (28 countries)
Retail	Loan-to-asset ratio
Revenue	Non - interest income / Total Revenue
Tier1	Tier 1 capital ratio
Equity_ratio	Total shareholders' equity / Total assets
Dummies	
SMP	Securities Market Program
OMT	Outright Monetary Transactions dummy
WIT	"Whatever it takes" speech dummy
GDR	Greek Debt Restructuring dummy
EFSF	European Financial Stability Facility dummy
S&P	S&P's Announcements (changes, credit watch & outlooks)on Sovereign debts
Moody's	Moody's Announcements (changes, credit watch & outlooks)on Sovereign debts

Source: Datastream-Thomson Reuters

For further and more detailed information on the iTraxx indices please refer to:

http://www.markit.com/assets/en/docs/products/data/indices/credit-index-annexes/iTraxx_SovX%20WE_Series%207.pdf.

http://www.markit.com/assets/en/docs/products/data/indices/credit-index-annexes/iTraxx%20Europe%20annex_Series%2017.pdf

Table 3: Panel-Data Unit-Root tests

Panel A: *Im - Pesaran - Shin panel-data unit-root test - Peripheral Banks*

Variable	Critical Values			*Jan. 2005 - Dec. 2007*		*Jan. 2008 - Dec. 2009*		*Jan. 2010 - Dec. 2014*	
	1%	5%	10%	t-stat.	p-value	t-stat.	p-value	t-stat.	p-value
Endogenous									
CDS	-2.07	-1.90	-1.82	-0.682	0.999	-3.694	0.000	-4.191	0.000
R	-2.07	-1.90	-1.82	-3.257	0.000	-1.889	0.035	-3.939	0.000
Vol30	-2.07	-1.90	-1.82	-4.447	0.000	-3.556	0.000	-7.148	0.000
S.R.	-2.07	-1.90	-1.82	-3.054	0.000	-2.224	0.004	-3.064	0.000
Exogenous									
iTraxx	-2.07	-1.90	-1.82	-1.538	0.264	-5.092	0.000	-4.893	0.000
Vstoxx	-2.07	-1.90	-1.82	-5.171	0.000	-2.646	0.000	-5.558	0.000
K*f*W	-2.07	-1.90	-1.82	-4.845	0.000	-3.180	0.000	-1.739	0.109

Panel B: *Im - Pesaran - Shin panel-data unit-root test - Core Banks*

Variable	Critical Values			*Jan. 2005 - Dec. 2007*		*Jan. 2008 - Dec. 2009*		*Jan. 2010- Dec. 2014*	
	1%	5%	10%	t-stat.	p-value	t-stat.	p-value	t-stat.	p-value
Endogenous									
CDS	-2.14	-1.95	-1.85	-0.738	1.000	-2.568	0.000	-4.330	0.000
R	-2.14	-1.95	-1.85	-2.517	0.004	-1.946	0.025	-4.691	0.000
Vol30	-2.14	-1.95	-1.85	-4.318	0.000	-3.449	0.004	-5.725	0.000
S.R.	-2.14	-1.95	-1.85	-3.054	0.000	-2.241	0.000	-3.064	0.000

Table 4: Lag-order selection statistics for panel VAR

Panel A: *Peripheral Banks (MAIC)*

	2005-2007		**2008-2009**		**2010-2014**	
lag	CD	MAIC	CD	MAIC	CD	MAIC
1	.257	4.07e-31	.732	1.51e-31	.533	1.25e-30
2	.484	2.69e-30	.918	1.94e-30	.723	3.04e-30
3	.859	2.16e-29	.973	3.88e-30	.816	6.39e-30
4	.899	2.34e-28	.989	1.98e-28	.886	1.26e-29

Panel B: *Core Banks (MAIC)*

	2005-2007		**2008-2009**		**2010-2014**	
lag	CD	MAIC	CD	MAIC	CD	MAIC
1	.230	2.83e-31	.389	2.85e-31	.640	1.15e-30
2	.673	3.60e-30	.723	1.43e-30	.691	2.25e-30
3	.917	6.46e-29	.823	3.26e-30	.663	1.27e-29
4	.936	4.48e-28	.827	1.36e-29	.049	6.33e-29

