The comovement between sovereign and bank credit risk during the financial crisis:

the case of the Euro area

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May 2011

Abstract

We investigate the comovement between sovereign and bank credit risk of the Euro area over the period 2008-2010. We construct two synthetic credit risk measures of the European sovereign and banking sectors that can be used for macro-prudential supervision. We estimate a Vector error-correction model and we obtain empirical evidence of a cointegration relationship between sovereign and bank credit risk. Moreover, we find that deviations from this equilibrium relationship are adjusted through the banking sector. Finally, impulse response functions show that it is possible to distinguish between a *permanent* sovereign shock and a *transitory* banking shock.

Keywords: financial stability, sovereign credit risk, banking sector credit risk, n^{th}-to-default CDS, portfolio credit risk management

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† *Aknowledgements*: I would like to thank Renzo G. Avesani, Carlo A. Favero, Antonio Garcia Pascual, Tor Jacobson and Andrea Sironi for very useful comments and discussions.

I. INTRODUCTION

This paper investigates the comovement between sovereign and banking sector credit risk during the financial turmoil occurred between 2008 and 2010 and contributes to the literature about financial stability and macro-prudential banking supervision specifically for the Euro area.

From an historical point of view, the relationship between the state and the banking system dates back at least at the Middle Ages. However, this link has evolved over time and, as pointed out by Alessandri and Haldane (2009), the Great Depression "*marked a regime-shift in state support to the banking system*". In other words, while in the past it was the state that was supported by the banks, since the Great Depression it has become very common for the state to act as lender of last resort of the banking sector. The current financial crisis is certainly contributing to enhance this trend.

Indeed, the relationship between sovereign and bank credit risk has dramatically re-emerged over the last couple of years and, with the banking sector rescue packages implemented in many countries, the risk has been transferred once again from banks to governments. However, while in the US and the UK the state has been able to provide aid to the banks without undermining its credibility and without affecting too much its strength, in Europe the situation has been different. In fact, the European Monetary Union has entered the crisis in a particular bad shape given that part of its banking system was under-capitalised, endowed with insufficient liquidity buffers and burdened with low-quality assets. Besides, the size of the national banking sector relative to GDP has soundly enlarged during the last decade for many EU countries (see Fig.1) and this has contributed to make more difficult the action of support of governments. Last but not least, the finances of some EU sovereign members were already under stress given the high level of domestic sovereign debt. In this framework, European sovereign bond and credit default swap spreads have boomed over the last two years, as a mirror of the market perception that some country could not have the financial strength to bail-out troubled financial institutions and/or to pay back the interests on its debt following the widening of budget deficits. Put it differently, it seems that the bank credit crisis has started to interact with other long-lasting structural problems affecting the Euro area[1]. This has undermined the level of trust of financial markets in the European Monetary Union and the well-established view that the default of a sovereign member of the Euro-area is an impossible event.

Motivated by these considerations, in this paper we turn on the microscope on the comovement between the European sovereign and bank credit crisis and analyse it empirically. The underlying idea is that the establishment of an econometric relationship between these two phenomena can be of help to understand the economics behind them.

The link between the European sovereign and banking credit risk has received growing attention in the recent literature. The papers closer to ours are Gerlach et al. (2010) and Ejsing and Lemke (2009). However, while these works perform a country-by-country analysis by using panel-data techniques, we differentiate by adopting a portfolio credit risk perspective. In fact, following the methodologies designed by Avesani et al. (2006) and Gibson (2004) for portfolio credit risk models and CDO (Collateralized Debt Obligation) pricing, we construct two synthetic credit risk indicators related to the European Monetary Union: the first one concerns the sovereign sector, while the second one concerns the banking sector. In order to form these indicators, we put 11 Euro-area sovereign entities and 20 Euro-area main banks into two separated baskets of credit default swaps[2] (CDS) and use this type of financial instrument as a tool to compute default probabilities. Preliminary to this, we first carry out a principal component analysis of the correlation matrix of the changes of the sovereign and bank credit spreads. Then, we model CDS premia[3] changes through factor analysis, which provides the inputs that are necessary to the calculation of the two credit risk measures.

Our *aggregate* perspective allows us to decrease the level of noise that characterizes single-country time series and to work with two unique measures at the European level of sovereign and bank credit risk as perceived by financial markets. In this respect our work contributes to the literature concerning financial stability and macro-

[1] E.g. low economic growth, fiscal deficits, ageing of the population, unemployment and the lack of coordination in fiscal policies.

[2] See the empirical section for a description of the credit default swap baskets.

[3] Following a convention arising from the credit risk literature, in this paper we use the terms "credit spreads" and "CDS premia" as synonyms.

prudential banking supervision. In fact, our indicator of risk of the banking sector can be used by financial authorities to monitor the level of risk of the European banking system. Moreover, we are among the first to extend the macro-prudential approach, traditionally limited to the supervision of financial institutions, to the supervision of European sovereign entities. In fact, the latest events concerning the Greek sovereign crisis[4] show that financial stability can be seriously affected by the risk of default of a European country and as a consequence we argue that a *thermometer* of the likelihood of such event can be a useful tool for vigilance.

Next, we analyse the inter-linkages between the European sovereign and bank credit risk measures through a Vector error-correction model (VECM). In particular, following a preliminary specification analysis, we test and find evidence of the hypothesis that a combination of the two risk measures is stationary. This allows us to conclude that the European sovereign and bank credit risk are cointegrated and share a common stochastic trend. In other terms, this means that an equilibrium relationship has characterised them over the period 2008-2010.
Finally, we perform standard impulse response functions analysis. We find that it is possible to distinguish between a *permanent* sovereign shock and a *transitory* banking shock. These findings may be used to draw policy-implications aimed to stop contagion.

The paper will be organised as follows. In section 2 we describe our dataset, while in section 3 we give details about our empirical analysis. Section 4 provides final remarks and concludes.

II. DATA

The source of our dataset is Reuters Datastream. We collect daily 5-years senior CDS bid and ask premia for 11 European sovereign entities and 20 European banks from 14/5/2008 to 30/09/2010. More specifically, we focus on 11 European countries which are part of the European Union at 12 members (Luxembourg is excluded) and on 20 banks which are domiciliated in these countries. The group of banks is formed

[4]Or more in general the worries related to the financial situation of the GIIPS (Greece, Ireland, Italy, Portugal and Spain) countries.

by taking 2 banks for each country (with the exception of Finland). The banks are chosen according to data availability (see Table 1 for the entire list) and all the financial institutions of our sample are among those stress-tested by the European Banking Authority (EBA) in July 2010. Descriptive statistics of the sovereign and bank CDS premia are shown, respectively, in Table 2 and Table 3, while their patterns are shown in Figure 2 and 3. The behaviour of the CDS premia reflect the market perception of higher default-risk for both European sovereign entities and banks. By looking at the graphs it is evident that the cost of insurance against default has risen dramatically over the last two years, with Ireland and Greece particularly hit both at a financial institutions and at a country level.

