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Contagion effect due to Lehman Brothers' bankruptcy and the global financial crisis - From the perspective of the Credit Default Swaps' G14 dealers.

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Abstract:

This article investigates the dynamics of conditional correlation among the G14 banks' dealer for the credit default swap market from January 2004 until May 2009. By using the asymmetric dynamic conditional correlation model developed by Cappiello, Engle and Sheppard (2006), we examine if there is contagion during the global financial crisis, following Lehman Brothers' bankruptcy of September 15th, 2008. The main contribution of this article is to analyze if the interdependence structure between the G14 banks changed significantly during the crisis period. We try to identify the banks which were the most or the least affected by losses induced by the crisis and we draw some conclusions in terms of their vulnerability to financial shocks. We find that all banks became highly interdependent during Lehman Brothers' bankruptcy (short term impact), but only some banks faced high contagion during the global financial crisis (long term impact). Regulators who try to reinforce banks' stability with the Basel 3 reforms proposals should be interested by these results.

Keywords: Financial Crisis, Contagion, Credit Default Swap, Lehman Brothers, Asymmetric Dynamic Conditional Correlation.

JEL classification: G01, G15, G21, G33.

Résumé:

Ce papier s'intéresse aux corrélations conditionnelles dynamiques entre les credit default swap des 14 banques les plus actives sur le marché des CDS entre janvier 2004 et mai 2009. En recourant au modèle de corrélation conditionnelle asymétrique dynamique de Cappiello, Engle et Sheppard (2006), nous regardons s'il y a un effet de contagion durant la crise financière globale débutant avec la faillite de Lehman Brothers le 15 septembre 2008. La contribution principale de cet article est d'analyser si la structure d'interdépendance entre les banques G14 a changé significativement durant la période de crise financière. Nous identifions les banques les plus et les moins affectées par les pertes dues à la crise, ce qui nous conduit à élaborer quelques hypothèses en termes de leur vulnérabilité face aux chocs financiers. Nos résultats montrent que toutes les banques sont devenues interdépendantes suite à la faillite de Lehman Brothers (impact à court terme), mais seulement quelques banques ont été contaminées durant la crise financière (impact à long terme). Les régulateurs qui essaient de renforcer la stabilité du système financier la réforme Bâle 3 devraient être intéressés par ces résultats.

Mots clés: Crise financière, Contagion, Credit Default Swap, Lehman Brothers, Corrélation Conditionnelle Asymétrique Dynamique.

Classification JEL: G01, G15, G21, G33.

1. Introduction

The common traditional distinction between risks, illiquidity and insolvency risk is attributed to Bagehot (1873) and it applies to traditional banking, and especially commercial banks. This typology of risks is important in terms of policy implications as central banks' intervention should be discretionary in function of the risks confronted by the banks (Bagehot, 1873). Central banks should distinguish between institutions that are insolvent and those that are merely illiquid. They should lend their hand to solvent financial institutions even if they face liquidity problems. In the case of insolvency, central banks should not intervene as the lender of last resort, but let the financial institutions go into bankruptcy. However, the distinction between illiquidity and insolvency is sometimes hard to define and there exist a strong interaction between illiquidity and insolvency risks (see for example Frank et al. (2008). Insolvency risk could be the consequence of decrease in asset prices that could then trigger liquidity crisis. Bagehot's distinction ignores market factors that impact illiquidity and insolvency risks and seems irrelevant in the case of the global financial crisis of 2008-2009.

The global financial crisis is not similar to past crisis (see Dungey (2008) among many others). This crisis appears to be the most devastating since those that have preceded the Great Depression in the United States and the banking crisis prior to the First World War. Traditionally, banking crises occur when depositors queue up to withdraw their money in a panic (Diamond and Dybvig (1983)). These banking crises appeared with a run on the bank, but they had evolved in time and incorporated different types of risks. Northern Rock in September 2007 went through a 'bank run'. This 'bank run' was a consequence of the difficulty faced by Northern Rock's access to interbank market during the subprime mortgage crisis. A crisis of confidence appeared as depositors were aware of the funding difficulties faced by the bank. This was one of the dramatic indications that difficulties at the beginning of the crisis were spreading beyond the United States. The 'traditional' banking system in which commercial banks used to hold loans until they were repaid transformed into 'modern' banking in which all sorts of loans were pooled together, tranched, and then resold via securitization. This financial innovation was called the 'originate and distribute' model (see for example Brunnermeier (2009)). This financial innovation ultimately led to a decline in lending standards contrary to its first function of making the banking system more stable by transferring risk to those who were capable to bear it.

During the subprime crisis, 'modern' runs occurred in financial markets, especially within the interbank and money markets, mainly because of financial innovations. Banks stopped granting credit to each other because of their fear of contaminated subprime loans. The fear that the securities issued against mortgage loans, serving as collateral, to their own financing may have to be written off. Therefore, it is important to take into account the new risks associated with crisis that heavily depend on the development of financial innovations, such as credit derivatives. Credit derivatives are financial assets whose payoffs depend on credit risk of a financial institution. The most popular credit derivative during the subprime crisis was the Credit Default Swap (now on as CDS). CDS account for approximately 70 percent of total credit derivatives negotiated all over the world. CDS contracts are financial instruments to hedge the default risk born by creditors and to transfer it to other agents. Three agents intervene: the buyer (assured), the seller (insurer) and the reference entity (borrower of the underlying asset). The CDS contract allows the buyer to hedge against the default risk of the reference entity and the seller to get compensation to ensure this hedging. Many financial institutions or insurer companies during the subprime crisis, such as American International Group (now on as AIG) or Lehman Brothers (now on as LB) faced a sudden lack of funding because of their positions (as seller) on the CDS market. The bankruptcy of AIG would have generated great financial difficulties for the buyers, who had their major investments in American commercial banks. LB was a major dealer on the CDS market with positions as seller as well as reference entity. In the case of AIG, it was appealing to be a net seller of CDS as its' insurance were subject to different prudential regulations and could find interest in bearing credit risk if compensation was appealing. With the default of a major counterparty on the CDS market, financial institutions ran the risk of illiquidity. The failure of certain financial institutions would have lead to systemic risk.

The CDS market could become contagious, as opposed to its first function of diversification of risks. Four factors may ignite contagion in this market. The first vulnerability factor in this market is due to the positions' imbrications. Financial institutions in this market have to hold a reverse position to cancel their first position. The second factor is a huge concentration of risks due to the exposition of financial sector to this market. The G14 banks' dealer[1] (Bank of International Settlements) realized the majority of transactions in this market. The third factor is the opacity of the market. It can create doubts about the capacity of sellers to honor their contracts. The last factor is the counterparty risk, or credit risk. The bankruptcy of a major financial institution (now on FI) can create difficulties for other FI because of their mutual positions. Moreover the fact that the notional value of credit default swaps was a large multiple of the value of the underlying bonds created the danger of a domino effect if one large issuer of default swaps was to fail. With the subprime crisis, counterparty risk associated with CDS clearly appeared and financial institutions which were first considered as safe appeared as risky. Doubts about the capacity of CDS's sellers to insure their contracts appeared as a factor of contagion.

The nature of credit risk changed due to securitization. Before the financial engineering era, credit risk was sustained by banks themselves while granting loans. Banks were subject to prudential regulations such as capital requirements. Securitization which developed in the 1990s, allowed the bank to pool heterogeneous loans, trench them, and resell the same to other investors on financial markets with the intervention of brokers. Banks became capable of transferring the credit risk and

[1] See table 1 for a description of the sample.

hence required lesser capital to meet regulatory requirements. Since derivative markets are over-the-counter markets (OTC), they involve the difficulty of estimating credit risk even if CDS premiums depend on the default probability of a reference entity. Credit risk spread and moral hazard allowed banks to become less prudent. The banks now knew, how to sell the credit, and were not obliged to keep them on their balance sheet. It is due to this fact that we focus on credit risk and measure contagion effect on the CDS market.

Liquidity risk did not draw much attention from regulators compared to credit risk or market risk. With the subprime crisis, managing liquidity risk became a priority[2]. In a modern market-based financial system, the vehicle of contagion is the price changes, just not only the default on loans (Adrian and Shin, 2008). The first factor that caused crisis was the sudden fall in house prices. Thus, mortgages default started increasing due to the fact that these subprime loans were issued with variable interest rate, relax lending practices, and without borrower income assessment to support such circumstances. The subprime mortgages fell in value and they became volatile and more difficult to price. Banks possessed most of such financial derivatives that were mainly financed by leverage (a capital structure that heavily relied on short-term debt). As a consequence, banks became illiquid. Further, as banks tried to sell out their positions, prices decreased and concerns about illiquidity turned to insolvency. Banks had to face decrease in their asset value which did not match the liabilities. Bank runs started and the interbank market froze up. Banks refused lending each other and preferred hoarding their funds. Schema 1 shows how the risks evolved during the subprime crisis.