Notes: CD is the overall Coefficient of Determination and MAIC the MMSC-Akaike's. Andrews and Lu (2001) proposed consistent Moment and Model Selection Criteria (MMSC) for GMM models based on Hansen's (1982) statistic of over-identifying restrictions. Their proposed MMSC are analogous to various commonly used maximum likelihood-based model selection criteria, namely the Akaike information criteria (AIC) (Akaike, 1969). The criteria select the pair of (p,q) that minimizes the: $MMSC_{BIC,n}(k,p,q) = J_n(k^2p, k^2q) - (|q| - |p|)k^2 \ln n$, where $J_n(k,p,q)$ is the J statistic of over-identifying restriction for a k-variate panel VAR of order p and moment conditions based on q lags of the dependent variables with sample size n. It is available only when q>p.

Table 5: Residual Correlation Matrix

Table 5a: Residual Correlation Matrix – Peripheral Banks

Panel A: Jan. 2005 - Dec. 2007

	R	S.R.	Vol30	CDS
R	1.00			
S.R.	0.27	1.00		
	0.00			
Vol30	0.27	0.27	1.00	
	0.00	0.00		
CDS	-0.13	-0.01	-0.14	1.00
	0.14	0.90	0.12	

Panel B: Jan. 2008 - Dec. 2009

	R	S.R.	Vol30	CDS
R	1.00			
S.R.	-0.67	1.00		
	0.00			
Vol30	0.44	-0.44	1.00	
	0.00	0.00		
CDS	-0.00	-0.04	0.18	1.00
	0.94	0.70	0.09	

Panel C: Jan. 2010 - Oct. 2015

	R	S.R.	Vol30	CDS
R	1.00			
S.R.	-0.29	1.00		
	0.00			
Vol30	0.09	-0.23	1.00	
	0.13	0.00		
CDS	-0.02	0.08	-0.02	1.00
	0.65	0.19	0.68	

Table 5b: Residual Correlation Matrix – Core Banks

Panel A: Jan. 2005 - Dec. 2007

	R	S.R.	Vol30	CDS
R	1.00			
S.R.	-0.01	1.00		
	0.89			
Vol30	0.24	0.06	1.00	
	0.01	0.53		
CDS	-0.03	0.10	-0.04	1.00
	0.72	0.30	0.68	

Panel B: Jan. 2008 - Dec. 2009

	R	S.R.	Vol30	CDS
R	1.00			
S.R.	-0.24	1.00		
	0.02			
Vol30	0.16	-0.47	1.00	
	0.15	0.00		
CDS	-0.01	-0.19	0.43	1.00
	0.87	0.07	0.00	

Panel C: Jan. 2010 - Oct. 2015

	R	S.R.	Vol30	CDS
R	1.00			
S.R.	0.05	1.00		
	0.39			
Vol30	0.13	-0.29	1.00	
	0.05	0.00		
CDS	0.00	-0.00	0.08	1.00
	0.92	0.99	0.08	

Table 6: Coefficient of Structural Model

Table 6a: Coefficients of Structural model – Peripheral Banks

Panel A: Jan. 2005 – Dec. 2007

	R	Vol30	S.R.	CDS
R(-1)	0.0384	0.540*	0.347	-1.516***
	(0.119)	(0.295)	(0.282)	(0.455)
Vol30(-1)	-0.0207	-0.353***	0.147	-0.098
	(0.034)	(0.113)	(0.112)	(0.185)
S.R.(-1)	-0.024	0.266***	-0.067	-0.235
	(0.039)	(0.096)	(0.086)	(0.318)
CDS(-1)	0.0165	0.123	-0.084	0.553**
	(0.038)	(0.119)	(0.091)	(0.229)

Panel B: Jan. 2008 – Dec. 2009

	R	Vol30	S.R.	CDS
R(-1)	0.423***	-0.576***	-0.254	-0.888***
	(0.139)	(0.150)	(0.261)	(0.286)
Vol30(-1)	-0.143	-0.418***	0.171	0.554***
	(0.098)	(0.121)	(0.330)	(0.188)
S.R.(-1)	0.103**	0.094	0.278***	-0.0162
	(0.050)	(0.068)	(0.102)	(0.118)
CDS(-1)	-0.008	0.009	0.100	-0.108
	(0.026)	(0.031)	(0.080)	(0.121)

