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Can Bank be a Cause of Contagion during the Global Financial Crisis?

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ABSTRACT: This paper examines whether the bank can be a cause of contagion during the global financial crisis. This paper utilizes a Dynamic Conditional Correlation Model to examine the financial contagion phenomenon following the recent financial crisis. This model, which is already developed by Engle (2002) as a novel specification of multivariate models' conditional correlations, allows tracking the correlation progress between two assets. Our sample consists of six developed countries, including the American market where the crisis started. Data frequencies are on a weekly basis reflecting between the period January 2006 and December 2011. Overall, the empirical evidence indicates that the past return shocks emanating from the banking sector have a significant impact not only on aggregate stock markets, but also on their prices, suggesting that bank can be a major source of contagion during the crisis.

Keywords: Global crisis; International financial contagion; Multivariate GARCH-DCC.
JEL Classifications: F3; G14; G21

1. Introduction

It is well-known that the banking crisis cannot only generate substantial real costs for the country in which they occur, but also spill-over to new countries and aggravate the crisis. The global financial crisis of 2009 was largely unanticipated and characterized by sharp falls in the currency values and stock prices in some countries simultaneously. A number of complex factors triggered the financial crisis in Europe, other than, fundamentally, unbridled growth and subsequent contraction of the banking lending played a leading role. Kaminsky and Reinhart (2000) systematically study the links between banking and currency crisis and indicate that the problems in the banking sector typically precede a currency crisis. One of the biggest challenges facing the scholars studying the European financial crisis is to explain this contagion in which a crisis emanating from one country soon sweeps across all the countries of the region.

This financial contagion caused by the common bank lenders will not be measured as a ‘‘pure contagion effect’’ according to Masson (1998). Instead, it will be categorized as a ‘‘spill-over effect’’ caused by financial interdependence. However, the second type of financial contagion can be caused by the pure contagion effect because the contagion of financial crises is not due to financial interdependence and it cannot be explained by changes in the fundamentals.

The aim of this paper is to test whether bank can be a source of contagion during the 2008 European crisis using asset return data from a subprime crisis. In particular, we study whether the banking sector can produce contagious effects in conditional volatilities of its bank stock returns during the crisis. Previous studies on contagion failed to take into account the important distinction between the concepts of interdependence and contagion[2]. The dynamic correlation conditional test

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results show that contagion effects appear to be multidirectional since the return shocks emanating from the banking sector can sweep across all markets, but contagion in-volatility effects are mostly driven by the negative return shocks originating in the banking sector. This empirical finding indicates that not only can bank return shocks become contagious at volatility level, but can also become contagious at mean level, suggesting that the bank can be a major source of contagion during the crisis.

The crisis took a new dimension in the summer of 2007, when two hedge funds (investment funds) of the investment bank Bear Stern was unable to respond to requests for the depositor's withdrawal and the refuse of their creditors to roll over their credits. Although there is no equivalent subprime market in Europe, the European banks that had taken many positions on securities backed by subprime, were also affected. Two German banks, IKB Deutsche Industriebank and Landesbank Sachsen, owed their salvation to the credit lines made available by the German public bank (nearly 9 billion €) and a group of regional banks, Landesbanken (more than 17 billion €) (Okomito, 2008).

On August 10, 2007, BNP-Paribas, the largest bank in the eurozone, announced the temporary suspension of the calculation of net asset value of three funds consisting of the Asset Backed Securities (ABS), the collateralized loan portfolios, including mortgages - the Parvest Dynamics ABS, BNP-Paribas ABS Euribor and BNP-Paribas ABS Eonia. In September 2007, it was the turn of England to enter into turmoil. Northern Rock, the fifth English bank mortgage (77% of its assets were loans, half concerned individuals), began to have some difficulty to refine the markets. It had no choice but to turn to the Bank of England (BoE), which granted it an emergency funding. The American central banks, the European and the Japanese were largely brought to lend to commercial banks ($ 35 billion, respectively, 95 and 61 billion Euros in the form of a tender for three days; 1000 billion yen) to quickly restore trust among the financial players and save the financing of the economy (Guo et al, 2011).