Although there is a widespread agreement that the current financial turmoil gets back at least to summer 2007[5], our sample still covers - at the moment of writing - the most important events like the collapse of Lehman Brothers (15 of September 2008), the massive intervention of the Federal Reserve authorities with the TARP[6], the rescue package to the European banking sector implemented by European governments (begin of October 2008) and the Greek sovereign debt crisis culminated with the joint intervention of the IMF and the European Union (May 2010). While on the one hand it would be very interesting to study the comovement between the European sovereign and bank credit risk before the beginning of the financial crisis, on the other hand by focusing on a shorter sample period we are able to work with data of better quality. In fact, the time series of European sovereign and bank CDS are very often characterised by interruptions due to, for instance, lack of trading and/or to liquidity issues. This has been one of the main reasons that has prevented the use of CDS in empirical research concerning the Euro area. Another reason is that, at least until the current financial turmoil, the risk of default of a country or a bank in the 12-members Euro area was considered an extremely unlikely event.

As a consequence, since it focuses on a relatively short time horizon for which good times series are available, this is one of the first studies about European sovereign and bank credit risk that can benefit of the informative content of CDS data.

[5]E.g. when we have assisted to the worsening of the sub-prime crisis.

[6]Troubled Asset Relief Program.

III. EMPIRICAL ANALYSIS

Factor Analysis

The starting point of our study is a principal components analysis of the correlation matrix of the daily changes of 5-years CDS premia[7] of Euro area sovereign entities and banks. Results of the principal components analysis are shown in Table 4.

Our results are consistent with previous studies (Longstaff et al. 2011, Hawkesby et al. 2005, 2007) which obtain evidence of a strong degree of commonality both in the sovereign and bank credit spreads. This is very interesting because these papers concentrate on different groups of sovereign entities and banks. In particular, the study by Longstaff et al. (2010) focuses on a large group of developed and less-developed countries (without considering any of the European countries that are in our sample), while the papers by Hawkesby et al. (2005), (2007), focus mainly on large and complex financial institutions. In our case the first PC explains about 67% and 57% of the variation in EU sovereign and bank CDS premia, respectively. This should not be surprising since the evidence of a high degree of commonality is not a new feature of financial markets, especially during crises. In fact, as noted among others by Ang and Bekaert (2002), correlations tend to increase during these periods.

The second step of our analysis is the modelling of CDS premia changes through factor analysis. As noted by Johnson and Wichern (2008), factor analysis is a statistical technique that aims to describe, whenever it is possible, the rich covariance structure which may exist among many variables in terms of a few underlying random quantities called *factors*. In this sense factor analysis is particularly indicated for our study since it allows us to get a proxy of the copula default correlation matrices among the sovereign entities and among the banks. More specifically, we express the CDS premia changes in terms of a basic factor model of the form:

$$X = \mu + AF + U \qquad F \sim N(0, I) \qquad U \sim N(0, \Psi) \tag{1}$$

where X is a vector of observed CDS premia changes, μ is a vector of intercepts, A is a factor loadings matrix, F is a common latent factor (which is usually interpreted as a *level* factor describing business cycle conditions), U is the error term and Ψ is the

[7] We take the mean between the bid and ask CDS premia.

variance-covariance matrix (assumed to be diagonal) of the error term.

We first estimate the model in equation (1) through Maximum Likelihood (ML) for the countries in our sample, and then we repeat the same exercise for the banks. In both cases, the estimation is performed using rolling windows of 65 days. For each rolling window we store the estimated factor loadings and the estimates of the common factor (i.e. the factor score), thereby obtaining a set of inputs that - as it will be clear in the next section - are needed for the construction of our synthetic risk measures. It is worth stressing here that if, on the one hand, one could argue that the CDS premia changes could be expressed by M common factors (with M >1), on the other hand the findings from the principal component analysis show that by limiting to a single common factor we can get still an acceptable proxy of the correlation matrix among the variables in X. This is very important because the working-assumption of one common factor (that is nevertheless very common also among practitioners) eases the speed of computation and the implementation of our procedure.

The construction of the two credit risk measures

To construct our credit risk measures we focus on the informative content of a particular financial instrument, the n^{th}-to-default CDS basket. The CDS basket can be thought as a simple kind of insurance in which the seller of protection (investor) provides the protection buyer with a pay-off just when the specific event (i.e. the n^{th} default) has taken place. By adopting a portfolio risk management perspective, we form two baskets of CDS, one for the sovereign entities and one for the banks, and use their informative content to compute default probabilities by implementing the methodology proposed by Gibson (2004) and Avesani et al. (2006). In the following, we briefly describe this methodology and provide its main intuitions deferring to those papers for more details.

As initial step to construct the two risk measures, we compute the conditional probability of default for each sovereign entity/bank in our sample according to

$$Pr\{x_i < \bar{x}_i | M\} = Pr(Z_i < \frac{\bar{x}_i - a_i M}{\sqrt{1 - a_i^2}}) \tag{2}$$

where M is a common factor, Z_i is an idiosyncratic factor, a_i are factor loadings and

$$x_i = a_i M + Z_i \sqrt{1 - a_i^2} \tag{3}$$

Eq.2 and Eq.3 imply that each sovereign entity/bank is assumed to default whenever $x_i < \bar{x}_i$, i.e when the value of the assets (x_i) falls below a certain threshold ($\bar{x}_i$). This approach is fairly standard in the portfolio credit risk literature (see Merton 1974 and Vasicek 1987) and it is usually applied to financial institutions or listed firms rather than to sovereign entities. However, there exists a new strand in the literature about sovereign credit risk (see, among the others, Gray et al. 2007) which advocates for the application of portfolio credit risk techniques to sovereign entities, thereby providing support to our strategy. At this point it should be clear how factor analysis provides us the *ingredients* needed in Eq.2 and Eq.3. In fact, we can use the factor score as an estimate of the common factor M and the ML estimates of factor loadings as a proxy for the true ones.

Next, we compute the unconditional probabilities of observing n defaults by time t among the N reference entities in the CDS basket as

$$p^N(n,t) = \int_{-\infty}^{\infty} p^N(n,t \mid M) g(M) dM \tag{4}$$

where $g(M)$ is the probability density of M (the common factor), N is the number of reference entities in the CDS basket and n is the number of defaults. The individual conditional probabilities of default that are calculated in Eq.2 are used in Eq.4 to compute, through a recursive formula (see Gibson 2004 and Avesani et al. 2006), the conditional probabilities of default in the CDS basket, i.e. $p^N(n,t \mid M)$.