In this paper, we emphasize the impact of Lehman Brothers (LB)'s bankruptcy on 15th September 2008 on the CDS market. This date is largely accepted by researchers, policy makers and the practitioners as the starting point of the global financial crisis. For some authors, this bankruptcy led to systemic risk (Acharya, Philippon, Richardson and Roubini (2009)). We focus on LB's bankruptcy since it was a major dealer in the CDS market. The default of a large insurer such as LB could lead to a domino's effect which became evident just after its announcement of bankruptcy. This announcement gave birth to fears concerning the capacity of the CDS market to bear such shocks. The questions we investigate in this paper are as follows: First, did the interdependence structure among banks remain constant or did it change with time? Second, were all banks affected with the same magnitude during the global financial crisis? Third, did Lehman Brothors' failure have a short term or long-term impact on time varying pair correlations? To answer these questions, we consider two event windows. A short event window of four weeks following Lehman's collapse was considered since Lehman announced its bankruptcy on September 15, 2008 and CDS were settled through an auction three weeks later on October 10, 2008. A longer window of 37 weeks following LB's bankruptcy was considered in order to capture the impact of the global financial crisis that ended on May 27, 2009

[2] Basel 3 introduced the liquidity coverage ratio (LCR) for the short-term and the Net Stable Funding Ratio (NSFR) for the long-term.

according to Greenspan. The definition of contagion used in this paper is similar to the literature (see for example Forbes and Rigobon (2000, 2002), Coudert and Gex (2008), Yiu et al. (2010), Tamakoshi et al. (2012)). Contagion is defined as a significant increase of dynamic conditional correlations between banks' CDS during the GFC relative to the correlations during the pre-crisis period. We measure contagion with conditional correlations following Forbes (2009). Contagion in this paper is measured from Lehman Brothers' bankruptcy to other banks. No assumption is made concerning the contagion effect among the other banks. It is a measure of the impact of Lehman Brothers' bankruptcy on conditional correlation of CDS between each couple of banks.

This paper makes several contributions to the existing literature on contagion effect during the global financial crisis. First, as far as we can tell, this is the first attempt to empirically model the impact of LB's bankruptcy on the CDS market with the Asymmetric Dynamic Conditional Correlation (ADCC) model. Empirical studies focusing on financial institutions' CDS mainly concentrated on principal component analysis and dynamic panel (Eichengreen, 2009) or robust panel estimates (Raunig and Scheicher, 2009). As Forbes (2009) stated, DCC is a good method to measure contagion. Second, this study specifically addresses the issue of contagion from a microeconomic perspective and not a global level. By focusing directly on financial institutions' CDS, we measure bank contagion and not financial or global contagion as previous literature did. Many studies focus on stock market indices or CDS sovereign bonds. Our methodology focuses on individual banks, thus allowing us to distinguish between the most affected FIs instead of taking a global approach to countries or market indices. Besides, estimating the market assessment of bank credit risk or default is relevant to policy implications and more especially to macro prudential policies. Regulators who try to reinforce banks' strength with the Basel 3 reform proposals should be interested by this methodology. For policy-makers, the predictions of the dynamic correlation between banks could be a useful tool for preventing systemic risk during crisis period. Third, by using multivariate GARCH (Generalized Auto-regressive Conditional Heteroskedasticity) models instead of the univariate GARCH model, we jointly analyze the volatility of two financial institutions and assess the links between these two series. The GARCH framework allows for the modeling of the heteroscedasticity of the data, in addition to interpreting conditional variance as a time-varying risk measure. Engle (2002) proposes the Dynamic Conditional Correlation (DCC) model to alleviate the dimensionality problem of the general Multivariate GARCH (MGARCH) model. Engle's DCC model comprises two steps, fitting each series to univariate GARCH model to get the residuals and then deriving the dynamic conditional estimates. This model was modified by Cappiello, Engle and Sheppard (2006), the Asymmetric Dynamic Conditional Correlation (ADCC) to allow for the possibility of having asymmetric impact of positive innovations and negative innovations on the dynamics of the conditional correlations. As the DCC model by Engle (2002) can lead to inconsistency problem with the DCC estimator (Aielli, 2008), we thus decide to implement the ADCC model by Cappiello, Engle and Sheppard (2006) which allows incorporating heterogeneity in the data, such as asymmetric news impact and no smoothing parameters for all pairs of variables.

The rest of the paper is organized as follows. In the second section, we focus on the literature review. In the third section, we develop the database. In the fourth section, we present the econometric methodology. In the fifth section, we present the main empirical results. In the sixth section, we conclude and present future areas for research.

2. Risk typology and literature review

2.1 Risk typology

We review the risks occurring during the global financial crisis (Table 2). We identified types of financial risks: insolvency risk, illiquidity risk and credit risk. Some variables depending on the macroeconomic environment can lead to a modification of those risks, they are mainly prices and interest rates. Systemic risk is also detected during the subprime crisis.

The 2008-2009 financial crises led to a differentiation in illiquidity risk (Brunnermeir, 2009): 1/funding liquidity (individual liquidity risk) and 2/market liquidity (systemic liquidity risk). Funding liquidity appears when a bank is unable to easily obtain funding (for instance, at excessive costs, and/or with a limited amount) from the interbank market. Market liquidity risk appears when a bank is unable to sell its assets at or near their fair value due to market disruption or when a bank's reputation has been undermined. Transactions for complex financial products occur in over-the-counter (OTC) markets, thus these markets are not centralized making them difficult to evaluate. They are valued through models that incorporate product characteristics. With the crisis, these models did not give prices any longer for the underlying assets which made banks unable to value some of their financial assets / products. Funding illiquidity risk then materialized and banks became concerned about their future access to capital markets and started hoarding funds. As a consequence, banks tried to sell off some of their positions. This effect was reinforced by the fact that banks heavily relied on leverage, such as short-term borrowing. Market illiquidity risk was observed through a sharp drop in asset prices. The market liquidity crisis is a new risk that appeared with the crisis and can be viewed as one factor of contagion. Central banks clearly intervened from summer 2007 following the freeze on the interbank market[3]. Usually financial institutions could obtain funds at short term on this market. The risk not considered beforehand by financial regulators in Basel 2 before the crisis, became important with the request of international criteria for managing liquidity risk. The importance of an increase in

[3] Central banks have extended the nature of collateral for mortgages loans and started granting exceptional loans to investment banks and insurance not submitted to the same regulation. Meanwhile, interest rates were lowered significantly in order to restore bank profitability.

liquidity risk during the crisis entailed many interventions of central banks to inject funds in order to avoid a freeze on the markets.

Table 2: ***Risks during the financial crisis.***
Source: Authors.

Risk	Name	Definitions
Financial risks	**Illiquidity risk** (market liquidity and funding liquidity)	A financial institution even if solvent either does not have enough financial resources to allow it to meet its obligations when they are due, or can obtain such funds only at excessive cost (Brunnermier and Pederson (2008) and Brunnermier (2009).
	Insolvency risk	A financial institution has more liabilities than the reasonable market value of its assets. In this case, the bank is insolvent. Insolvency risk can result from illiquidity risk.
	Credit risk (or counterparty risk)	The counterparty may face a default and failing to repay its debt. This risk becomes harder to evaluate with the development of complex financial products due to securitization.
Macroeconomic risks	**Interest rate risk**	Changing the value of an investment due to a change in interest rate. The subprime loan holders had variable interest rates.
	Price changes risk	The collapse of a market leads to a decrease of asset prices. In general, we observe a risk premium variation (Adrian and Shin (2008).
Contagion risk	**Systemic risk**	The widespread failures of financial institutions or freezing up of capital markets that can substantially reduce the supply of capital to the real economy (Acharya et al, 2009).

During the financial crisis, after prices decreased and financial products could not be valued, banks tried to shrink their balance sheets and deleverage as they discovered their capital eroding. There was a transformation of illiquidity risk into insolvency risk (i.e. bank assets were not enough to match the liability side).

The systemic risk is the consequence of higher interconnection between FIs. The bankruptcy of a FI could lead to the bankruptcy of the whole financial system because of the linkages between the FIs. Systemic risk may imply 'Too Big To Fail' label for institutions. This designation can become *ex-ante* costly since it induces moral hazard with banks becoming less prudent regarding risks they face. Systemic risk *ex-post* can be the consequence of several mechanisms that amplify and propagate liquidity shocks across financial markets. This transmission can appear directly between banks' balance sheet, and indirectly through asset prices (Adrian and Shin, 2007).