Panel C: Jan. 2010 – Dec. 2014

	R	Vol30	S.R.	CDS
R(-1)	0.097	-0.017	0.074	-0.633***
	(0.083)	(0.064)	(0.077)	(0.092)
Vol30(-1)	0.003	-0.453***	-0.178*	0.251***
	(0.075)	(0.053)	(0.095)	(0.096)
S.R.(-1)	0.256***	-0.123***	0.327***	-0.338***
	(0.044)	(0.041)	(0.057)	(0.098)
CDS(-1)	0.021	-0.070***	0.176***	0.0244
	(0.028)	(0.024)	(0.060)	(0.046)

Note: ***1% , **5%, *10%

Table 6b: Coefficients of Structural model – Core Banks

Panel A: Jan. 2005 – Dec. 2007

	R	Vol30	S.R.	CDS
R(-1)	0.141	0.529***	0.623***	-1.994**
	(0.131)	(0.195)	(0.206)	(0.889)
Vol30(-1)	0.002	-0.388***	-0.040	-0.233
	(0.068)	(0.096)	(0.134)	(0.577)
S.R.(-1)	-0.018	0.066	-0.022	-1.061**
	(0.038)	(0.081)	(0.079)	(0.491)
CDS(-1)	0.009	0.008	0.015	-0.173
	(0.011)	(0.016)	(0.015)	(0.124)

Panel B: Jan. 2008 – Dec. 2009

	R	Vol30	S.R.	CDS
R(-1)	0.569***	-0.537***	0.0778	-0.222
	(0.146)	(0.114)	(0.180)	(0.302)
Vol30(-1)	-0.692***	-0.274**	-0.335	0.966***
	(0.158)	(0.125)	(0.227)	(0.249)
S.R.(-1)	-0.112	0.376***	-0.032	-0.388**
	(0.094)	(0.074)	(0.105)	(0.192)
CDS(-1)	0.003	0.014	0.008	0.134
	(0.066)	(0.036)	(0.072)	(0.089)

Panel C: Jan. 2010 – Dec. 2014

	R	Vol30	S.R.	CDS
R(-1)	-0.255**	-0.021	0.088	-0.402***
	(0.105)	(0.092)	(0.078)	(0.129)
Vol30(-1)	0.096	-0.326***	0.115	0.567***
	(0.087)	(0.095)	(0.071)	(0.090)
S.R.(-1)	0.397***	-0.056	0.338***	-0.274***
	(0.079)	(0.071)	(0.072)	(0.086)
CDS(-1)	0.160***	-0.212***	0.254***	0.030
	(0.059)	(0.047)	(0.075)	(0.039)

Note: ***1% , **5%, *10%

Table 7: Systemic Factor

Table 7a: Systemic factor effect (Modified structural model) – Peripheral Banks

Panel A: Jan. 2005 – Dec. 2007

	R	Vol30	S.R.	CDS
R(-1)	0.087	0.737*	-0.121	-1.502**
	(0.135)	(0.383)	(0.300)	(0.764)
Vol30(-1)	-0.032	-0.351***	0.046	-0.064
	(0.034)	(0.121)	(0.102)	(0.156)
S.R.(-1)	0.056	0.275***	0.105	-0.372
	(0.053)	(0.096)	(0.120)	(0.227)
CDS(-1)	0.082**	0.228**	0.074	0.430*
	(0.039)	(0.104)	(0.115)	(0.221)
iTraxx	-0.219***	-0.065	-0.995***	0.478
	(0.079)	(0.217)	(0.176)	(0.566)
Vstoxx	-0.112	0.374**	0.344*	0.040
	(0.076)	(0.163)	(0.197)	(0.249)
K*f*W	1.178***	3.824***	0.854	-1.974
	(0.397)	(1.261)	(1.140)	(3.267)