The outcome of Eq.4 is the object of our ultimate interest and, intuitively, we can think about the two CDS baskets just as two machines that allow us to compute default probabilities at an aggregate level. In fact, by using Eq.4, we can calculate the two-years ahead probabilities of observing one default in the two groups of European countries and banks and use them as *synthetic indicators of credit risk*. The time-series of the default probabilities are shown in Fig.4. As it possible to see, for the most of our sample, the credit risk associated to the European banking sector is higher than the credit risk of the European sovereign sector. However, the two indicators intersect during the uprising of the Greek sovereign crisis (May 2010).

It is worth noting that to construct the credit risk measures we could have computed (and used) different probabilities either in terms of the number of defaults in the CDS basket or in terms of time-horizon[8]. The rationale behind our choice of focusing on the

[8] While on the one hand this choice can affect the magnitude of the risk measures, on the other

two-years ahead probabilities of one default is twofold. First, we argue that a single default (or the risk of a single default) of a European sovereign entity or a bank can be enough to undermine the trust that financial markets have in the European Monetary Union or in the very connected banking sector. Second, we think that two years represent a good horizon for monitoring and vigilance purposes. Hence, we claim that the risk indicators could be inserted among the set of instruments for macro-prudential supervision of the European sovereign and banking sector with the caveat that they should be used more as *thermometers* of distress rather than as pure forecasting-tools.

As a by-product of our approach, we are able to produce another possible tool for supervisory purposes, namely a term structure of default probabilities for both the European sovereign and banking sector. These term structures are computed by joining unconditional probabilities that differ in terms of time-horizons and number of defaults in the CDS basket. For instance, in Fig.5 and in Fig.6, we show these two term structures as measured at 30/09/2010. By comparing them, it is interesting to note that the financial markets perceive the risk of contagion in the banking sector higher than in the sovereign sector. In fact, at the 20-quarter ahead horizon, while in the European banking sector the most likely event is the occurring of 2 defaults (green line), in the sovereign sector the most likely event is the occurring of 0 default (blue line).

It is important to point out that the source of contagion in our framework is given by the exposure of the reference entities in the CDS baskets towards the common factor. In other words, since we rely on the Vasicek approach, any kind of inter-dependence among defaults that goes beyond the common factor cannot be captured. However, we believe that this feature does not limit too much our study given the high degree of commonality that we find in the data.

It is also worth to stress that these term structures of default probabilities are sensitive to the day in which they are computed. For instance, if we had computed them in the middle of the Greek sovereign crisis (i.e. end of April - begin of May 2010) we could have end-up with a different evidence suggesting a higher risk of contagion in the European sovereign sector. However, this aspect increases the importance of

hand it does not affect the quality of our results. In fact, there is no reason to believe that, *ceteris paribus*, the degree of observed comovement between the sovereign and bank credit risk will change.

calculating term structures of default probabilities since they represent a useful tool, available on a daily basis, to measure financial market sentiments about the likelihood of multiple defaults.

Vector error correction model

The visual inspection of Fig.4 evidences that in the last 2 years there has been a strong comovement between sovereign and bank credit risk in the Euro area and that the two time series could share a common-stochastic trend. In order to test this hypothesis we model our two synthetic risk indicators jointly in a bivariate VECM:

$$\Gamma(L)\Delta y_t = \delta_0 + \alpha\beta' y_{t-1} + \delta_1 D_t + u_t \tag{5}$$

where the vector Δy_t contains the first difference of the sovereign credit risk measure and the first difference of the bank credit risk measure, L is the lag operator, $\alpha\beta' y_{t-1}$ is the error-correction term, $\delta_1 D_t$ is a *crash*-dummies term whose meaning will be explained later in this section and u_t represent the structural shocks.

Specification Analysis

Before estimating the VECM model, we determine the lag-order of the system according to standard model selection procedures (AIC, FPE, SC, HQ and FML). While the AIC and the FPE suggest the inclusion of at least 9 lags (see Table 5), the SC, the FML and the HQ criteria provide evidence for a more parsimonious system (3 lags from the SC and the FML criteria, 7 lags from the HQ criterion). Among these possibilities, we choose to follow the HQ (Hannan-Quinn) information criterion. In fact, if on the one hand it is always good to save some degrees of freedom, on the other hand we must pay attention to the risk of choosing a too small lag order since this can produce a biased estimate of the cointegration vector (see Jacobson, 1995). Hence, in our case, the HQ criterion seems to be a good compromise among the different alternatives.

Next, we estimate the model in Eq.5 and perform residuals analysis. This is very important since the analysis of the residuals can be used to point out possible miss-specifications of model. Moreover, residuals that are too far from the NIID (Normally, Independently and Identically Distributed) hypothesis may invalidate any inference obtained through OLS estimation of the VECM system. Given that our sample covers an extremely turbulent period characterised by big market over-reactions, we insert in our model a group of *crash*-dummies that aim to mild the effects of the most dramatic days. This is reflected by the term $\delta_1 D_t$ in Eq.5. Overall, we end up with 23 *crash*-dummies associated with those days in which important events[9] have taken place. The asymptotic and bootstrapped[10] tests for serial correlation are shown in Table 6. The histogram of the residuals are plotted in Figure 7 together with some descriptive statistics and the results of the Jarque-Bera test. Both the distributions of the residuals are characterised by high kurtosis and positive skewness. The Jarque-Bera tests reject the null hypothesis of normality, while according to Table 6 there is evidence of serial correlation at one lag level. Although these evidences are disappointing, it is worth to remind that we work with high-frequency financial variables. Thus, the behaviour of the residuals may be a consequence of this factor rather than of model miss-specification. The shapes of the histogram, in fact, do not contradict entirely the hypothesis of normality and it is very likely that by introducing more dummies we would end up with well-shaped residuals. However, we prefer not to over-fit our model with too many dummies and we argue that by working with 23 dummies out of 556 observations we can still safely estimate the model of Eq.5 by OLS.

Cointegration rank, cointegration relation, shocks identification and impulse response functions

The aim of this sub-section is to test for the cointegration relationship between the sovereign and the bank credit risk measures and, in case of supportive evidence, to get some economic intuitions about it. In order to find empirical evidence about our hypothesis, we rely on the LR trace test. The asymptotic and bootstrapped quantiles of the test are shown in Table 7. Overall, both the tests allow us to reject the null hypothesis of $r = 0$ and, conversely, to accept the null of $r = 1$, where r is the cointegrating rank. Asymptotically, we reject the null hypothesis of no cointegration and, viceversa, accept the null hypothesis of one cointegrating vector at the 5% confidence level. Using the bootstrapped distribution, we can reject the null of no cointegration at the 5% confidence level, while we can still safely accept the null hypothesis of existence of a cointegrating vector.