2.2 Review of literature

Table 3 synthesizes the principal studies which deal with contagion, either related to finance or banking. Assessing contagion through the use of correlations is increasingly used in literature. From unconditional correlations to dynamic conditional correlations (DCC) by Engle (2002) and to Asymmetric DCC specification by Cappiello et al. (2006), techniques to detect contagion through correlation have improved. This last specification allows taking into account the dynamics of correlation and structural breaks. The first specification by Engle (2002) implies that the conditional correlations are mean reverting to their constant long-run unconditional average, so that the shock is transitory. Under the DCC specification by Capiello et al. (2006), the subprime crisis can be modeled as a structural break in the data generating processes, rather than a transitory shock. Aielli (2008) shows that the DCC estimator model by Engle (2002) can be inconsistent and lead to the existence of bias in the estimated parameters of the model. Aielli (2008) shows that the bias depends on the persistence of the DCC dynamic parameters and that the sample estimator of the correlation matrix of the standardized residuals used in the second step of the DCC estimation method is inconsistent, thereby also affecting the consistency of the third step. Frank et al. (2008) also prefer the DCC estimation methodology of Cappiello et al. (2006). Other versions of the DCC model have been implemented such as DCC-EGARCH (Alraigbat (2011)), G-DCC (Hafner and Franses (2009)), DCC-GARCH (Wang and Moore (2012)). These studies generally use the log likelihood estimator which allows for consistent standard errors robust to non-normality.

In order to study financial contagion, researcher use stock market returns (see for example Naoui, et al. (2010), and Alrgaibat (2011) among many others) or exchange rate returns (see Celik (2012)). Yet, some studies focus on bank specific variables and look at banking contagion. Risks are identified, and proxy for each type of risk is captured with macroeconomic variables to control for shocks. Concerning the variables, credit risk is proxied by Credit Default Swaps (CDS), either bank CDS or sovereign bond CDS. CDS spreads reflect the market’s assessment of credit risk (Longstaff et al. (2007)) and is an important indicator of the depth of the crisis (Wang and Moore (2012). Eichengreen et al. (2009) using data on banks’ CDS for 45 banks in developed economies, investigate the importance of common factors to explain their spreads. Athanasoglou and al. (2008) implement a series of bank-variables for Greece such as credit risk to assess the determinants of Greek commercial banks’ profitability. Whereas, other studies focus on bank performance determinants or bank liquidity risk using a panel database.

In this study, we focus on 2008-2009 financial crises and extend aforementioned studies. Tamakoshi et al. (2012) use the ADCC model to study the time-varying correlations between Greece and 6 other European countries from January 2007 to March 2011. They find that correlations showed significant decline during the sovereign debt crisis. Yiu et al.(2010) investigate contagion effects of global financial crisis in Asian markets by applying ADCC model. They perform principal components analysis to extract single latent factor to represent whole of Asia and with the ADCC they estimate the correlation between the Asian factor and the US stock market. They find evidence that there is contagion from the US to the Asian markets. Frank, Gonzalez-Hermosillo and Hesse (2008) with ADCC-GARCH model of Cappiello et al. (2006) show that the interaction between U.S. market and funding illiquidity increased sharply during the subprime crisis and bank solvency became an important issue. Wang and Moore (2012) by using the DCC of Engle (2002) and data on the CDS sovereign bonds find that LBs' bankruptcy strengthened the integration between sovereign bond CDS of developed economies with the USA. In terms of the driving factors of this correlation, they conclude that CDS bonds markets were mainly driven by USA interest rates. They focus on the unconditional correlations of weekly changes in CDS spreads between the US and others markets and on the conditional correlations between US and non-US CDS spreads. By looking at the DCC series for each pair of countries, they find that the pattern of correlation changed significantly before and after the LBs' bankruptcy. They conclude that LBs' bankruptcy was seen as a major event during the crisis and contributed to the integration of the CDS markets amongst advanced economies. Raunig and Scheicher (2009) with a different method of fixed effects and random effects focusing on individual bank data of CDS, find that after August 2007 investors increased their perception of risk concerning banks. Eichengreen (2009) with principal component analysis and CDS data on individual banks show that common factors for banks' CDS play a major role in explaining the spillover effects between banks. Finally these studies have the common point of dealing with the impact of the 2008-2009 financial crises.

3. The data

Our dataset comprises of weekly returns of bank CDS premiums pertaining to G14 banks (281 observations per bank) from January 14, 2004 to May 27, 2009. The reference period is supposed to begin early January 2004 since the American business cycle was no more affected by the 2001 recession and this year highlighted the return of the US business cycle with a tightening monetary policy stance by the Federal Reserve. The end of the period is May 2009 since this is the official date of the end of the global financial crisis (Greenspan). The CDS premiums reflect the default risk on the FIs of the sample.

The G14 banks incorporated in our analysis are : Citigroup (United States), Goldman Sachs (United States), JP Morgan (United States), Morgan Stanley (United States), Wells Fargo (United States), Bank of America (United States), BNP Paribas (France), Deutsche Bank (Germany), HSBC (United Kingdom), Royal Bank of Scotland (United Kingdom), Société Générale (France), UBS (Switzerland), Barclays (United Kingdom) and Crédit Suisse (Switzerland). By focusing exclusively on the G14 banks' dealer, we assume that G14 banks are most active on the CDS market and they should be affected by any market downturn. This assumption is also based on the large scale of exposure of these banks to the market events.

All the CDS premiums are extracted from Bloomberg and denominated in dollar currency in order to avoid any local currency effects such as inflation. Similar to Cappiello et al. (2006) and Yui et al. (2010), we calculated Wednesday-on-Wednesday weekly returns, and we multiply them by 100 to express as percentages[4]. We use weekly returns because they are less noisy compared to daily data and in order to avoid any non-synchronous trading effect between countries. They also preserve the adequacy of data with sufficient frequency contrary to monthly data. Figures 1 and 2 show respectively CDS premiums and CDS returns for the G14 banks. Figure 1 shows that from 2004 until mid-2007 the CDS were relatively low driven by a market impact. From mid-2007, CDS premiums started increasing with investors' expectations of higher default. At the beginning of the GFC, we observe market downturn for CDS premiums. But early 2009, tensions on this market started again resulting in the rise of risk premiums.

Summary statistics of the weekly returns are presented in table 4. The descriptive statistics are presented for the whole period (January 14, 2004 to May 27, 2009), the pre-crisis period (January 14, 2004 to September 10, 2008) and crisis period (September 17, 2008 to May 27, 2009). The first moment is positive for all banks for the whole period, as well as for the pre-crisis period. On the contrary, it is negative for three banks (GS, JPM and WF) for the GFC period, CG and RBS got even more positive returns, a sign that their CDS premiums were traded with a higher probability of default. These FI had shorted considerable amount of Collateralized Debt Obligations before the crisis and even if they had subscribed insurance by buying CDS in case of default, this did not reassure investors. Standard deviation is higher for all banks during the GFC than during the pre-crisis period, a sign of higher tension and volatility in the market. By looking at the kurtosis and the skewness coefficients, 10 banks have lower value of kurtosis and skewness during the GFC compared to the pre-crisis period. This is not the case for 4 banks (GS, MS, UBS and CS). Higher values for the second moment during the GFC period rather than the tranquil period are also confirmed by the maximum values which are higher during the GFC.

4. Methodology

We study time varying correlations among the weekly returns of the CDS premiums of G14 banks from January 2004 to May 2009. We adopt a three stage approach.

[4] The weekly returns are computed as: (CDS premium for bank i at t – CDS premium for bank I at t-1)/CDS premium for bank i at t-1)*100. Then we interpret positive CDS return as the CDS premium for bank i in t is superior to CDS premium for bank i in t-1, a sign of higher default risk for bank i. The bank i is considered by investors as more risky.

First, we estimate the conditional variance for each of 14 CDS returns series using a univariate EGARCH specification and selecting the best EGARCH (p,q) models[5]. By using an EGARCH specification for the variance conditional equation we want to test if there is any asymmetry on the conditional variance due to a bad news. If so, a bad news would have a more impact on the variance than a good news. The EGARCH(p,q) framework may be presented as follows :

(1) Mean equation:

$$r_{it} = \varphi_0 + \sum_{l=1}^{k} \varphi_i r_{t-l} + \varepsilon_t \qquad (1)$$

(2) Conditional variance equation:

$$\log(d_{it}) = \omega_i + \sum_{l=1}^{p} \left[\alpha_{ij} \frac{\varepsilon_{it-l}}{\sigma_{it-l}} + \gamma_{ij} \left|\frac{\varepsilon_{it-l}}{\sigma_{it-l}}\right| \right] + \sum_{l=1}^{q} \beta_i \log(d_{t-l}) \qquad (2)$$

In our econometric framework the estimated conditional variance equation is specified as:

$$\log(d_{it}) = C + \sum_{l=1}^{p} \left[A \frac{\varepsilon_{it-l}}{\sigma_{it-l}} + D \left|\frac{\varepsilon_{it-l}}{\sigma_{it-l}}\right| \right] + \sum_{l=1}^{q} B \log(d_{t-l}) \qquad (3)$$

Second, we derive the time-varying conditional correlations with the asymmetric DCC model developed by Cappiello et al. (2006). The estimation procedure is close to the original DCC. The residuals obtained from the first step are standardized:

$$\varepsilon_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{d_{i,t}}}$$

The negative standardized residuals for capturing asymmetric impacts of good and bad news are defined by:

$$\eta_{i,t} = \varepsilon_{i,t} \; if \; \varepsilon_{i,t} > 0$$

$$= 0 \; otherwise$$

Given the standardized residuals and the standardized negative residuals, the dynamics of the conditional correlation matrix denoted by P_t in the asymmetric DCC is given by the following two equations:

$$Q_t = \left(1 - \sum_{j=1}^{s} a_j - \sum_{j=1}^{u} b_j\right)P - \sum_{j=1}^{s} g_j N + \sum_{j=1}^{s} a_j \varepsilon_{t-j}\varepsilon'_{t-j} + \sum_{j=1}^{s} g_j \eta_{t-j}\eta'_{t-j} + \sum_{j=1}^{u} b_j Q_{t-j}$$

(4)

[5] To determine the lag structures (*p*,*q*) we use Akaike, and Schwarz / Bayesian information criteria. It should be noted that Akaike criterion overshoots when *p* is increased (see Bierens (2009)). *p* and *q* are selected by minimizing AIC and BIC.