Panel B: Jan. 2008 – Dec. 2009

	R	Vol30	S.R.	CDS
R(-1)	0.379	0.189	-0.337	-0.668
	(1.411)	(0.237)	(1.055)	(1.088)
Vol30(-1)	-3.346	0.140	2.864	-2.972
	(4.877)	(0.904)	(3.724)	(3.823)
S.R.(-1)	5.598	-0.863	-3.410	5.986
	(8.427)	(1.511)	(6.414)	(6.565)
CDS(-1)	-0.506	0.011	0.405	-0.761
	(0.874)	(0.156)	(0.672)	(0.661)
iTraxx	7.852	-1.006	-7.462	9.416
	(13.13)	(2.370)	(9.990)	(10.23)
Vstoxx	-5.123	1.655	3.621	-5.188
	(7.060)	(1.284)	(5.392)	(5.526)
K*f*W	15.67	-1.383	-10.35	17.38
	(25.69)	(4.586)	(19.53)	(19.99)

Table 7a (continued)

Panel C: Jan. 2010 – Dec. 2014

	R	Vol30	S.R.	CDS
R(-1)	-0.020	0.057	0.096	-0.547***
	(0.088)	(0.062)	(0.063)	(0.090)
Vol30(-1)	-0.005	-0.422***	-0.320***	0.244***
	(0.070)	(0.048)	(0.068)	(0.091)
S.R.(-1)	0.189***	-0.0671*	0.296***	-0.260***
	(0.036)	(0.036)	(0.032)	(0.083)
CDS(-1)	0.059**	-0.074***	-0.017	-0.081
	(0.029)	(0.028)	(0.046)	(0.054)
iTraxx	-0.246*	0.375***	-0.539***	0.772***
	(0.132)	(0.109)	(0.088)	(0.172)
Vstoxx	-0.0949	-0.030	-0.044	-0.486***
	(0.111)	(0.094)	(0.069)	(0.141)
K*f*W	-0.271***	0.097**	0.610***	0.355***
	(0.051)	(0.047)	(0.078)	(0.076)

Note: ***1% , **5%, *10%

Table 7b: Systemic factor effect (Modified structural model) – Core Banks

Panel A: Jan. 2005 – Dec. 2007

	R	Vol30	S.R.	CDS
R(-1)	0.238	-0.454	-0.314	-4.335**
	(0.152)	(0.337)	(0.361)	(1.907)
Vol30(-1)	0.039	-0.559***	-0.191	-0.997
	(0.071)	(0.145)	(0.167)	(0.856)
S.R.(-1)	0.014	0.071	0.087	-0.550
	(0.054)	(0.100)	(0.131)	(0.519)
CDS(-1)	0.008	-0.024	-0.023	-0.231
	(0.016)	(0.021)	(0.021)	(0.187)
iTraxx	-0.185*	-0.642**	-1.177***	-2.488
	(0.111)	(0.259)	(0.238)	(1.382)
Vstoxx	-0.251***	0.917***	0.366	-0.290
	(0.091)	(0.195)	(0.250)	(0.989)
K*f*W	1.316***	-2.730***	-0.946	-11.76*
	(0.489)	(0.894)	(1.019)	(5.590)

Panel B: Jan. 2008 – Dec. 2009

	R	Vol30	S.R.	CDS
R(-1)	-0.080	-0.139	-0.0236	-0.214
	(0.292)	(0.135)	(0.029)	(0.613)
Vol30(-1)	-1.826*	-0.415	0.197**	-2.984
	-1.051	(0.338)	(0.096)	-1.984
S.R.(-1)	2.50	0.061	0.887***	8.146**
	-2.048	(0.655)	(0.191)	-4.140
CDS(-1)	0.031	-0.032	-0.002	-0.043
	(0.123)	(0.023)	(0.011)	(0.265)
iTraxx	4.346	0.255	-0.654*	14.75**
	-3.690	-1.152	(0.346)	-7461
Vstoxx	-3.770*	0.734	-0.039	-8.084**
	-2.050	(0.727)	(0.191)	-3.845
K*f*W	6.416	0.158	2.627***	23.60*
	-5.800	-1.653	(0.545)	(12.26)

Table 7b (continued)