The class of GARCH process is an appropriate response to address the characteristics of the volatility that cannot be taken into account by the "traditional" methods. Initially, this type of model is developed in a univariate framework. In fact, it leaves much room for the descriptive rather than the explanatory. The extension of this class of models in a multivariate framework has addressed the critical univariate models that are insufficient to justify the composition of the security portfolio. Indeed, financial theory postulates that the covariance between assets plays a crucial role in the decision making of the investors in their investment strategies. However, the univariate models remain essential in the choice of the bank stock return. Note, however, that the development of the multivariate GARCH led to the inflation of the parameters to be estimated.

They have therefore become difficult to use, if no additional constraint is imposed. Thus, different parameterization methods were developed two of which have been more successful than others. These are the methods proposed by Bollerslev (1990) and Engle (2002).

Bollerslev (1990) suggested adopting models where conditional correlations between the disturbances are constant over time (Constant Conditional Correlation). The advantage of this hypothesis is that it significantly reduces the number of parameters to be estimated in the class of multivariate GARCH models. Engle (2002) designed a new approach (the Dynamic Conditional Correlation) in two stages, where the correlations are dynamic. This new class of GARCH Multivariate models stands out for its simplicity in the sense that the univariate GARCH specifications are estimated for each series separately. The dynamic correlations are estimated in a second step, from standardized residuals in the first step.

The methodology is the so-called dynamic conditional correlations, developed by Engle. The main advantage of using the DCC-GARCH models is that the detection of plausible changes in the relationships between the variables remains the underlying studied data.

The remainder of the paper is organized as follows; Section 2 describes the econometric methodology applied to estimate the model. Section 3 describes the data and the empirical results. Some conclusions are presented in the final section.

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[2] Specifically, in this paper we define contagion as significant spillovers of asset-specific idiosyncratic shocks during the crisis after the economic fundamentals or systematic risks have been accounted for Forbes and Rigobon (2002).

2. Econometric Methodology

2.1. Detecting for structural breakpoint

We first adopt the ICSS algorithm of Inclan and Tiao (1994) to detect the structural breakpoints on stock and currency market of the six countries during study period. Next, a set of dummy variables is created in order to seize the normalized volatility of return.

Let the closing stock price at the end of the day be $\left(P_{i,t}\right)$ then the banks stock return $\left(r_{i,t}\right)$ for market i at day t is

$$r_{i,t} = \left(\log P_{it} - \log P_{it-1}\right) \times 100 \tag{2.1}$$

We define

$$a_{i,t} = r_{i,t} - \mu_i \tag{2.2}$$

$\left\{a_{i,t}\right\}$ is with zero mean and unconditional variable σ_t^2, μ_i denotes the average return of market i.

Let $C_k = \sum_{t=1}^{k} a_t^2, k = 1,...,T$ be the cumulative sums of squares of $\left\{a_t\right\}$ series, then D_k statistic can be calculated as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, k = 1,....,T and\ D_0 = D_T = 0 \tag{2.3}$$

The iterated cumulative sum of squares (ICSS) algorithm based on the statistic D_k to detect for multiple breaks in the unconditional variance of $\left\{a_{i,t}\right\}$ series. Thus, the ICSS algorithm based on the statistic D_k begins by testing for a structural break over the entire sample. If the ICSS detects a significant break, then the algorithm applies the new statistic to test for a break over each of the two sub-samples defined by the break. The algorithm proceeds in this manner until the statistic is insignificant for all of the sub-samples defined by any significant breaks; see Inclan and Tiao (1994) testing steps of the ICSS algorithm for more details.

2.2. Multivariate GARCH -DCC model

In this section, we present the two-stage model of the dynamic conditional correlations proposed by Engle (2002). For example, let's consider a vector consisting of any two variables $Y_t = \left[y_{1t} y_{2t}\right]'$. Each variable is a constant function and its own past values. Thus, the reduced form of the autoregressive process is written as:

$$A\left(L\right)Y_t = c + \varepsilon_t \text{ avec } \varepsilon_t \to N\left(0, H_t\right), \forall t = 1,2,...,T \tag{2.4}$$

Where $A\left(L\right)$ is the polynomial delay and $\varepsilon_t = \left[\varepsilon_{1t}\varepsilon_{2t}\right]'$ is a vector of residuals from the estimation auto regression process for each variable whose variance-covariance matrix is described by $H_t = \left\{h_i\right\}_t$ with $i = 1,2$.