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} (5)$$

Where $P_t = E[\varepsilon_t \varepsilon'_t]$, $N_t = E[\eta_t \eta'_t]$ and Q_t^* is a diagonal matrix with square root of i-th diagonal element of conditional correlation matrix on its i-th diagonal position.

If N equals zero, then the ADDC becomes a DCC model.

For ADCC(1,1), the equation (4) may presented as follows:

$$Q_t = (1 - AFIX - BFIX)P - GFIX * N + A\varepsilon_{t-1}\varepsilon'_{t-1} + GFIX\ \eta_{t-1}\eta'_{t-1} + BFIX\ Q_{t-1} \quad (6)$$

The log-likelihood of the estimators of the asymmetric DCC is identical to the case of original DCC except the modification in P_t. Denote θ to be the vectors of parameters to be estimated, and the log-likelihood is given by:

$$log(\theta) = -\frac{1}{2} \sum_{t=1}^{T} [(n \log(2\pi) + 2logdet(D_t) + \varepsilon'_t D_t^{-1} D_t^{-1} \varepsilon_t + \ (logdet(P_t) + \ \varepsilon'_t P_t^{-1} \varepsilon'_t - \varepsilon'_t \varepsilon_t)] \quad (7)$$

Where n and T are the number of series (in our case 14) and the number of observations, respectively. We note $\rho_{ij,t}$ the estimated DCC coefficient between banks i and j at time t.

Third, we model the estimated DCC coefficient $\rho_{ij,t}$ for each couple of banks i and j as an AR model. Specifically the dummy variable signifying the global financial crisis (GFC) (from September 17, 2008 to May 27, 2009 which represents 37 weeks) is included in order to test whether the GFC significantly altered the dynamics of the estimated conditional correlations between the G14 banks. We estimate the following model 1:

$$\rho_{ij,t} = \delta_0 + \sum_{l=1}^{p} \delta_1 \rho_{ij,t-l} \ + \ \xi_1\ GFC \ + \ \nu_t \ (8)$$

Where $\rho_{ij,t}$ is the estimated dynamic conditional correlation coefficient between banks i and j at time t. δ_0, δ_1 and ξ_1 are the estimated coefficients respectively to the constant term, the lagged ADCC coefficient and the GFC dummy variable.

This model is modified to take into account a shorter window event focusing on Lehman Brothers' bankruptcy (now on as LBB). We consider a dummy variable equals to one for the period from September 17, 2008 until October 8, 2008 (4 weeks). The model 2 estimated is the following:

$$\rho_{ij,t} = \delta_0 + \sum_{l=1}^{p} \delta_1 \rho_{ij,t-l} \ + \ \xi_1\ GFC \ + \ \xi_2\ LBB + \nu_t \ (9)$$

With ξ_2 as the estimated coefficient associated with the dummy LBB variable.

In order to capture the short term impact of LBB the window size is set equal to four weeks. The choice of four weeks is based on the fact that it took exactly four weeks between the declaration of Lehman Brothers bankruptcy and its auction i.e. October 10 2008. On the other hand, the event window of 37 weeks reflects the long term impact on the market due to GFC.

5. Empirical results

We present the results of the three steps presented in section 4. First we deal with EGARCH specification, second we focus on the estimation of asymmetric DCC model and third we present the results of the AR model for the estimated asymmetric dynamic conditional correlation.

In the first step, we estimate conditional variances for each bank using EGARCH methodology of Nelson (1991). The results are presented in table 5. We find that most of the time the mean equation is not significant for our banks. This result is in line with the literature as in Cappiello et al. (2006) and Tamakoshi et al. (2012). However, the ARCH and GARCH terms of the variance equation are highly significant with the asymmetric parameter significantly negative for 9 banks which means that the model fits well the data. We test heteroscedasticity of the residuals with an ARCH test (Engle (1982)) and we test residuals for not being autocorrelated with the Ljung-Box and Mc Leod-Li tests. The results suggest the acceptance of null hypothesis of no autocorrelation up to 20 lags for standardized residuals and standardized residuals squared. Economically, this means that the standard deviation of the residuals do not depend on its past values, so that there is no persistence of shocks. As our analysis focuses on the dynamics of correlations of CDS returns, the well-fitted variance equations allow us to conclude that our EGARCH models fit the dataset in a very reasonable way.

In the second step, we deal with the estimation of the asymmetric DCC models. Table 6 presents the estimates of ADCC model. Both the estimates on the parameter of standardized residuals (AFIX), and the parameter of innovations in the dynamics of the conditional correlation matrix (BFIX) are statistically significant. AFIX means that the effect of past shocks is significant and BFIX that that effect of past covariance is significant. However, the estimate on the parameter of the standardized negative residuals (GFIX) is not significant even at 10% level for all the banks which means positive and negative news would have the same effect on the conditional correlation of CDS returns. According to the literature, the non-significance of the asymmetric parameter is common to empirical results, Yiu et al. (2010) and Cappiello, Engle and Sheppard (2006). Figure 3 describes the estimates on time-varying conditional correlations between each pair of banks. The figure shows the time-varying pattern of correlations between banks. For all graphs, we see a peak in correlation during the GFC that started with LB's bankruptcy.

In the third step, we present the results of AR model for the estimated dynamic conditional correlation. Our last step is to apply AR(1) with a dummy variable for the GFC period to the evolution of the estimated DCC. Table 7 shows the estimated parameters of AR equations of the estimated conditional correlations. We look at the results for model 1. We interpret three parameters: 1/ The constant term whose meaning is the link between pairs of banks. It can be either positive or negative. 2/ The coefficients of the AR term are significant and since they are less than unity, they indicate the stationary of our data. 3/ The coefficients of the GFC dummy are also found to be significant for some banks, which means some banks are subject to the effects of the GFC while other are not. The relative high level of R^2 ensures the quality of the adjustment of the regression.

Four banks appeared vulnerable to the GFC since they have positive significant dummy crisis coefficient; GS, MS, BOA and UBS. For instance, they have 10 out of their 13 total correlations that had been significantly impacted by the GFC. More precisely, the pair correlation increases in the GFC more sharply than in the pre-crisis period. Goldman Sachs was severely affected by the crisis, for instance its correlation with BNP Paribas increased by 1.07% during the GFC, its correlation with HSBC increased by 1.09% and with UBS by 1.01%. Bank of America also had higher correlations during the GFC. Its correlation with HSBC increased by 1.03% during the GFC and its correlation with Goldman Sachs increased by 0.61%. UBS correlation with Goldman Sachs increased by 1.01% during the GFC, and with Morgan Stanley by 1.06%. Then, we find HSBC and RBS, these two British banks have been impacted, with 7 dummy GFC coefficients significant. We have then Citigroup, Deutsche Bank and Barclays and the two French banks BNP Paribas and Société Générale. And finally the less affected banks during the GFC are JP Morgan, Wells Fargo and Credit Suisse. For JP Morgan and Crédit Suisse, 3 out of 13 of their ADCC increased significantly during the GFC (and respectively 4 for Wells Fargo) but they had non-significant increase in their correlation with other banks.

With the objective to test if the contagion that we observe during the GFC period was mainly due to Lehman Brothers' bankruptcy on September 2008 (see Table 7), we look at the results for model 2. We find that the dummy variable GFC is no more significant for majority of banks, even at the 10% level when adding the LBB's dummy variable. On the contrary, the dummy LBB variable is highly significant at 1% or 5% for all banks. This result shows that the significant increasing correlation for some banks found in the GFC is due to LBB. This analysis is supported by the graphics in Figure 3. We also observe that the ADCC increased significantly on September 17, 2008. This is the highest points in correlation for all banks during the period starting from 2004 until 2009. The ADCC in the graphs decreased in the shadow period of GFC. These results suggest that the effect on banks dynamic correlation during the GFC period is mainly due to LBB. The banks that do not have significant pair correlation during the GFC had managed to smooth the impact of LBB. These banks seemed less vulnerable to shocks and these results allow us to assess that all banks were not affected uniformly during the GFC.