Panel C: Jan. 2010 – Dec. 2014

	R	Vol30	S.R.	CDS
R(-1)	-0.263**	-0.0620	0.154**	-0.389***
	(0.104)	(0.082)	(0.065)	(0.127)
Vol30(-1)	0.046	-0.175*	-0.129**	0.496***
	(0.091)	(0.097)	(0.063)	(0.089)
S.R.(-1)	0.289***	0.046	0.270***	-0.240***
	(0.072)	(0.068)	(0.044)	(0.070)
CDS(-1)	0.136**	-0.047	-0.075	-0.102**
	(0.066)	(0.056)	(0.051)	(0.048)
iTraxx	-0.057	0.655***	-0.537***	0.260*
	(0.224)	(0.230)	(0.096)	(0.150)
Vstoxx	-0.294	-0.118	-0.081	-0.300**
	(0.187)	(0.199)	(0.076)	(0.122)
K*f*W	-0.318***	-0.173**	0.620***	0.331***
	(0.091)	(0.078)	(0.088)	(0.082)

Note: ***1% , **5%, *10%

Table 8: Bank-specific characteristics

Table 10a: Balance Sheet Variables (Modified structural model) – Peripheral Banks

Panel A: Jan. 2005 – Dec. 2007

	R	Vol30	S.R.	CDS
L.R	-0.409	0.115	0.865	0.243
	(0.149)	(0.470)	(0.413)	(0.458)
L.Vol30	0.025	-0.448***	0.165	-0.046
	(0.062)	(0.160)	(0.155)	(0.403)
L.S.R.	-0.045	0.318*	-0.043	-0.152
	(0.068)	(0.166)	(0.110)	(0.426)
L.CDS	0.012	0.050	-0.072	0.579***
	(0.040)	(0.128)	(0.079)	(0.126)
Size	4.275	-16.41	6.201	-35.06
	(26.96)	(47.10)	(59.75)	(189.4)
Retail	1.362	-4.279	-0.457	-16.19
	(1.813)	(3.231)	(0.346)	(10.72)
Revenue	0.645*	-0.443	-0.034	0.003
	(0.364)	(0.715)	(0.768)	-1.758
tier1	0.072	-0.153	-0.037	-0.173
	(0.055)	(0.146)	(0.155)	(0.362)

Panel B: Jan. 2008 – Dec. 2009

	R	Vol30	S.R.	CDS
R(-1)	0.414**	-0.506***	-0.663*	-0.761**
	(0.165)	(0.158)	(0.348)	(0.333)
Vol30(-1)	-0.181	-0.294*	0.389	0.623**
	(0.180)	(0.160)	(0.394)	(0.313)
S.R.(-1)	0.073	0.149*	0.441**	-0.048
	(0.097)	(0.085)	(0.180)	(0.165)
CDS(-1)	-0.040	0.009	0.347***	-0.248
	(0.056)	(0.054)	(0.123)	(0.235)
Size	122.8	-76.72	-307.2	65.01
	(131.8)	(100.5)	(283.3)	(131.1)
Retail	2.574	1.107	-9.627**	12.75***
	(3.546)	(2.559)	(7.160)	(4.350)
Revenue	-0.044	0.039	0.881	-0.388
	(0.485)	(0.367)	(0.633)	(0.883)
tier1	0.048	-0.061	0.107	0.075
	(0.068)	(0.051)	(0.121)	(0.137)

Table 8a (continued)

Panel C: Jan. 2010 – Dec. 2014

	R	Vol30	S.R.	CDS
R(-1)	0.097	-0.0246	0.0396	-0.645***
	(0.120)	(0.113)	(0.144)	(0.168)
Vol30(-1)	0.116	-0.538***	-0.253*	0.123
	(0.107)	(0.102)	(0.132)	(0.150)
S.R.(-1)	0.244***	-0.109**	0.325***	-0.255**
	(0.059)	(0.053)	(0.070)	(0.109)
CDS(-1)	0.075*	-0.111**	0.151**	-0.062
	(0.045)	(0.043)	(0.071)	(0.072)
Size	-21.78	16.34	2.430	35.37
	(21.47)	(16.12)	(27.90)	(36.56)
Retail	-4.212*	2.623	1.380	4.949
	(2.443)	(1.760)	(3.018)	(4.042)
Revenue	-0.057	0.086	0.008	-0.307*
	(0.133)	(0.116)	(0.154)	(0.177)
tier1	-0.025	0.015	0.0301	0.005
	(0.020)	(0.018)	(0.020)	(0.028)