The DCC-GARCH model can be easily apprehended by rewriting the matrix of variance-covariance H_t such as: $H_t = D_t R_t D_t$

where $D_t = diag\left\{\sqrt{h_{it}}\right\}$ is a diagonal matrix of the standard deviations temporally different variable from the estimation of the two previous equations in a process univariate GARCH; $R_t = \left\{\rho_{ij,t}\right\}$ which represents the matrix of the conditional correlation coefficients. The elements contained in D_t are generated in a GARCH (P,Q) process, which can be formulated as:

$$h_{it} = w_i + \sum_{p=1}^{P} \alpha_{ip}\varepsilon_{it-p}^2 + \sum_{q=1}^{Q} \beta_{iq} h_{it-q} \tag{2.5}$$

In addition, Engle (2002) adopts a GARCH-type structure in its modelling of the dynamics of correlations. Thus, a DCC process of the order (M, N) can be described by:

$$R_t = \left(Q^*_t\right)^{-1} Q_t \left(Q^*_t\right)^{-1}$$
$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\bar{Q} + \sum_{m=1}^{M} a_m \left(\xi_{t-m}\xi'_{t-m}\right) + \sum_{n=1}^{N} b_n Q_{t-n} \tag{2.6}$$

where $\xi_t = \left\{\varepsilon_{it} / \sqrt{h_{it}}\right\}$ is the vector containing the standardized residuals from the univariate GARCH model estimation, which is the matrix of the conditional variance-covariance of these standardized residuals, whereas $Q_t = \left\{q_{ij,t}\right\}$ is the matrix of the unconditional variance-covariance, which are temporally invariant. The parameters $\left(a_m; b_n\right)$ are supposed to intercept, respectively, the effects of the shock and delay the dynamic correlations on the level of recent contemporary. As for Q^*_t it is a diagonal matrix containing the square root of the main diagonal elements of Q_t. According to our example this matrix is written as:

$$Q^*_t = \begin{pmatrix} \sqrt{q_{11}} & \\ 0 & \sqrt{q_{22}} \end{pmatrix} \tag{2.7}$$

$\rho_{12,t} = \dfrac{q_{12,t}}{\sqrt{q_{11,t}\, q_{22,t}}}$ is the dynamic conditional correlations which are the matrix elements R_t whose main diagonal consists of 1.

The model parameters are estimated by the DCC method of maximum likelihood. Engle (2002) showed that the log-likelihood function can be expressed as:

$$L = -\frac{1}{2}\sum_{t=1}^{T}\left\{2\log\left(2\pi\right) + 2\log\left|D_t\right| + \log\left|R_t\right| + \xi_t R_t^{-1} \xi_t\right\} \tag{2.8}$$

The estimation process involves two steps. The first is the substitution of an identity matrix to matrix R_t in the function of the log-likelihood. The advantage of this method is that it allows for the sum of the likelihood function of the GARCH univariate models. In other words, through this first step, we obtain the parameters of equation (2.5). The second step is devoted to the estimation of the equation (2.6) parameters by adopting the original likelihood function described by equation (2.8). This allows for the dynamic correlations between the studied variables.

Van Royen (2002) reported that the existence of two estimators a_m and b_n makes the use of statistics of Hausman (1987) possible, to implement the DCC tests. Two estimators are possible to learn and value a_m and b_n. The difference is $\hat{q} = a_m - b_n$, as it has a limit equal to zero, however, its limit diverges from zero. The static test is then:

$$S_c = N\hat{q}'\hat{V}\left(\hat{q}\right)^{-1}\hat{q} \tag{2.9}$$

Where, N is the number of observations over the periods of crisis and non crisis. $\hat{V}\left(\hat{q}\right)$ is the variance of $\hat{q}$. Under H_0, S_c follows a chi-square distribution χ^2. The rejection of H_0 indicate the existence of an average number of shocks, for a while; the transmission mechanism is changed when there is an evidence of contagion.

3. Data and Summary Statistics

The data used in this study are the weekly returns on stock-price indices from January 2006, to December 2011, leaving 312 observations about six developed market that were seriously affected by the subprime crisis. The data set of the developed markets consists of daily returns on the stock indices of the United States (Bear Stearns (BES)), Germany (Deutsche bank (DEB)), French (BNP Parisbas (BNP)), Spain (Banco Santander (BAS)), Portugal (Banco BPI (BPI)) and Allied Irish Bank (AIB). All the data were obtained from the datastream.