The existence of a cointegration relationship between the sovereign and the bank credit risk over the last two years allows us to go one step further in the investigation

[9] Like, for instance, the collapse of Lehman Brothers or the Greek debt crisis.

[10] In all our bootstrap simulations we use 1000 replications.

of the observed comovement. We do that in two ways. First, we test for a restriction on the cointegrating vector and examine the cointegration relationship more in depth, second we perform standard impulse response analysis in order to evaluate the effect of shocks on our synthetic risk measures. The restriction on the cointegrating vector that we test is $\beta' = (1\ \text{-}1)$. We show asymptotic and bootstrapped quantiles of the test in Table 8. Both the asymptotic and the bootstrapped inference imply that the restriction is binding. This reinforces the statement that the sovereign and the bank credit risk have been characterised by an equilibrium relationship during the current financial turmoil. The cointegration relationship is plotted in Figure 8. The economic interpretation of this equilibrium is tricky since there is no well-established theory that can guide us[11]. However, it is very interesting to examine how each variable in the system relates to the equilibrium and, in particular, how (and if) the risk measures work in order to restore it. As a preliminary step, we examine the estimated *speed of adjustment* coefficients in Eq.5, i.e. the element of the α vector. While this coefficient is close to zero and not significant for the sovereign credit risk measure, we find a positive and significant *speed of adjustment* coefficient for the bank credit risk measure[12]. Intuitively, this means that the restoring of the equilibrium relationship comes from the banking sector side. In order to stress this feature, in Figure 9 we show scatter plots of the changes of the sovereign and bank credit risk measures versus the cointegration relationship and we add in each plot a regression line. The graph shows that the slope of the regression line is almost zero for the sovereign sector case while the regression line is upward sloping for the bank credit risk. This means that, on average, when the error term of the cointegration relationship is positive, we observe an increase in the risk measure of the banking sector, while this does not hold for the sovereign sector. We interpret this as an evidence of the *leadership* of the sovereign credit risk in the sense that it drives the bank credit risk, at least at the aggregate

[11] The economic interpretation of the cointegration relationship can be an interesting topic of research for another paper. In particular, it would be nice to understand what the common stochastic trend shared by the two risk measures really represents. One interpretation is that it represents a liquidity shock affecting the Euro-area during the financial turmoil and/or a sudden increase in investors' risk aversion.

[12] The estimated coefficients are: 0.0003(0.06) and 0.023(3.36), respectively. T-statistics are in parenthesis.

level.

The last step of our empirical analysis concerns how shocks can influence the risk measures trough the examination of the impulse response functions that we get by imposing the restriction on the cointegrating vector. In order to identify the shocks, we distinguish between a *permanent* sovereign sector shock and a *transitory* banking sector shock. Thus, following the approach designed by Cochrane (1994) in his study about permanent and transitory components of GNP, we orthogonalize the VECM error terms such that the sovereign sector credit risk indicator does not respond contemporaneously to a banking sector credit risk shock.
Impulse response functions at 60-days ahead horizon are shown in Figure 10 jointly with 95% confidence bands. The results support our conjecture about the predominant role of the sovereign sector credit risk and our identification strategy. As intuition would suggest, all the shocks produce an increase in the risk measures. Moreover, the magnitude of the responses confirm the predominance of the sovereign sector as the shocks to the sovereign credit risk measure have a dramatic impact both on the sovereign sector itself but also on the banking sector, especially at the long-horizon. Viceversa, the shocks on the bank credit risk measure affect the sovereign sector but their impact is weaker.

IV. CONCLUSIONS

We construct two synthetic measures of sovereign and bank credit risk for the Euro area over the period 2008-2010. These measures could be used by vigilance and regulatory authorities as *thermometers* of Euro-area distress according to a macro-prudential perspective. We calculate the term structures of default-probabilities and show how these can be used to get a daily measure of contagion-effect inside the European sovereign and banking sectors. In fact, they represent a useful tool, available on a daily basis, to measure financial market sentiments about the likelihood of multiple defaults. We analyze the degree of comovement between sovereign and banking credit risk and we find evidence of a cointegration relationship. Moreover, shocks to the sovereign credit risk measure have, overall, a large impact not only to the sovereign credit risk measure itself but also on the bank credit risk indicator as the analysis of

the impulse response functions suggests.
Our results look compatible to what we observed (and to what we are still observing) during the financial turmoil and they can be useful to get a better understanding of the European sovereign and bank credit crisis.

First, the evidence of a cointegration relationship provides empirical confirmation of the strong nexus that exists between the European sovereign and banking sector in terms of credit risk.

Second, the evidence of a sort of *leadership* of the sovereign sector may have important policy implications. In fact, our empirical exercise suggests the existence of an equilibrium relationship between the European sovereign and banking sector. While it is difficult to attach a clear economic meaning to this equilibrium relationship, its dynamic is intuitively appealing since it shows that it is the banking sector that has to move to re-establish deviation from the equilibrium. In terms of policy implications, this underlines the importance of fixing the European banking sector to contain the credit risk attached to the sovereign sector and, as a consequence, stresses the need of implementing measures that facilitate the re-capitalisation of European banks and that may increase the level of liquidity into the banking system.

The analysis of the impulse response functions can be used as well to get some policy guidelines. First, they point out that shocks that affect the sovereign sector can have a larger long-horizon impact on the banking sector than shocks to the banking sector itself. This evidence reinforces the view that European financial authorities should monitor very carefully the evolution of the current crisis to prevent the dramatic consequences that a negative loop that goes from the banks to the sovereign entities and then goes back to the banking sector may have. Second, the magnitude of the effects that the shocks to the sovereign credit risk measure have on the sovereign risk measure itself calls for an intervention also at sovereign entities-level in order to limit the possibility of contagion among them. In other terms, our results provide also a clear support to policies that aim to contain and reduce Euro-area governments budget deficits. In fact, these policies could strengthen the position of the most indebted countries and help them to absorb negative spill-over effects arising from the banking sector or from other sovereign entities.