Note: ***1% , **5%, *10%

Table 8b: Balance Sheet Variables (Modified structural model) – Core Banks

Panel A: Jan. 2005 – Dec. 2007

	R	Vol30	S.R.	CDS
R(-1)	1.532	-1.264	-0.372	-12.06
	(2.143)	(2.851)	(2.263)	(15.36)
Vol30(-1)	0.345	-0.824	-0.347	-2.175
	(0.613)	(0.773)	(0.653)	(4.371)
S.R.(-1)	-0.973	1.280	0.832	5.574
	(1.183)	(1.546)	(1.197)	(8.588)
CDS(-1)	0.008	0.005	0.028	-0.234
	(0.105)	(0.153)	(0.105)	(0.762)
Size	6.256	-7.776	-5.981	-41.04
	(9.978)	(12.96)	(9.909)	(72.70)
Retail	27.38	-37.82	-25.97	-182.3
	(40.48)	(52.63)	(40.52)	(294.2)
Revenue	1.739	-2.611	-1.920	-13.80
	(3.081)	(3.909)	(2.986)	(22.20)
tier1	0.555	-0.688	-0.571	-3.783
	(0.739)	(0.955)	(0.761)	(5.412)

Panel B: Jan. 2008 – Dec. 2009

	R	Vol30	S.R.	CDS
R(-1)	0.987*	-0.691***	0.112	0.0822
	(0.525)	(0.199)	(0.274)	(0.465)
Vol30(-1)	-0.656	-0.318*	-0.396	1.282***
	(0.428)	(0.172)	(0.365)	(0.420)
S.R.(-1)	0.0131	0.372***	-0.0700	0.0901
	(0.280)	(0.122)	(0.176)	(0.274)
CDS(-1)	-0.157	-0.0306	-0.0553	0.110
	(0.202)	(0.0750)	(0.199)	(0.240)
Size	3.276	-1.697	0.339	9.260
	(8.718)	(3.654)	(5.644)	(11.33)
Retail	-13.29	1.169	-0.446	-4.815
	(8.330)	(2.925)	(4.322)	(6.677)
Revenue	0.560	-0.261	-0.100	0.680
	(0.407)	(0.176)	(0.325)	(0.418)
tier1	-0.203	0.0854	0.0156	-0.282***
	(0.187)	(0.0583)	(0.0899)	(0.0956)

Table 8b (continued)

Panel C: Jan. 2010 – Dec. 2014

	R	Vol30	S.R.	CDS
R(-1)	-0.163	-0.120	0.195	-0.443***
	(0.208)	(0.216)	(0.261)	(0.171)
Vol30(-1)	0.031	-0.359**	-0.189	0.367**
	(0.169)	(0.156)	(0.255)	(0.164)
S.R.(-1)	0.301	-0.076	0.127	-0.284
	(0.212)	(0.165)	(0.296)	(0.223)
CDS(-1)	0.230**	-0.266***	0.163	-0.022
	(0.093)	(0.074)	(0.145)	(0.106)
Size	-4.368	2.443	4.663	3.801
	(5.669)	(2.852)	(3.044)	(2.342)
Retail	-0.347	0.050	1.145**	0.576
	(0.397)	(0.285)	(0.560)	(0.432)
Revenue	1.396	0.569	0.385	0.204
	(0.907)	(0.567)	(0.374)	(0.637)
tier1	-0.025	0.015	0.030	0.005
	(0.020)	(0.018)	(0.020)	(0.028)

Note: ***1% , **5%, *10%

Table 9: Unconventional Monetary Policy Measures

Panel A: Core Banks Jan.2010-Dec.2014

	R	Vol30	S.R.	CDS
R(-1)	-0.251**	-0.048	0.037	-0.404***
	(0.111)	(0.100)	(0.079)	(0.147)
Vol30(-1)	0.092	-0.321***	0.079	0.585***
	(0.089)	(0.099)	(0.071)	(0.093)
S.R.(-1)	0.402***	-0.042	0.317***	-0.247***
	(0.085)	(0.080)	(0.071)	(0.089)
CDS(-1)	0.259***	-0.207**	0.419***	0.021
	(0.092)	(0.093)	(0.124)	(0.061)
SMP	-0.085**	0.102*	-0.171***	0.131**
	(0.042)	(0.057)	(0.024)	(0.057)
OMT	0.182***	-0.095**	0.004	0.008
	(0.056)	(0.048)	(0.030)	(0.056)
GDR	-0.174	-0.032	-0.394**	0.041
	(0.122)	(0.109)	(0.158)	(0.096)