Table 1. The structural breaks and their emergence dates

n_i	BES	DEB	BNP	BPI	BAS	AIB
1	02/09/08	29/09/08	27/10/08	01/01/07	17/12/07	26/05/08
2	06/10/08	16/03/09	02/03/09	17/12/07	22/09/08	22/09/08
3	01/12/08	13/09/10	17/09/09	11/05/09	30/03/09	25/05/09
4	17/02/09	18/07/11	26/07/10	23/05/11	-	14/02/11
5	02/03/09	-	13/06/11	-	-	18/07/11
6	22/03/10	-	-	-	-	-
7	07/09/10	-	-	-	-	-
8	20/09/10	-	-	-	-	-
9	07/11/11	-	-	-	-	-

The graphs (Figure 2, see Appendix) from the GARCH (1,1) show a high market volatility at specific dates: September 2008, March 2009, April 2010. In addition, most of these dates coincide with the banking crises in different markets (bankruptcy of several banks and banking crises) where returns on indices are negative. Everything confirms the asymmetric behavior of the volatility shocks. Furthermore, this observation of high volatility suggests a change in the trend of the variance in these particular periods and the existence of break points (ICSS algorithm). Sanso et al (2004) could detect multiple break points for each series. The series having generally distinct break dates do not prevent the existence of joint periods corresponding to the major events showing some structural break (Table1).

We define two sub-periods: a stable period, between January 2006 and September 2008 including an average of 138 observations for each country and a crisis period, starting in September 2008 and ending in December 2011, with a number of 174 observations for each country. The Bear Stearns of America is noted as the crisis-originating country.

Table 2. The descriptive statistics of the bank stock returns

	BES	DEB	BNP	BPI	BAS	AIB
T	312	312	312	312	312	312
Mean	0.04	-0.33	-0.27	-0.67	-0.19	-1.34
var	5.19	50.80	49.03	28.47	38.94	284.20
Skewness	-0.35	-0.64	-0.27	-0.13	-0.67	2.23
kurtosis	10.84	14.09	6.10	1.92	4.29	21.88
J.B	1536*	2602*	488.61*	49.38*	264.23*	6487.90*
ARCH	7.13 (0.01)	4.15 (0.02)	1.53 (0.00)	2.23 (0.03)	3.15 (0.04)	2.45 (0.01)
LB (10)	14.23 (0.01)	18.23 (0.11)	22.11 (0.03)	18.26 (0.07)	17.24 (0.09)	11.23 (0.12)
LB^2 (10)	50.02 (0.00)	30.28 (0.01)	41.28 (0.00)	26.35 (0.02)	36.13 (0.01)	20.13 (0.07)

Note (i) J-B is the statistic of Jarque-Bera normal distribution test. (ii) LB(10) is the 10-day lag return of Ljung-Box statistic, $LB^2(10)$ is the 10-day lag square return of Ljung-Box statistic. * denotes 5% significant level.

Table 2 presents summary statistics of the six banks. As can be seen from the studied banks, all the banks, except the Bear Stearns, have negative monthly average returns, indicating that not only the banking sector performs poorly, but also the currency of the studied countries was depreciating against the US dollar during the sample period. However, the overall dollar stock market performed relatively well with a positive average return of 4%. Considering the standard deviation, we can see that the equity returns are more volatile than those of the currency. All the returns' series are not normally distributed (Skewness ≠0 and Kurtosis > 3). We also notice as well high kurtosis values, generally superior to 3. These suggest that the distributions of the different markets' returns are leptokurtic. Ljung-Box test statistics for raw returns (LB (10)) and squared returns (LB (10)) are all significant at any conventional level except for the world equity returns, indicating strong linear and nonlinear dependencies on both currency and equity returns for the studied banks. This is consistent with the volatility clustering observed in most equities suggesting that the use of a conditional heteroscedasticity model is sensible.

Table 3. Results of the GARCH-DCC (1,1) Bivariate[3] models

	BES - DEB	BES - BNP	BES - BPI	BES - BAS	BES - AIB
a_m	0.15 (0.00)	0.013 (0.60)	0.094 (0.00)	0.037 (0.10)	0.19 (0.03)
b_n	0.962 (0.00)	0.96 (0.00)	0.905 (0.00)	0.956 (0.01)	0.864 (0.02)
S_c	7.56 (0.03)	6.58 (0.02)	3.54 (0.01)	4.23 (0.10)	2.89 (0.09)
$\overline{\rho}_{ij}$	0.053	0.066	0.041	0.061	0.064
LMC	18.65	47.25	53.26	43.56	59.24

Note: (i) Log L is maximum likelihood function (ii) inside (.) is p-value. (iii) * and ** denote the significant level of 5% and 10%. LMC, as suggested by Tse (2000), is used to test for constant correlation coefficient.