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Table 1: List of Banks

Bank	Country
ERSTE	Austria
RAIFFEISSEN	”
KBC	Belgium
DEXIA	”
BNP PARIBAS	France
CREDIT AGRICOLE	”
DEUTSCHE BANK	Germany
COMMERZBANK	”
EFG (from 09/09/2009)	Greece
ALPHA BANK (”)	”
ANGLO-IRISH	Ireland
ALLIED IRISH BANKS	”
UNICREDIT	Italy
INTESA SANPAOLO	”
FORTIS	Netherlands
ING BANK	”
BANCO COMERCIAL PORTUGUES	Portugal
BANCO ESPIRITO SANTO	”
BANCO SANTANDER	Spain
BBVA	”

Table 2: Descriptive Statistics for Sovereign Credit Default Swaps Premia

	Mean	Standard Deviation	Minimum	Median	Maximum
Austria	81.97	50.28	7.00	78.85	273.00
Belgium	66.91	37.72	14.80	57.99	157.75
Germany	32.89	17.51	5.10	33.50	91.85
Finland	31.26	17.55	6.50	28.43	93.92
France	44.10	24.34	6.90	40.56	99.97
Greece	291.27	264.57	35.10	179.31	1125.81
Ireland	174.00	95.62	17.50	163.43	489.77
Italy	113.31	53.42	25.10	107.20	244.70
Netherlands	44.25	27.64	6.70	38.95	131.00
Spain	111.06	62.41	24.20	97.12	274.58
Portugal	125.04	98.30	24.90	83.17	461.32

Notes: The table reports descriptive statistics for daily 5-year sovereign CDS contracts for the period 14/08/2008 - 30/09/2010. The descriptive statistics concern the mean between the bid and the ask CDS premia.

Table 3: Descriptive Statistics for Bank Credit Default Swaps Premia

	Mean	Standard Deviation	Minimum	Median	Maximum
Erste	180.46	75.96	75.00	160.00	487.13
Raiffesen	205.06	89.32	70.90	180.04	535.00
KBC	165.90	71.73	54.80	145.05	343.30
Dexia	254.32	81.87	75.50	239.15	550.00
BNP	75.72	22.86	34.50	69.27	155.38
Credit A.	100.38	28.42	56.20	90.90	237.81
Deutsche	105.69	27.33	56.30	101.04	187.95
Commerzbank	91.04	23.85	52.79	85.20	170.52
EFG	515.60	274.34	149.61	444.30	1236.70
Alpha B	514.90	279.51	139.60	440.78	1048.80
Anglo I.	451.03	173.78	153.70	412.30	959.04
Allied I.	284.81	138.95	82.50	253.72	646.72
Unicredit	115.00	40.72	43.50	109.95	278.74
Intesa S.	87.13	35.98	32.50	75.17	200.00
Fortis	94.37	45.26	48.88	82.01	666.70
ING	95.42	28.35	47.50	88.25	188.30
BCP	162.89	117.96	53.50	105.49	572.28
BES	185.61	128.96	60.00	126.04	635.58
Santander	111.96	39.61	43.70	98.65	260.51
BBVA	117.96	51.34	44.80	97.59	295.16

Notes: The table reports descriptive statistics for daily 5-year banks CDS contracts for the period 14/08/2008 - 30/09/2010. The descriptive statistics concern the mean between the bid and the ask CDS premia. Figures of EFG and Alpha Bank are related to the period 09/09/2009 - 30/09/2010.

Table 4: Principal component analysis

	Sovereign		**Bank**	
Principal Component	Percent Explained	Total	Percent Explained	Total
First	66.53	66.53	56.88	56.88
Second	12.37	78.90	8.29	65.17
Third	4.22	83.12	6.55	71.72
Forth	3.24	86.36	6.13	77.85
Fifth	2.88	89.24	4.88	82.73

Notes: The table report results of the Principal Component (PC) analysis of the correlation matrices of the changes of the sovereign and bank CDS premia, respectively. Since CDS premia of EFG and Alpha Bank are available for a shorter time-horizon, we have excluded them by the PC analysis.

Table 5: Lag-order selection

Lags	Rank	AIC	log(FPE)	HQ	SC	FML
1	2	-21.1658	-21.1656	-21.0032	-20.7502	-31.1853
1	1	-21.1661	-21.1659	-21.0097	-20.7664	-31.2047
1	0	-21.1114	-21.1113	-20.9676	-20.7437	-31.1805
2	2	-21.2400	-21.2398	-21.0649	-20.7924	-31.2274
2	1	-21.2386	-21.2384	-21.0697	-20.8070	-31.2450
2	0	-21.2075	-21.2074	-21.0512	-20.8079	-31.2444
3	2	-21.3187	-21.3184	-21.1311	-20.8391	-31.2739
3	1	-21.3168	-21.3166	-21.1354	-20.8532	-31.2910
3	0	-21.2996	-21.2995	-21.1308	**-20.8680***	**-31.3043***
4	2	-21.3236	-21.3233	-21.1235	-20.8121	-31.2467
4	1	-21.3221	-21.3218	-21.1282	-20.8265	-31.2642
4	0	-21.3073	-21.3071	-21.1260	-20.8438	-31.2799
5	2	-21.3558	-21.3555	-21.1432	-20.8123	-31.2468
5	1	-21.3560	-21.3557	-21.1496	-20.8285	-31.2660
5	0	-21.3377	-21.3375	-21.1439	-20.8422	-31.2781
6	2	-21.3748	-21.3744	-21.1497	-20.7994	-31.2338
6	1	-21.3739	-21.3736	-21.1551	-20.8145	-31.2519
6	0	-21.3566	-21.3563	-21.1502	-20.8290	-31.2648
7	2	-21.3961	-21.3957	-21.1585	-20.7887	-31.2231
7	1	-21.3927	-21.3922	**-21.1613***	-20.8012	-31.2385
7	0	-21.3763	-21.3759	-21.1574	-20.8168	-31.2524
8	2	-21.3933	-21.3928	-21.1432	-20.7539	-31.1883
8	1	-21.3906	-21.3901	-21.1467	-20.7672	-31.2045
8	0	-21.3749	-21.3745	-21.1435	-20.7834	-31.2190
9	2	**-21.4086***	**-21.4079***	-21.1459	-20.7372	-31.1715
9	1	-21.4049	-21.4043	-21.1485	-20.7495	-31.1868
9	0	-21.3943	-21.3938	-21.1504	-20.7709	-31.2065
10	2	-21.3968	-21.3961	-21.1216	-20.6934	-31.1278
10	1	-21.3929	-21.3922	-21.1240	-20.7055	-31.1429
10	0	-21.3824	-21.3818	-21.1260	-20.7270	-31.1626
11	2	-21.3930	-21.3922	-21.1053	-20.6577	-31.0922
11	1	-21.3891	-21.3883	-21.1077	-20.6697	-31.1071
11	0	-21.3793	-21.3786	-21.1103	-20.6919	-31.1275
12	2	-21.3944	-21.3934	-21.0942	-20.6270	-31.0617
12	1	-21.3901	-21.3892	-21.0961	-20.6387	-31.0762
12	0	-21.3831	-21.3823	-21.1017	-20.6638	-31.0995

Notes: The table reports result of the lag-order selection criteria. Minimum values are represented by an asterisk.