We summarize these results in a symmetric matrix in tables 8 and 9. These tables synthesize the results of the effect of the GFC on banks pair correlations. On table 8, only are represented the significance level of the estimated coefficient associated with the dummy crisis, and on table 9 the estimated coefficient associated with the dummy global financial crisis.

For illustrative purpose, we propose a qualitative assessment on the probable link between the fundamentals ratios of banks and the probable impact of being affected by the crisis. While making some assumptions on the effect of the global financial crisis on the banks' pair correlation, we use a rating system from +++, ++ to +, which represents the qualitative likely degree of contagion during the GFC period. For instance, a rating of +++ corresponds to banks which are very likely to be impacted by the GFC and ++ for banks which are likely to be affected. On the contrary, a + rating means probably no impact of the GFC on the pair correlation. Our quantitative criteria for the qualitative rating are explained in table 11. By looking at the consolidated statements of the G14 banks at end of 2008, we consider four categories of ratios: asset quality, capital, operations and liquidity. In each of the four categories, we keep the most significant ratios.

Asset quality. We have the loan loss provisions/net interest revenue ratio. It measures a non-cash expense for banks to account for future losses on loan defaults. Banks assume that a certain percentage of loans will default or become slow paying. We also have the ratio i:paired loans/gross loans which represents the loss the lender is likely to bear when he cannot collect the full value of the loan because the creditworthiness of the borrower has fallen.

Capital. We have the tier 1 ratio which measures the banking firm's core equity capital divided by the total risk weighted assets. The equity on total asset ratio helps to determine how much shareholders would receive in the event of a company-wide liquidation.

Operations. We have the net interest margin, a performance ratio that examines how successful a firm's investment decisions are compared to its debt situation. The Return on Average Asset (ROAA) is an indicator used to assess the profitability of a firm's asset. It is calculated by taking the net income and dividing by average total assets.

Liquidity. We have the net loans/total assets which measures the total loans outstanding as a percentage of total assets. And the liquid asset/total deposit and borrowings which measrues the liquid asset to total deposits and borrowings.

For each of the ratios, we used three intervals to translate the numerical value of the ratios into our system of rating from +++, ++ to +. Our three intervals are created by subtracting the maximum value of a ratio with its minimum value between banks. We then divide by three the amplitude of the values of the ratios to obtain equally weighted intervals. Finally we obtain three intervals for each of the eight ratios. For example, a bank which has a loan loss provisions/net interest revenue ratio comprised between 44.69% and 62.72% at the end of 2008 would be classify as having a high probability (+++) of being impacted by the global financial crisis. On the contrary, if its ratio is between 8.64% and 26.67%, it would be classify as probably no impact of the GFC (+). In the middle, a bank with a ratio comprised between 26.68% and 44.68% as having a medium probability of being impact by the GFC.

Table 11: Rating criteria for qualitative assessment.

Source: Bankscope and authors.

Categories	Ratios	Expected value	Qualitative rating		
			+++	++	+
Asset quality	Loan loss provisions/net interest revenue	low	44,69% - 62,72%	26,68% - 44,68%	8,64% - 26,67%
	Impaired loans/gross loans	low	2,78% - 3,78%	1,78% - 2,77%	0,77% - 1,77%
Capital	Tier 1 ratio	high	7,8% - 9,63%	9,64% - 11,46%	11,47% - 13,30%
	Equity/total asset	high	1,45% - 4,29%	4,30% - 7,12%	7,13% - 9,97%
Operations	Net interest margin	high	0,31% - 1,26%	1,27% - 2,21%	2,22% - 3,17%
	ROAA	high	- 1,61% - 0,87%	0,88% - 3,34%	3,35% - 5,83%
Liquidity	Net loans/total assets	low	44,62% - 66,44%	22,82% - 44,61%	0,99% - 22,81%
	Liquid assets/total dep & Bor	low	51,12% - 71,00%	31,26% - 51,11%	11,37% - 31,25%

The symmetric matrix in table 12 shows the probable impact of the GFC on the banks' correlations of the G14 banks using our qualitative rating. This table allows us to synthesize our assumptions concerning the most and the less affected banks by the GFC. In order to fill in correctly the matrix, we had a careful look on the balance sheets of the G14 banks of our sample at the end of 2008. We add then the number of + to create our proper qualitative rating for each couple financial institutions. Using the same method than for the ratio, we created three final intervals. Our final intervals are the following: for each couple of FI, the ones with more than 37 + are considered as having a very likely probability of contagion during the GFC. Each couple of FI with more than 30 + and less than 37 are considered as having a moderate probability of contagion and those under 31 + as having no probably impact of the GFC.

Table 12: ***Likely impact on pair correlations during the global financial crisis.***

Source: Authors.

This table shows the probable impact of the global financial crisis on pair correlation. We use a rating from +++, ++ to + to measure the degree of contagion. +++ stands for a very likely impact of the GFC on the pair correlation, ++ stands for likely impact of the GFC and + stands for a no likely impact of the GFC. This table is a symmetric matrix with the banks in line and in column.

	C	**GS**	**JPM**	**MS**	**WF**	**BOA**	**BNP**	**DB**	**HSBC**	**RBS**	**SG**	**UBS**	**BAR**	**CS**
C		++	+	+	+	++	++	++	++	++	++	++	++	+
GS	++		+	++	++	++	++	++	+++	+++	+++	+++	++	++
JPM	+	+		+	+	+	+	+	++	++	++	++	+	+
MS	+	++	+		+	++	++	++	++	++	++	++	++	+
WF	+	++	+	+		++	++	++	++	++	++	++	++	+
BOA	++	++	+	++	++		++	++	++	+++	+++	++	++	+
BNP	++	++	+	++	++	++		++	+++	+++	+++	++	++	+
DB	++	++	+	++	++	++	++		++	+++	+++	++	++	+
HSBC	++	+++	++	++	++	++	+++	++		+++	+++	+++	++	++
RBS	++	+++	++	++	++	+++	+++	+++	+++		+++	+++	+++	++
SG	++	+++	++	++	++	+++	+++	+++	+++	+++		+++	+++	++
UBS	++	+++	++	++	++	++	++	++	+++	+++	+++		+++	++
BAR	++	++	+	++	++	++	++	++	++	+++	+++	+++		+
CS	+	++	+	+	+	+	+	+	++	++	++	++	+	

Source: Authors.

Our empirical results (tables 7, 8 & 9) are consistent with our qualitative assessment (table 12). Our qualitative rating allows us to classify banks which were affected by contagion during the GFC based on their fundamental ratios. At the top of our qualitative rating, we find SG, RBS, HSBC, UBS, GS, BOA and BNP. In the bottom of our qualitative rating, we find DB, BAR, WF, C, MS, CS and JPM. Rational contagion during the GFC crisis with Lehman Brothers' bankruptcy is observed since the banks the most affected are also the one whose fundamentals ratios were most penalizing.

We find evidence of interdependence due to Lehman Brothers' bankruptcy for all banks, but contagion during the global financial crisis is significant for some banks. We look at the subprime write downs and losses of Mortgage Backed Securities (MBS) and Collateralized Debt Obligation (CDO) during the crisis (Table 13). We find that the more the banks announced subprime writedowns, the more they are affected by contagion during the GFC. Citigroup, UBS, HSBC, Bank of America, Royal Bank of Scotland, Morgan Stanley and JP Morgan were the banks in the top ranking that announced writedowns and losses. These banks are the ones whose the number of pair of correlations increased significantly during the global financial crisis (except for JP Morgan). In the top down ranking of writedowns announcements, we find Deutsche Bank, Crédit Suisse, Wells Fargo, Barclays, Société Générale, BNP Paribas and Goldman Sachs. These banks were also the less affected by contagion in our model (except for Goldman Sachs).

Our empirical results are similar as Salloy (2012). The author finds rational contagion during the GFC especially due to Lehman Brothers' bankruptcy with some banks less affected than other. For instance, JP Morgan when studying contagion with abnormal returns did not show significant negative abnormal returns. In this study, the bank holding company resisted to the GFC. We also find consistent results with Acharya et al. (2009) who consider LB' bankruptcy as a triggering event for systemic risk. Also with Wang and Moore (2012) who consider that LB had reinforced the integration between developed markets.

From our results, we distinguish the short term impact of LB's bankruptcy and the contagion. While all banks were affected by LB's bankruptcy, only some went through contagion during the GFC. Higher level of correlations during the LBB is an important indication of systematic impact and increased interdependence among the banks. This result can be explained by the structure of the CDS market. Notional value of the CDS contracts was a large multiple of the value of the underlying, which created the danger of domino effect. If one large insurer of credit default swap such as Lehman Brothers failed. This effect may have been exacerbated by the fact that the swaps were traded over the counter with limited liquidity and the absence of a clearing house mechanism. The authorities may have underestimated the threat from the CDS market by letting LB go into bankruptcy.