Table 3 shows that the correlation coefficients $\left(\overline{\rho}_{ij}\right)$ are pretty small, and all are below 0.5, indicating that the selected conditioning variables contain sufficiently orthogonal information. We find b_n being greater than a_m, under restriction that coefficients and $a_m + b_n < 1$. The evidence from these results suggests that a big shock just causes a small correction in the oncoming mutual fluctuation (or covariance) between the markets. Besides, the result of the LMC tests for constant correlation coefficient of Tse (2000) shows that five couple markets[4] reject the null hypothesis.

By examining Figure 3 (see Appendix), we can say that the evolution of correlations between the Bear Stearns bank returns with the other bank developed markets leads to the following observations:

All conditional correlations between the Bear Stearns stock index returns and the returns of the 5 developed countries are sometimes negative and sometimes positive. However, it is almost clear that by the end of the crisis, the correlations considerably increased to exceed 80% for all developed markets.

The conditional correlation has been much more pronounced since the beginning of the crisis in 2007. The coefficients are dynamic and reached a peak in 2009. We conclude that there is a contagious effect of the Bear Stearns index on the developed stock market indices. According to Kaminsky and Reinhart (1999, 2000) and Broner and Gelos (2003), it is possible to see that this contagion is triggered by the banking channel which reflects the relations between the developed countries in terms of equities or loan portfolios.

For the studied banks, the obtained results allow us to classify these countries into three groups according to the level of then correlation with the American market. The Bear Stearns with the Deutsche bank, Allied Irish Bank and the BNP Parisbas, including three countries with high a conditional correlation with the American market during the crisis; Germany, Ireland, and France. Indeed, the correlation levels for these countries reached 50%. The Bear Stearns with Banco Santander and the Banco BPI including two countries with moderate conditional correlations approximating 30%; Spain and Portugal.

Regarding the global financial crisis, with its psychological effects such as panic and mistrust vis-à-vis the banking and the financial markets, there has been contagion to Germany, France and Spain. This reflects in particular the importance of the banking sector in the European markets, the freezing of the assets of the suspected terrorist countries located in Europe and the other tax havens that has not been without impact on the confidence of the financial operators. Furthermore, the concern of the Americans and the rest of the world is the fearing proliferation of the financial crises on other targets which has had a negative impact especially on banking. We note here the historical relationship between the American banking market and the European markets. This relationship is

[3] The choice of this framework can be justified by the results of Bivariate GARCH models. These results show that there exists a phenomenon of contagion between markets studied coming directly from American market to the French, German, Spain, Portugal and Ireland.

[4] The modeled couples are: USA-Germany, USA-France, USA-Spain, USA-Portugal and USA-Ireland.

reinforced by a significant presence of European investors in the U.S. market particularly with the strong regional Bear Stearns bank, for example (Table 3).

The European Union (EU) governments have finally released funds for the Bear Stearns. However, the relief was short-lived for the financial markets as fresh concerns seem to be building on other heavily indebted countries. Moody's decision to downgrade the Portuguese government debt on July 4th is to provide the catalyst for another short period of risk aversion, with credit default swap spreads rising strongly. The major rating agencies have been very active throughout the sovereign crisis. They are keen to restore their own credibility after the accusations of being overly complacent on the safety of the subprime debt. However, they are not alone in expressing their concerns. The insuring cost against the Portugal's default has doubled in the year-to-date period, even before Moody's cut of the rating to "junk" status. On the cash market, the prices of the government bonds issued by smaller peripheral Euro-countries are trading at a deep discount, which may indicate the likelihood of a "hair cut" for private investors if a restructuring eventually takes place.

4. Conclusion

This paper attempts to test whether a bank can be a source of contagion during the 2009 financial crisis using asset return data from a the bankruptcy of the Bear Stearns. More precisely, we examine whether the banking sector can create contagious effects in both conditional means and volatilities of its stock markets banking during the crisis. Previous studies on contagion failed to take account of the important distinction between the two concepts of interdependence and contagion. In this paper, we define contagion as the significant spillovers of the asset-specific idiosyncratic shocks during the crisis after economic fundamentals or systematic risk. To control for the economic fundamental, we rely on an international capital asset pricing model, which provides a theoretical basis in selecting the economic fundamental.