AIC: Akaike Information Criterion

FPE: Final Prediction Error

HQ: Hannan-Quinn Information Criterion

SC: Schwarz Information Criterion

FML: Fractional Marginal Likelihood Criterion

Table 6: Serial correlation tests

	Bootstrapped distribution						
Quantiles	80%	90%	95%	98%	99%	Mean	SD
r=0							
lag							
1	5.93	7.68	9.05	11.07	13.72	3.95	2.83
12	6.17	7.81	9.77	12.29	13.69	3.99	2.97
r=1							
lag							
1	5.61	7.47	9.42	12.23	13.54	3.91	2.90
12	6.04	7.93	9.70	11.04	12.69	3.96	2.80
	Chi-square						
	5.98	7.77	9.48	11.66	13.27	4	2.82

	Likelihood ratio	**Empirical p-values**	**Asymptotic p-values**
r=0			
lag			
1	LM(4)= 40.59	<0.01	<0.01
12	LM(4)=5.61	0.229	0.230
r=1			
lag			
1	LM(4)=40.76	0.011	<0.01
12	LM(4)=3.98	0.407	0.401

Notes: The table reports results of the asymptotic and bootstrapped serial correlation tests of the residuals of the VECM. We report results for residuals lag order=1 and lag order=12. LM is a Lagrange multiplier test asymptotically distributed as a χ^2 with n^2 degrees of freedom. r indicates the number of cointegration relations. n indicates the number of endogenous variables in the VECM.

Table 7: Cointegration test

	Asymptotic distribution						
Quantiles	80%	90%	95%	98%	99%	Mean	SD
n-r							
1	5.93	7.80	9.49	11.98	13.83	4.14	2.71
2	15.23	18.01	20.13	23.32	25.29	11.87	4.44
	Bootstrapped distribution						
Quantiles	80%	90%	95%	98%	99%	Mean	SD
n-r							
1	5.36	6.83	8.44	9.76	10.96	3.40	2.51
2	13.77	16.06	19.29	22.83	25.75	10.21	4.74

Likelihood ratio	Empirical p-value	Asymptotic p-value
LR(r=0)=22.41	0.02	0.02
LR(r=1)=7.19	0.09	0.13

Notes: The table reports results of the asymptotic and bootstrapped cointegration tests. The empirical distributions are obtained using a parametric bootstrap procedure. r indicates the number of cointegration relations. n indicates the number of endogenous variables in the VECM.

Table 8: Restriction test on the cointegration vector

Quantiles	80%	90%	95%	98%	99%	Mean	SD
Bootstrap	2.67	4.33	5.93	8.61	10.82	1.62	2.20
Chi-square	1.64	2.71	3.84	5.41	6.63	1.00	1.41
Likelihood ratio	**Emp. p-val.**	**Asym. p-val.**					
LR(1)=3.21	0.17	0.07					

Notes: The table reports results of the asymptotic and bootstrapped tests of a restriction on the cointegration vector. The empirical distributions are obtained using a parametric bootstrap procedure.

Figure 1: Ratio between banking sector assets and GDP (source: Eurostat)

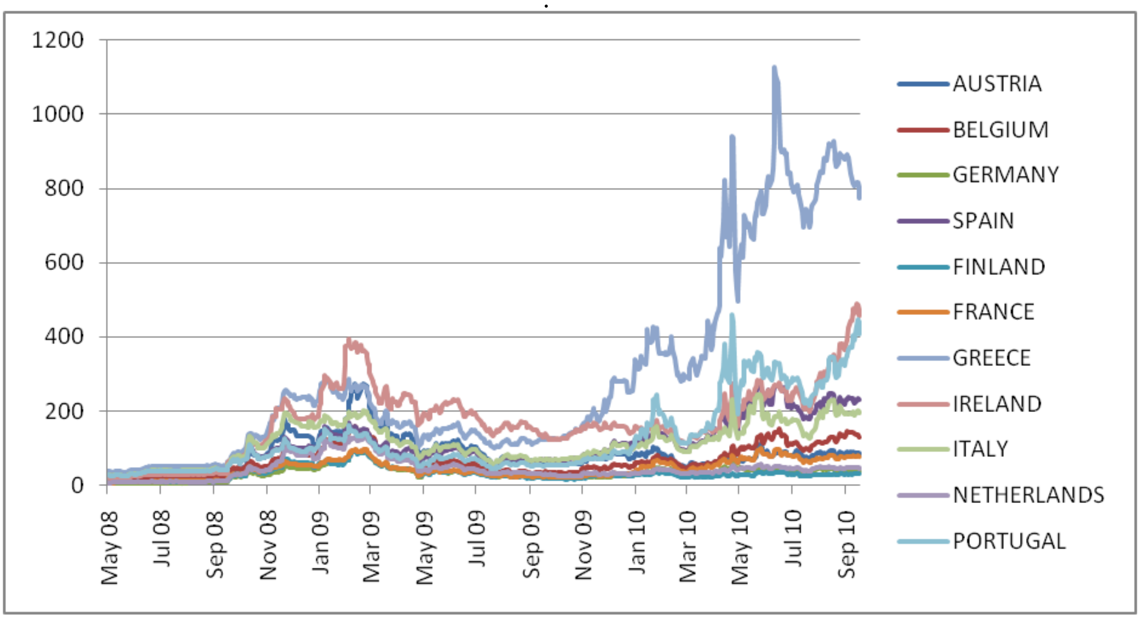

Figure 2: Sovereign CDS premia (source: Reuters Datastream)

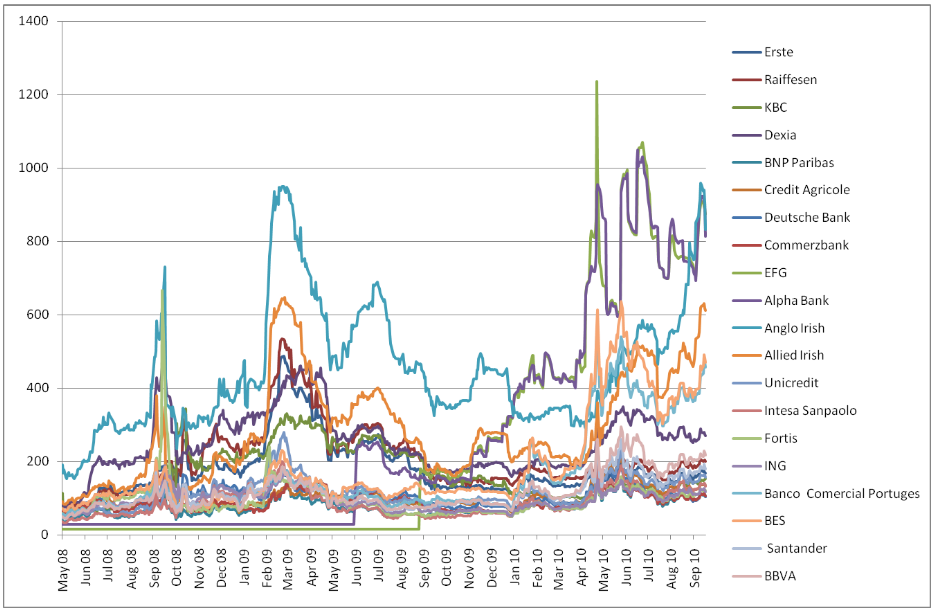

Figure 3: Banks CDS premia (source: Reuters Datastream)