The factors that could explain our results are as follows: 1/ the nature of business of a FI: Investment banks, universal banks and commercial banks are not regulated under same set of regulations. After the crisis, some investment banks were seen as too risky such as GS and MS and faced considerable amount of losses that they decided to transform into bank holding companies and access deposits on the wholesale market. In addition, investment banks generally carried out very complex credit operations off their balance-sheet, placing them away from investor control. 2/ Fundamental ratios: As revealed by our qualitative assessment, there is a link between the fundamental ratios of a FI and its degree of contamination during the crisis. The more robust banks are, the less they suffer due to crisis. 3/ Systemic risk is a global factor and cannot be completely attributed to FIs. LBB could have made investors realize that the "Too Big To Fail" doctrine was not always on purpose and thus could have caused run on other FIs. 4/ The rating agencies that did not give sufficient warning made investors aware of the default risk of FI. Since rating agencies are paid by FIs for their rating, there exists a conflict of interest.

6. Conclusion

In this article, we applied Asymmetric DCC (Cappiello et al. (2006)) to model the interdependence structure between the G14 dealer banks for the period January 2004 to May 2009. By doing this, we answer three questions; First, did the interdependence structure among G14 banks remained constant or did it changed with time? Second, were all the banks affected with the same magnitude during the global financial crisis? And third, was the impact of Lehman Brothers' failure short term or long term on banks' correlation? Our approach is innovative as we are interested in contagion and correlation in the credit default swap market. A particular focus was placed on analyzing the impact of the financial crisis starting with Lehman Brothers' bankruptcy on the dynamics of CDS banks' correlations. We also propose a qualitative rating based on fundamental criteria to compare with our empirical results.

Concerning the results, we find that (i) the interdependence structure among the banks was dynamic and change with time; (ii) we find that all banks were affected by Lehman Brothers' bankruptcy which points towards significant short term impact of such an event, (iii) only some banks faced contagion during the global financial crisis. From the estimates of the asymmetric DCC models, we do not find evidence of asymmetry. Thus, the impacts of bad news and good news on the correlation between banks are not different. The AR model of the estimated DCC series is used to test the existence of contagion by including a global financial crisis dummy variable. We find no significant effect of the GFC for all banks. Some banks appeared as less vulnerable than other and did not seem to be affected by the crisis. We notice that the contagion during the GFC is mainly due to LBB. All the major dealers' banks in the CDS market did not react in the same way. The more robust banks could then constitute good opportunity for investors. Regulators who try to reinforce banks capital with the Basel 3 reform proposals should be interested by this result. For policy-makers, the predictions of the dynamic correlation between banks could be a useful tool for preventing systematic risk during crisis period.

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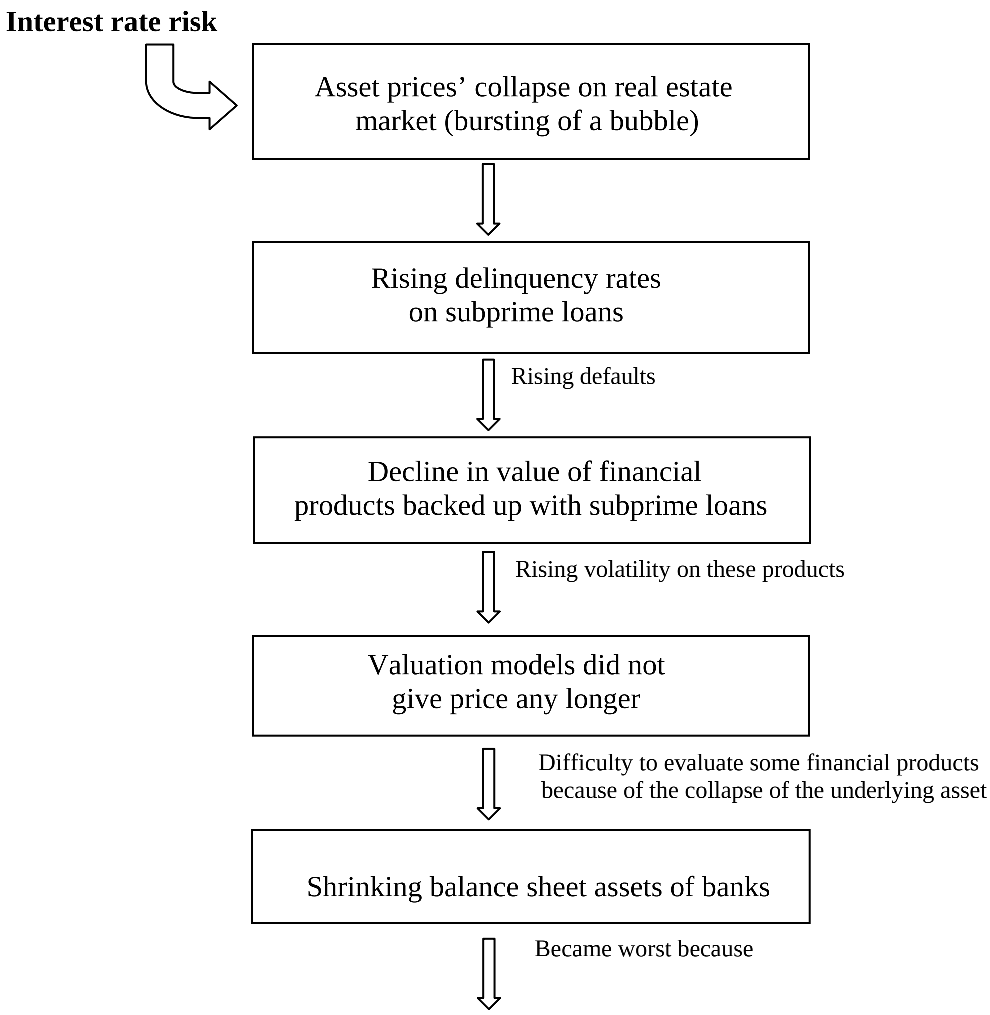
Appendix

Schema 1: Risks during the subprime crisis.
Source: Author.



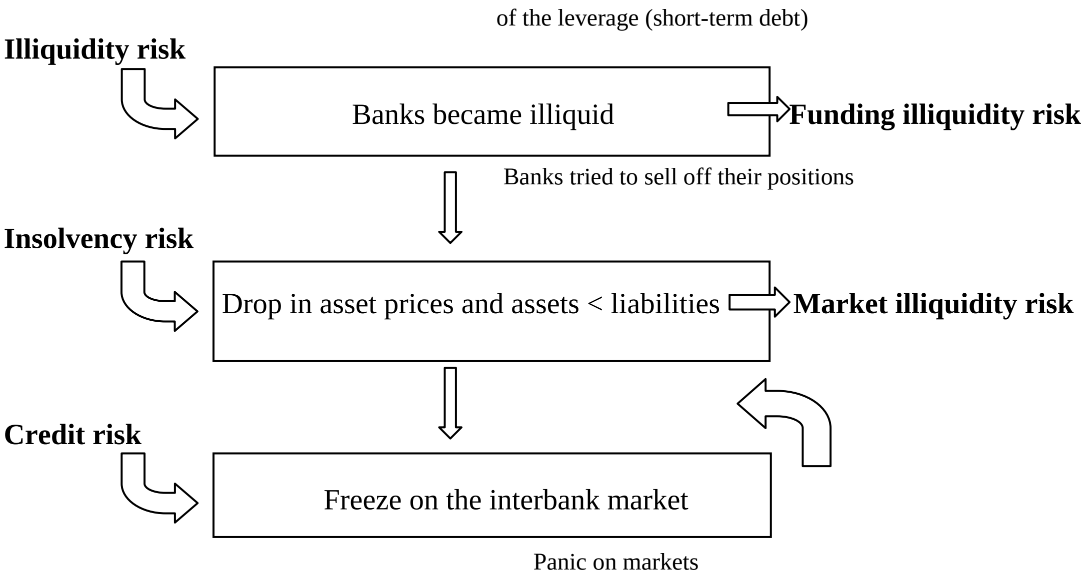


Table 1: ***Sample of the G14 dealers Financial Institutions.***

Name	Short name	Country	Business type
Citigroup	CG	UNITED STATES	Investment bank
Goldman Sachs	GS	UNITED STATES	Investment bank
JP Morgan	JM	UNITED STATES	Investment bank
Morgan Stanley	MS	UNITED STATES	Investment bank
Wells Fargo	WF	UNITED STATES	Commercial bank
Bank of America	BOA	UNITED STATES	Universal bank
BNP Paribas	BNP	FRANCE	Universal bank
Société Générale	SG	FRANCE	Universal bank
Deutsche Bank	DB	GERMANY	Investment bank
HSBC	HSBC	UNITED KINGDOM	Universal bank
Royal Bank of Scotland	RBS	UNITED KINGDOM	Universal bank
Barclays	BAR	UNITED KINGDOM	Investment bank
UBS	UBS	SWITZERLAND	Investment bank
Crédit Suisse	CS	SWITZERLAND	Investment bank

Table 3: ***Synthesis of the principal studies on contagion.***
Source: Authors.