The empirical results show that contagion-in-mean effects appear to be multidirectional since the shocks to banks' return emanating from any of the three asset markets can sweep across all the markets, but contagion-in-volatility effects are mainly driven by the negative return shocks originating in the banking sector. This empirical finding indicates that not only can shocks to banks' return become contagious at the volatility level, but also they can become contagious at the mean level, signifying that the bank can be a major cause of contagion during the crisis.

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Appendix

Figure 1. Banks stock return evolution during subprime crisis

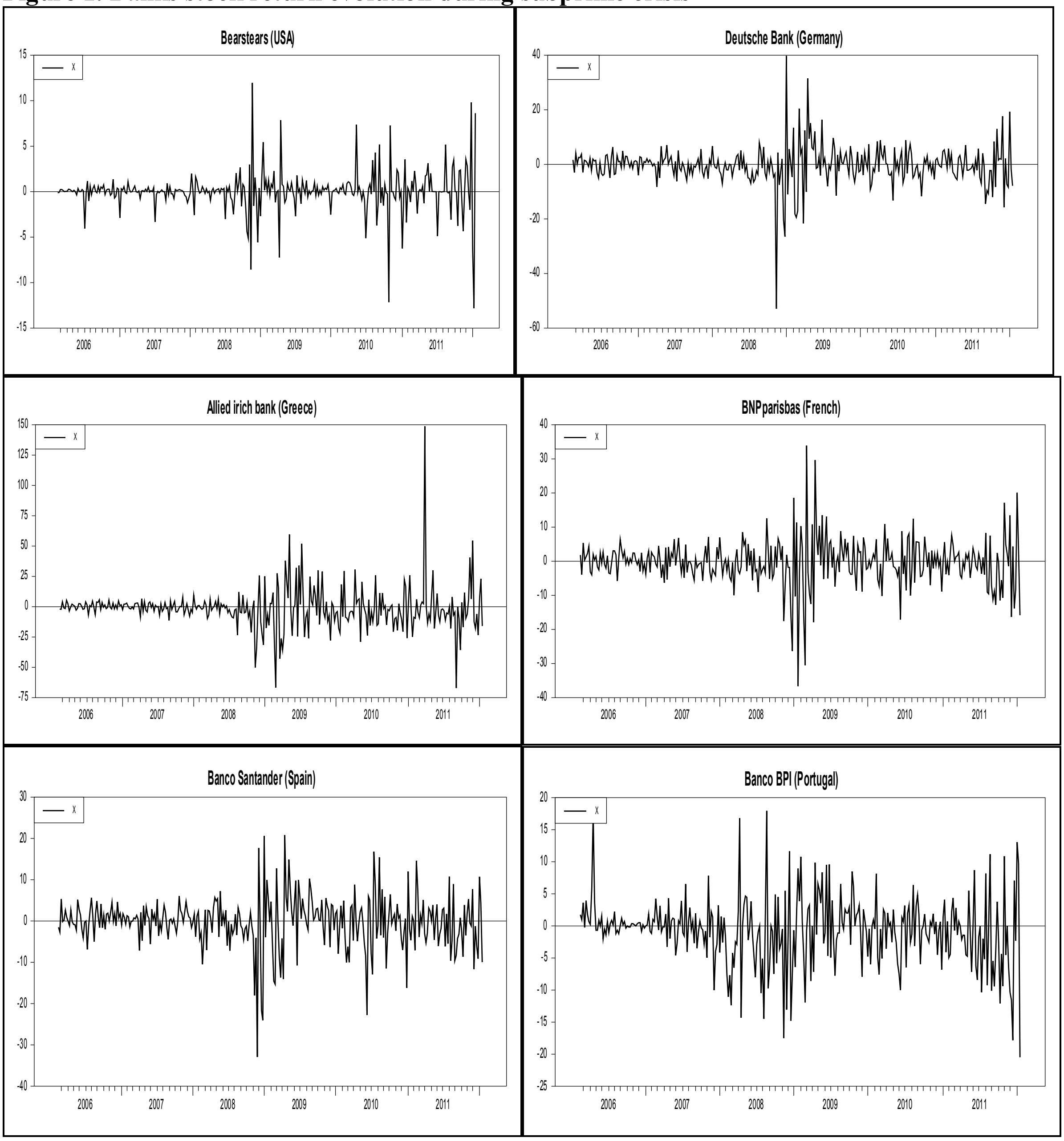

Figure 2. Bank volatility

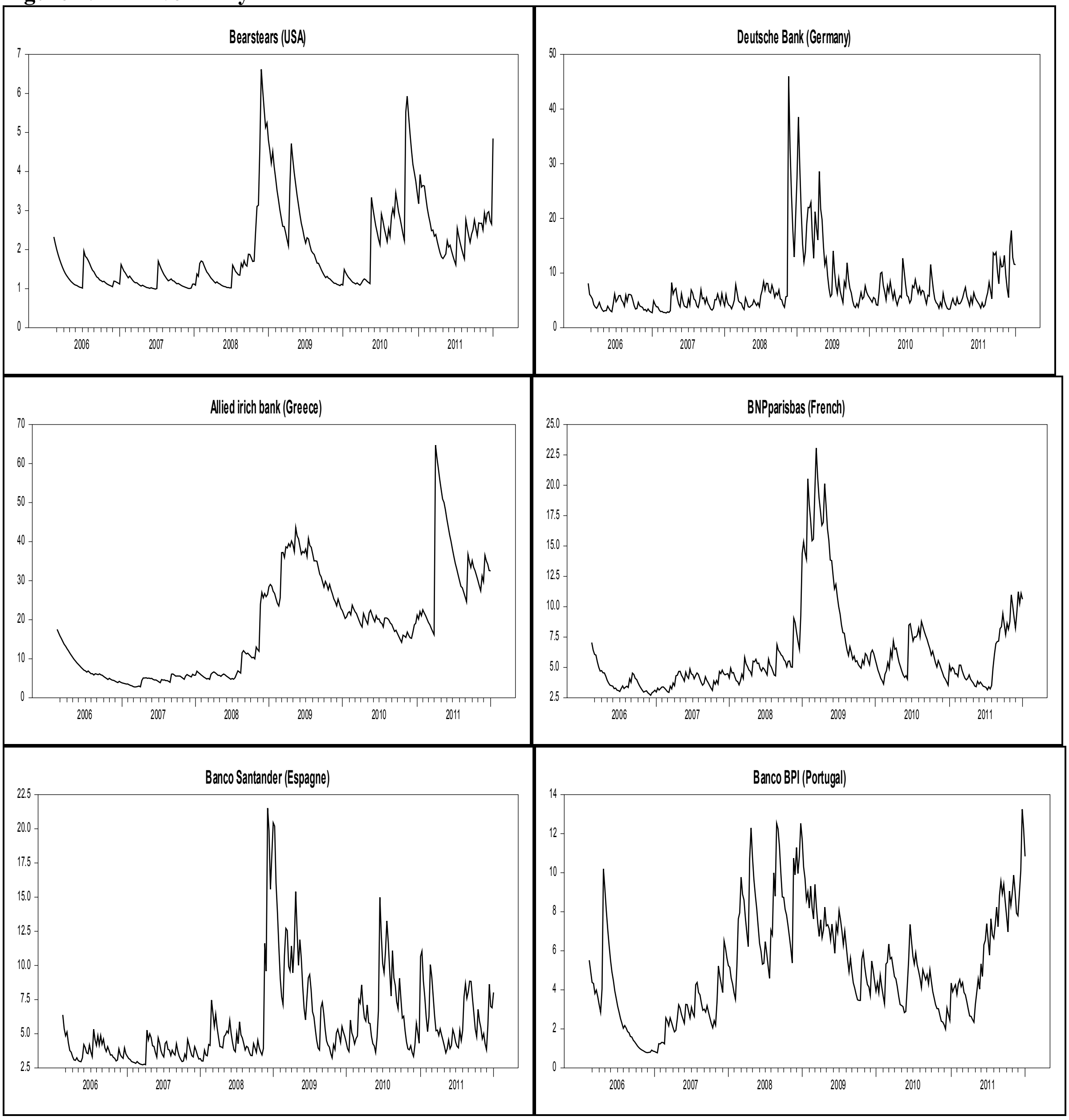

Figure 3. Dynamic Conditional Correlation of the Bear Stearns Bank with the other banks