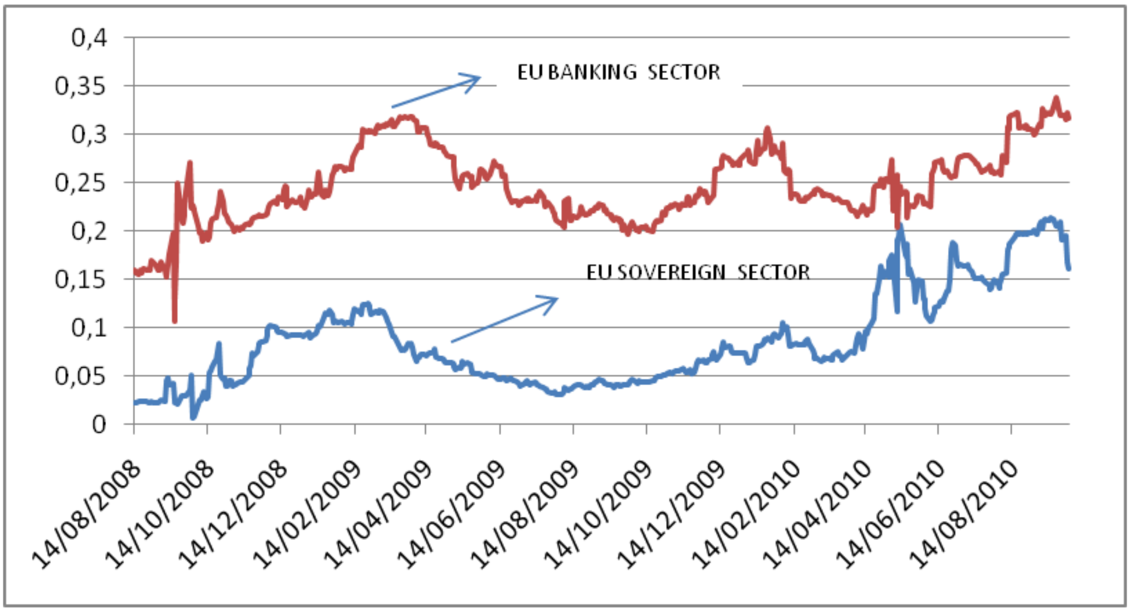

Figure 4: 2-years-ahead probabilities of 1 default: **European sovereign sector credit risk vs European banking sector credit risk**

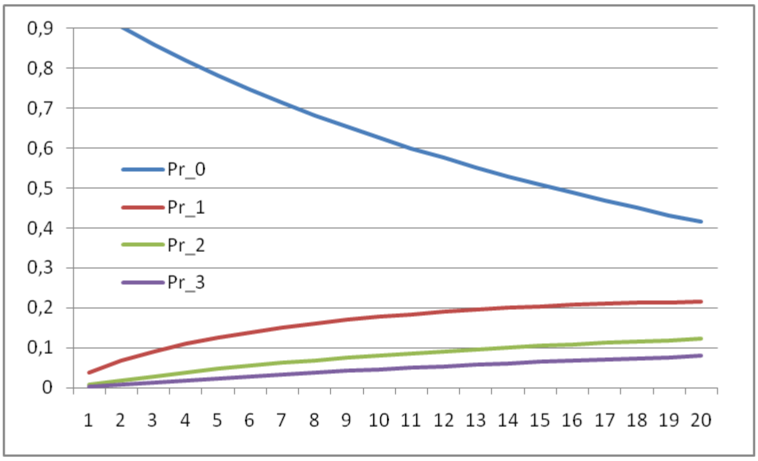

Figure 5: 1 to 20 quarters ahead term structure of default probabilities: **European sovereign sector**

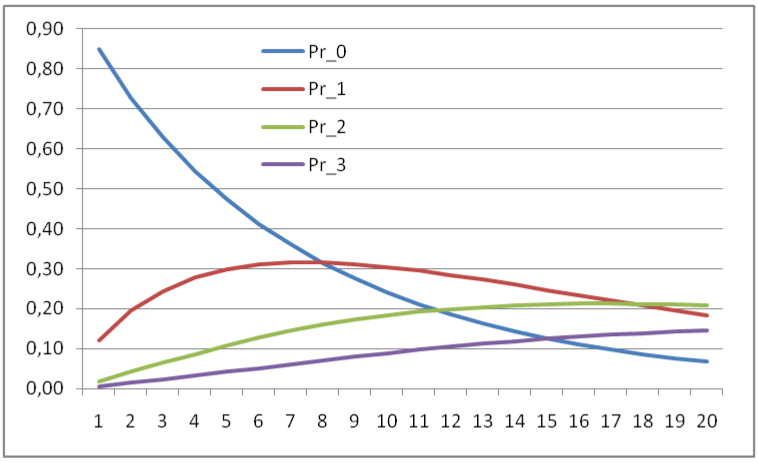

Figure 6: 1 to 20 quarters ahead term structure of default probabilities: **European banking sector**

Notes:

Pr_0 = Probability of observing 0 default in the CDS basket

Pr_1 = " 1 default "

Pr_2 = " 2 defaults "

Pr_3 = " 3 defaults "