Authors	Problem	Data	Contagion	Sample	Period	Country	Risks	Variables to explain	Methodology	Estimator	Results
Athanasoglou, Brissimis and Delis (2008)	Examined the effect of bank-specific, industry-specific and macroeconomic determinants of bank profitability.	Individual	Banking	38 Commercial banks	1985-2001	Greece	Credit risk	Profitability (ROA/ROE)	Dynamic panel	GMM	Profitability of Greek banks was shaped by bank-specific factors, macroeconomic, and control variables that were not the result of bank's managerial decision.
Eichengreen (2009)	Examined how the common factors influenced the movement of the 45 largest banks' CDS spreads at different time of the crisis.	Individual	Banking	45 developped banks	July 29, 2002- November 28, 2008 (weekly)	Developped	Credit risk/Liquidity risk/Interest rate risk	CDS of banks	1/Principal Component Analysis. 2/ Dynamic panel	GMM	Common factors played a major role ==> irrational contagion
Raunig and Scheicher (2009)	Examined how investors in the corporate debt market view banks.	Individual	Banking	41 banks (largest in EUR and USA) and 162 non-banks	January 2003- December 2007 (monthly)	US and EUROPE	Credit risk/Interest rate risk	CDS of banks	Fixed effect (FE) and random effect (RE) panel	Panel robust estimates	After August 2007 ==> investors viewed banks at least at risky as other firms.
Shen, Chen, Kao and Yeh (2009)	Causes of liquidity risk and the relationship between bank liquidity risk and performance.	Individual	Banking	12 commercial banks	1994-2006 (annual)	Developped	Liquidity risk	Financing gap ratio/short term funding/net loans to customers	Panel data instrumental/FE	2SLS	Liquidity risk decreased banks' profitability.
Frank, Gonzalez-Hermosillo and Hesse (2008)	Estimated the linkages between market and funding liquidity pressures, and their interaction with solvency issues during the 2007 subprime crisis.	Global	Financial	5 US financial markets	January 3rd 2003 - January 9th 2008	USA	Liquidity risk (funding and market)	Spreads	DCC-GARCH (2006 : Capiello, Engle and Sheppard)	1/ Monte carlo. 2/Boostrap	The interaction between market and funding illiquidity increased sharply during the subprime crisis and the bank solvency became important issue.

Authors	Problem	Data	Contagion	Sample	Period	Country	Risks	Variables to explain	Methodology	Estimator	Results
Dooley and Hutchison (2009)	Analysis of the spillover effect of the US subprime crisis on sovereign CDS spreads of emerging markets.	Global	Financial	14 emerging markets	January 1, 2007 - February, 2009 (dally)	Emerging	Credit risk	CDS sovereign bonds	1/ Event study on 15 types of news. 2/ VAR model	1/OLS.2/Granger causality test	Emerging markets were insulated from the subprime crisis before Lehman Brothers shock in 2008, but were infected after the Lehman crisis by the deteriorating situation of the US financial system.
Naoui, Liouane and Brahim (2010)	Examined financial contagion following the American subprime crisis using Dynamic Conditional Correlation Model.	Global	Financial	6 developped and 10 emerging	January 3, 2006 - February 26, 2010 (daily)	Developped/ Emerging	Market risk	Market indices	DCC-GARCH (Engle, 2002)	Log likelihood	Amplification of dynamic conditional correlations worldwide during the crisis period.
Yiu, Ho and Choi (2010)	Investigated the dynamics of correlation beween 11 Asian stock markets and the US stock market.	Global	Financial	11 Asian countries + USA	1993 - 2009 (weekly)	Asian countries	Market risk	Market indices	1/ Principal components. 2/ADCC	Log likelihood	There is contagion from the US to the Asian markets from late of 2007 but no contagion between from the US to Asian markets during the Asian financial crisis.
Alrgaibat (2011)	Examined the presence of a symmetric conditional second moments in major European stock markets.	Global	Financial	3 developped European countries	January 1990 - April 2009 (daily)	DAX 30/CAC40/FTS E100	Market risk	Market indices	DCC- EGARCH	Log likelihood	The index return series showed a great asymmetry in conditional volatility after a shock.
Wang and Moore (2012)	Invistigated the interaction of the CDS markets of 38 developped and emerging countries with the US market during the subprime crisis. Identification of the driving factors of this relationship.	Global	Financial	38 countries	January 2007 - December 2009 (weekly)	Developped/ Emerging	Credit risk/Interest rate risk	CDS sovereign bonds	1/DCC-Mutivariate GARCH (Engle, 2002). 2/Panel linear model of DCC	Quasi-maximum likelihood (consistant standard errors robust to non normality)	1/Lehman Brothers shock have strengthened the integration, in particular for developped markets. 2/ CDS market driven by the US interest rates.
Tamakoshi, Toyoshima and Hamori (2012)	Investigated whether the financial turmoil that originated from one nation's governmenet debt market can exert contagion effects on equity markets i other countries of the region.	Global	Financial	Greece and 6 other European countries	January 2007 - March 2011 (daily)	Developped	Market risk/Interest rate risk	Market indices	ADCC (2006)	Quasi-maximum likelihood	Correlations show significant decline during the sovereign debt crisis

Table 4: ***Descriptive statistics on the G14 CDS returns.***

Whole period (January 14, 2004 - May 27, 2009)

	RBAR	*RBNP*	*RBOA*	*RCG*	*RCS*	*RDB*	*RGS*	*RHSBC*	*RJPM*	*RMS*	*RSG*	*RRBS*	*RUBS*	*RWF*
Mean	0,94	0,69	0,80	1,08	0,64	0,63	0,57	0,68	0,57	0,76	0,76	0,97	0,90	0,67
Median	-0,23	-0,13	-0,25	-0,04	-0,34	-0,24	0,00	-0,67	-0,39	-0,04	-0,43	-0,41	-0,23	0,00
Maximum	62,40	59,64	47,05	73,24	67,47	69,58	117,13	61,87	46,94	111,26	61,74	84,75	90,69	58,72
Minimum	-62,48	-36,15	-45,68	-81,06	-41,39	-47,93	-62,39	-31,18	-44,04	-96,06	-47,83	-85,82	-38,32	-63,53
Std. Dev.	12,92	11,87	11,27	12,60	11,02	12,09	13,38	11,70	10,82	13,44	11,46	15,10	12,16	12,99
Skewness	0,38	0,99	0,46	0,82	0,92	0,64	2,02	1,25	0,33	0,89	1,18	0,00	1,74	0,26
Kurtosis	8,97	8,52	6,81	16,10	10,22	8,62	25,34	8,42	6,98	29,08	11,09	14,36	15,14	9,08
Jarque-Bera	423,75	402,24	179,63	2041,20	650,38	389,17	6035,23	416,84	190,35	7999,05	831,93	1509,72	1867,70	436,50
Observations	281	281	281	281	281	281	281	281	281	281	281	281	281	281

Pre-crisis period (January 14, 2004 - September 10, 2008)

	RBAR	*RBNP*	*RBOA*	*RCG*	*RCS*	*RDB*	*RGS*	*RHSBC*	*RJPM*	*RMS*	*RSG*	*RRBS*	*RUBS*	*RWF*
Mean	1,02	0,71	0,86	0,96	0,65	0,66	0,73	0,69	0,74	0,85	0,84	0,95	1,03	0,80
Median	-0,21	-0,17	-0,52	-0,01	-0,34	-0,25	0,00	-0,63	-0,40	0,00	-0,41	-0,43	-0,18	0,00
Maximum	62,40	59,64	47,05	69,87	47,44	42,18	51,93	61,87	42,07	44,25	61,74	84,75	51,63	54,92
Minimum	-32,83	-32,90	-29,26	-24,31	-32,24	-32,47	-36,58	-27,76	-24,48	-41,67	-32,20	-85,82	-32,45	-29,93
Std. Dev.	10,76	10,51	9,29	9,78	9,68	9,93	10,27	10,04	9,09	9,39	10,26	13,20	10,14	10,57
Skewness	1,14	1,52	0,95	2,23	0,72	0,58	0,42	1,42	0,80	0,00	1,74	0,49	1,18	1,15
Kurtosis	9,14	11,16	7,11	15,10	8,04	6,89	7,67	9,54	5,87	7,94	13,29	17,73	8,10	8,59
Jarque-Bera	435,94	771,31	208,35	1691,52	279,41	167,31	228,80	516,27	110,15	248,09	1200,57	2216,00	320,95	371,96
Observations	244	244	244	244	244	244	244	244	244	244	244	244	244	244

Global Financial Crisis period (September 17, 2008 - May 27, 2009)