Panel B: Peripheral Banks Jan.2010-Dec.2014

	R	Vol30	S.R.	CDS
R(-1)	0.119	-0.018	0.061	-0.628***
	(0.080)	(0.066)	(0.080)	(0.094)
Vol30(-1)	-0.025	-0.433***	-0.203**	0.290***
	(0.073)	(0.052)	(0.098)	(0.095)
S.R.(-1)	0.254***	-0.089**	0.289***	-0.283***
	(0.043)	(0.039)	(0.058)	(0.098)
CDS(-1)	0.041	-0.080***	0.202***	-0.006
	(0.030)	(0.029)	(0.065)	(0.051)
SMP	-0.143***	0.250***	-0.264***	0.418***
	(0.029)	(0.050)	(0.030)	(0.114)
OMT	0.182***	-0.019	-0.007	-0.049
	(0.047)	(0.043)	(0.032)	(0.093)
GDR	0.063	-0.055	-0.070	-0.003
	(0.0810	(0.041)	(0.055)	(0.062)

Note: ***1% , **5%, *10%

Table 10: Credit Ratings (Peripheral Banks, Jan.2010-Oct.2014)

Panel A: Peripheral Banks

	R	Vol30	S.R.	CDS
R(-1)	-0.172	0.108	0.335	-0.163
	(0.216)	(0.172)	(0.220)	(0.338)
Vol30(-1)	0.112	-0.503***	-0.283*	0.0613
	(0.149)	(0.101)	(0.158)	(0.221)
S.R.(-1)	0.198**	-0.096**	0.384***	-0.236*
	(0.085)	(0.046)	(0.092)	(0.140)
CDS(-1)	0.492	-0.290	-0.278	-0.795
	(0.426)	(0.288)	(0.452)	(0.599)
S&P	0.144	-0.067	-0.139	-0.251
	(0.128)	(0.086)	(0.136)	(0.180)

Panel B: Greek banks excluded

	R	Vol30	S.R.	CDS
R(-1)	-0.131	0.233	0.366**	-0.398**
	(0.150)	(0.146)	(0.158)	(0.164)
Vol30(-1)	0.214	-0.589***	-0.275**	0.089
	(0.135)	(0.117)	(0.125)	(0.129)
S.R.(-1)	0.147*	-0.085	0.390***	-0.260***
	(0.082)	(0.074)	(0.075)	(0.097)
CDS(-1)	0.461**	-0.449***	-0.140	-0.463**
	(0.181)	(0.162)	(0.191)	(0.205)
S&P	0.142**	-0.125**	-0.107*	-0.156**
	(0.056)	(0.051)	(0.059)	(0.062)

Notes: ***1% , **5%, *10%

Table 11: Forecast Error Variance Decomposition - Structural Model

Table 11a: Core countries

Panel A: Jan. 2005 - Dec. 2007

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.989	.000	.003	.005
Vol30	10	.098	.882	.016	.003
S.R.	10	.091	.004	.901	.002
CDS	10	.093	.035	.098	.772

Panel B: Jan. 2008 - Dec. 2009

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.855	.030	.095	.018
Vol30	10	.355	.454	.179	.010
S.R.	10	.126	.207	.662	.003
CDS	10	.366	.105	.143	.384

Panel C: Jan. 2010 - Dec. 2015

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.792	.006	.181	.019
Vol30	10	.113	.829	.016	.040
S.R.	10	.044	.060	.857	.037
CDS	10	.196	.198	.141	.463

Notes: The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t+h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t.