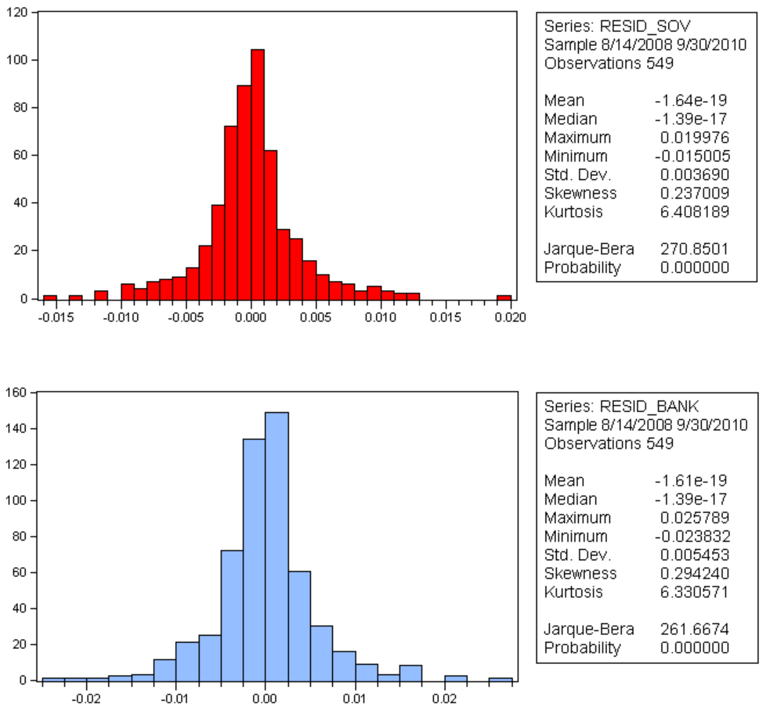

Figure 7: VECM residuals

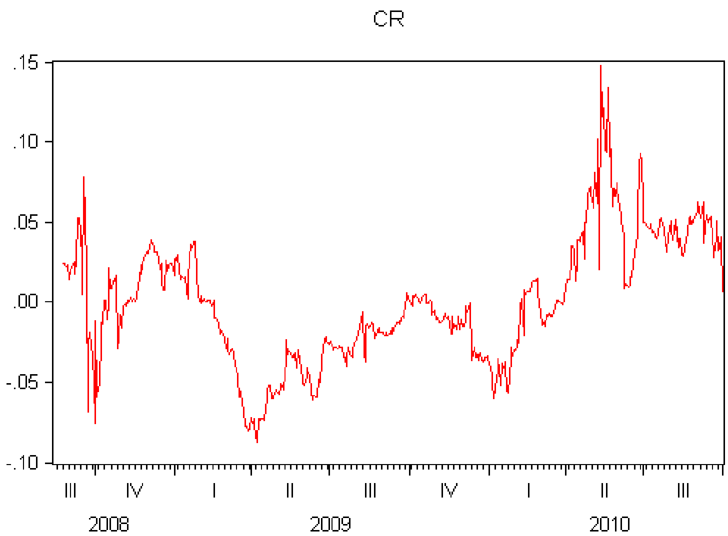

Figure 8: Cointegration relationship between the European sovereign and bank credit risk

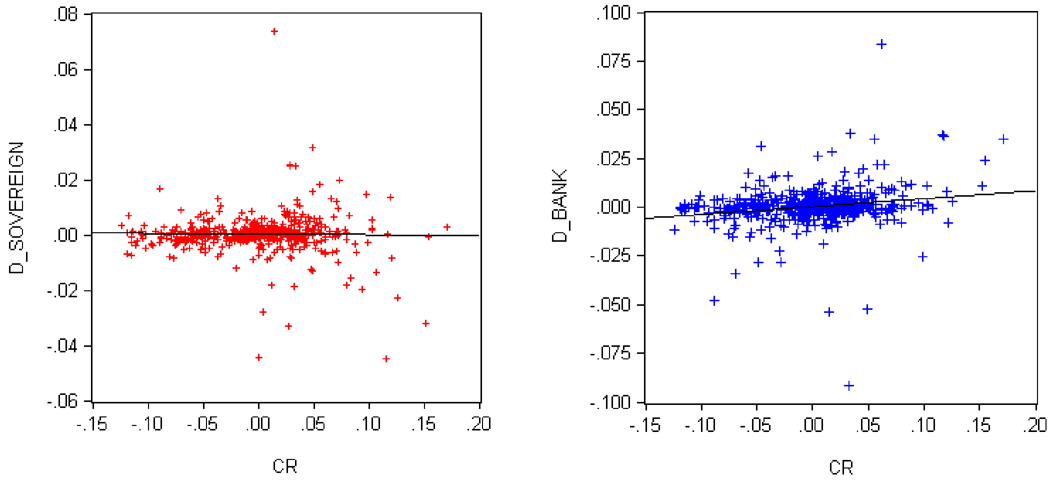

Figure 9: Changes in sovereign and bank credit risk measures vs cointegration relationship (CR)

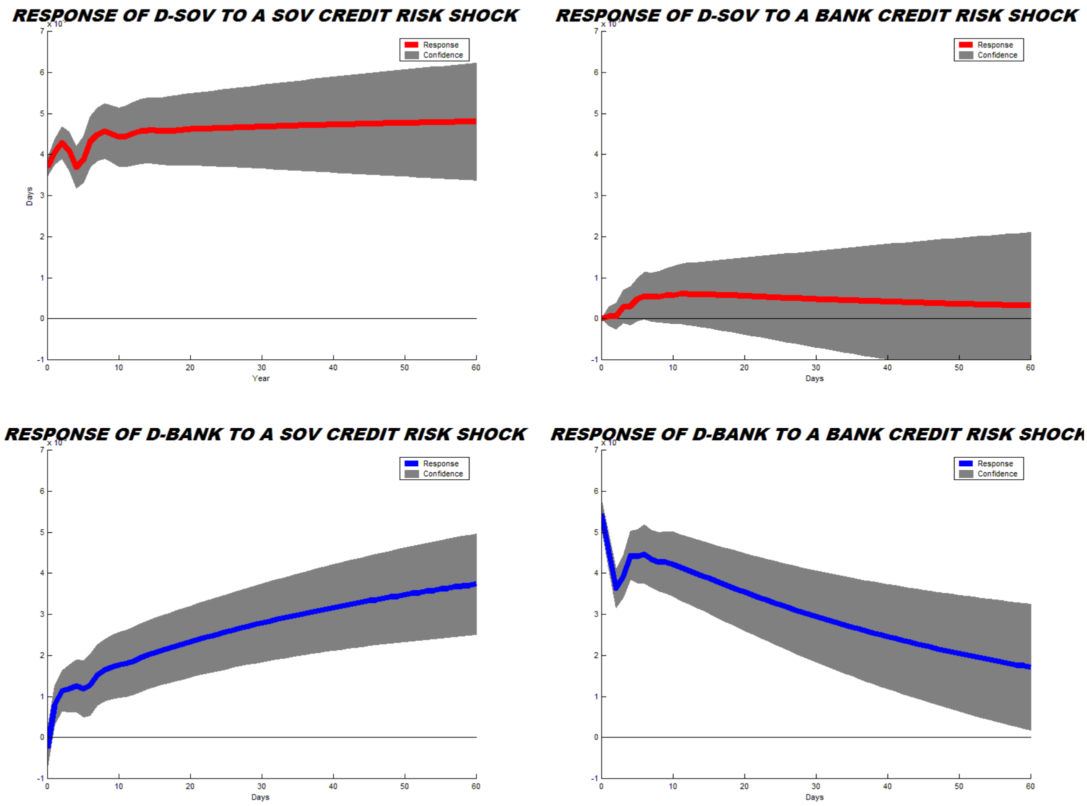

Figure 10: Impulse response functions with 95% confidence bands: 0 to 60 days-ahead