***1% , **5%, *10%

Table 11b: Peripheral countries

Panel A: Jan. 2005 - Dec. 2007

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.963	.002	.008	.024
Vol30	10	.146	.672	.077	.103
S.R.	10	.121	.040	.798	.040
CDS	10	.433	.001	.028	.536

Panel B: Jan. 2008 - Dec. 2009

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.973	.012	.013	.000
Vol30	10	.518	.435	.044	.001
S.R.	10	.275	.037	.683	.003
CDS	10	.432	.032	.047	.487

Panel C: Jan. 2010 - Dec. 2015

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.855	.008	.127	.008
Vol30	10	.066	.886	.031	.014
S.R.	10	.017	.065	.873	.042
CDS	10	.151	.036	.129	.682

Notes: The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t+h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t.

***1% , **5%, *10%

Table 12: Forecast Error Variance Decomposition - Systemic factor

Table 12a: Core countries

Panel A: Jan. 2005 - Dec. 2007

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.971	.021	.002	.005
Vol30	10	.025	.959	.007	.008
S.R.	10	.028	.118	.848	.004
CDS	10	.131	.317	.028	.522

Panel B: Jan. 2008 - Dec. 2009

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.672	.223	.100	.003
Vol30	10	.087	.879	.022	.010
S.R.	10	.480	.212	.302	.004
CDS	10	.344	.165	.202	.287

Panel C: Jan. 2010 - Dec. 2015

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.912	.006	.061	.020
Vol30	10	.012	.981	.002	.003
S.R.	10	.033	.016	.945	.004
CDS	10	.109	.137	.068	.684

Notes: The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t + h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t.

***1% , **5%, *10%

Table 12b: Peripheral countries

Panel A: Jan. 2005 – Dec. 2007

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.736	.004	.056	.202
Vol30	10	.145	.535	.115	.204
S.R.	10	.017	.006	.946	.030
CDS	10	.204	.004	.088	.702

Panel B: Jan. 2008 - Dec. 2009

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.988	.008	.002	.001
Vol30	10	.529	.383	.079	.007
S.R.	10	.756	.029	.200	.013
CDS	10	.444	.001	.175	.377

Panel C: Jan. 2010 - Dec. 2015

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.944	.001	.042	.011
Vol30	10	.003	.965	.005	.025
S.R.	10	.006	.050	.941	.001
CDS	10	.082	.013	.041	.862

Notes: The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t+h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t.

***1% , **5%, *10%

Table 13: Forecast Error Variance Decomposition - Bank characteristics

Table 13a: Core countries

Panel A: Jan. 2005 - Dec. 2007

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.956	.007	.033	.001
Vol30	10	.742	.219	.035	.002
S.R.	10	.459	.037	.491	.011
CDS	10	.536	.070	.030	.362

Panel B: Jan. 2008 - Dec. 2009

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.850	.028	.076	.045
Vol30	10	.040	.898	.009	.051
S.R.	10	.026	.088	.867	.017
CDS	10	.164	.164	.128	.542

Panel C: Jan. 2010 - Dec. 2015

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.794	.001	.177	.025
Vol30	10	.125	.766	.061	.045
S.R.	10	.094	.017	.871	.016
CDS	10	.261	.077	.311	.349

Notes: The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t + h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t.

***1% , **5%, *10%

Table 13b: Peripheral countries

Panel A: Jan. 2005 - Dec. 2007

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.964	.014	.007	.012
Vol30	10	.096	.844	.054	.004
S.R.	10	.194	.027	.749	.028
CDS	10	.551	.115	.003	.329

Panel B: Jan. 2008 - Dec. 2009

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.968	.003	.025	.001
Vol30	10	.563	.343	.083	.009
S.R.	10	.293	.007	.675	.023
CDS	10	.482	.046	.010	.460

Panel C: Jan. 2010 - Dec. 2015

	Impulse				
Response	step	R	Vol30	S.R.	CDS
R	10	.889	.005	.087	.016
Vol30	10	.093	.839	.030	.037
S.R.	10	.008	.061	.893	.037
CDS	10	.156	.007	.079	.756

Notes: The h-step ahead forecast-error is: $Y_{it+h} - E[Y_{it+h}] = \sum_{i=0}^{h-1} e_{i(t+h-i)}\Phi_i$, where Y_{it+h} is the observed vector at time $t+h$ and $E[Y_{it+h}]$ is the h-step ahead predicted vector made at time t.

***1% , **5%, *10%