	RBAR	*RBNP*	*RBOA*	*RCG*	*RCS*	*RDB*	*RGS*	*RHSBC*	*RJPM*	*RMS*	*RSG*	*RRBS*	*RUBS*	*RWF*
Mean	0,44	0,52	0,39	1,87	0,58	0,43	-0,46	0,58	-0,51	0,19	0,22	1,13	0,04	-0,15
Median	-2,76	1,33	2,05	-2,27	1,92	0,76	-0,03	-0,73	-0,18	-1,30	-1,39	0,48	-1,11	-0,19
Maximum	58,25	53,17	44,20	73,24	67,47	69,58	117,13	59,82	46,94	111,26	55,51	64,56	90,69	58,72
Minimum	-62,48	-36,15	-45,68	-81,06	-41,39	-47,93	-62,39	-31,18	-44,04	-96,06	-47,83	-83,30	-38,32	-63,53
Std. Dev.	22,71	18,75	20,14	24,26	17,65	21,68	26,05	19,62	18,73	28,45	17,65	24,42	21,33	23,63
Skewness	-0,23	0,16	0,04	-0,17	0,95	0,51	2,08	0,81	0,00	0,79	0,27	-0,54	1,76	-0,28
Kurtosis	4,26	3,31	3,09	6,61	7,35	4,55	13,09	3,98	3,89	10,94	5,23	6,26	10,14	4,17
Jarque-Bera	2,75	0,31	0,02	20,27	34,76	5,33	183,53	5,51	1,21	101,11	8,11	18,13	97,70	2,62
Observations	37	37	37	37	37	37	37	37	37	37	37	37	37	37

Table 5: ***EGARCH models – Whole sample (January 14, 2004 – May 27, 2009).***

This table shows the results of the estimates of the conditional variance for each bank of the sample. We use EGARCH model to allow for asymmetric effect in the conditional variance. To estimate the conditional variance, we need 2 equations, the mean equation and the variance equation. The following equations are estimated for each univariate serie : $r_{it} = \varphi_0 + \sum_{l=1}^{k} \varphi_i \, r_{t-l} + \varepsilon_t$ and $\log(d_{it}) = C + \sum_{j=1}^{p} \left[A \frac{\varepsilon_{it-j}}{\sigma_{it-j}} + D \left| \frac{\varepsilon_{it-j}}{\sigma_{it-j}} \right| \right] + \sum_{j=1}^{q} B \log(d_{t-j})$. This table shows also the results of the Q, Q^2 and ARCH test for 20 lags. *** denotes the significance level at 1%, ** denotes the significance level at 5%, * denotes the significance level at 10%. The values in parenthesis are the standard deviations. The value in [ ] are the P-value.

	MEAN	C	A	B	D	Q(20)	$Q^2(20)$	ARCH(20)
Citigroup	-0,47	1,121**	0,394***	0,764***	-0,259**	27,093	28,870*	1,139
	(0,292)	(0,524)	(0,089)	(0,038)	(0,105)	[0,133]	[0,050]	[0,310]
Goldman Sachs	-0,193	3,259**	1,131***	0,606***	-0,932***	6,770	2,103	0,099
	(0,344)	(1,395)	(0,303)	(0,069)	(0,282)	[0,997]	[0,100]	[1,000]
JP Morgan	-0,148	3,210***	0,328***	0,777***	-0,270***	25,441	20,968	0,945
	(0,411)	(1,101)	(0,088)	(0,053)	(0,088)	[0,185]	[0,281]	[0,531]
Morgan Stanley	-0,303	0,862*	0,460***	0,830***	-0,415***	14,633	1,360	0,064
	(0,308)	(0,453)	(0,106)	(0,022)	(0,137)	[0,797]	[1,000]	[1,000]
Wells Fargo	-0,170***	34,663***	0,278***	0,626***	-0,340***	19,628	11,516	0,520
	(0,008)	(0,51)	(0,001)	(0,001)	(0,002)	[0,481]	[0,871]	[0,957]
Bank of America	0,027	1,651**	0,199***	0,846***	-0,085	14,870	16,340	0,732
	(0,43)	(0,752)	(0,06)	(0,039)	(0,076)	[0,784]	[0,569]	[0,791]
BNP Paribas	-0,463	1,653**	0,380**	0,741***	-0,136	26,756	8,544	0,407
	(0,319)	(0,631)	(0,149)	(0,054)	(0,193)	[0,142]	[0,969]	[0,990]
Deutsche Bank	-0,605**	1,079*	0,379***	0,659***	0,25	19,880	6,139	0,302
	(0,294)	(0,634)	(0,109)	(0,064)	(0,188)	[0,465]	[0,996]	[0,999]
HSBC	0,225	1,140***	0,107***	0,952***	-0,177***	30,588*	13,836*	1,361
	(0,418)	(-0,286)	(0,017)	(0,014)	(0,036)	[0,061]	[0,086]	[0,199]
RBS	0,83	51,438**	0,430**	0,529***	-0,435**	25,193	2,639	0,105
	(0,683)	(16,141)	(0,167)	(0,129)	(0,176)	[0,194]	[0,999]	[1,000]
Société Générale	-0,292	1,647**	0,440**	0,725***	-0,239	22,534	6,759	0,268
	(0,29)	(0,595)	(0,168)	(0,061)	(-0,188)	[0,312]	[0,992]	[0,999]
UBS	-0,738**	1,530*	1,193**	0,583***	-0,778**	16,844	6,597	0,276
	(0,297)	(0,795)	(0,403)	(0,082)	(0,352)	[0,663]	[0,993]	[0,999]
Barclays	0,138	3,023**	0,241**	0,868***	-0,302***	26,176	13,869	0,649
	(0,408)	(1,099)	(0,076)	(0,042)	(0,08)	[0,160]	[0,738]	[0,872]
Credit Suisse	-0,417	1,460**	0,192**	0,824***	0,042	30,422*	8,550	0,371
	(0,381)	(0,56)	(0,065)	(0,052)	(0,102)	[0,063]	[0,969]	[0,994]

Table 6: ***DCC-GARCH model.***

These results are the estimation of the DCC-GARCH model for the 14 banks. The coefficient AFIX represents the effect of past shocks. The coefficient BFIX represents the effect of past covariance. And the coefficient of GFIX the effect of asymmetry. If the GFIX coefficient is significant, then means that a bad news would have a more negative effect on correlations than good news. The following equation is estimated for the multivariate series: $Q_t = (1 - AFIX - BFIX)P - GFIX * N + A\varepsilon_{t-1}\varepsilon'_{t-1} + GFIX\ \eta_{t-1}\eta'_{t-1} + BFIX\ Q_{t-1}$.

*** denotes the significance level at 1%, ** denotes the significance level at 5%, * denotes the significance level at 10%. The values in parenthesis are the standard deviations.

	Coefficient
AFIX	0,139*** (0,022)
BFIX	0,905*** (0,048)
GFIX	0,000 (0,056)

Table 7: ***Results from the ADCC-AR regression.***

This table shows the coefficient of the dummy GFC from the AR regression. The following equation for Model 1 is tested $\rho_{ij,t} = \delta_0 + \sum_{j=1}^{p} \delta_1 \rho_{ij,t-j} + \xi_1\ GFC + \nu_t$. For instance, the dynamic conditional correlation of Citigroup with Wells Fargo significantly increased by 0.93% during the global financial crisis. The results are presented for each banks of the sample. The coefficients for the correlation between Citigroup and Goldman Sachs are the same than the coefficients for the correlation between Goldman Sachs and Citigroup,etc. The following equation for Model 2 is tested : $\rho_{ij,t} = \delta_0 + \sum_{j=1}^{p} \delta_1 \rho_{ij,t-j} + \xi_1\ GFC + \xi_2\ LBB + \nu_t$.

We recall that the pair correlations are symmetric. So reporting the estimated coefficients for banks i with j is the same that reporting the estimated coefficient for banks j and i.

*** denotes the significance level at 1%, ** denotes the significance level at 5%, *denotes the significance level at 10%.

AR(1) Model CG	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRCG_GS	0,097***	0,848***	0,003	0,736	0,119***	0,814***	0,000	**0,029*** **	0,753
CORRCG_JPM	0,120***	0,824***	0,003	0,703	0,128***	0,812***	0,001	**0,021*** **	0,715
CORRCG_MS	0,098***	0,834***	0,002	0,702	0,123***	0,793***	-0,001	**0,037*** **	0,727
CORRCG_WF	0,114***	0,818***	0,009**	0,793	0,118***	0,812***	0,007**	**0,025*** **	0,802
CORRCG_BOA	0,084***	0,878***	0,003	0,794	0,093***	0,864***	0,001	**0,019*** **	0,800
CORRCG_BNP	0,062***	0,860***	0,005	0,769	0,076***	0,829***	0,001	**0,043*** **	0,791
CORRCG_DB	0,080***	0,828***	0,007*	0,720	0,091***	0,803***	0,003	**0,047*** **	0,739
CORRCG_HSBC	0,077***	0,825***	0,007**	0,730	0,092***	0,79***	0,003	**0,048*** **	0,756
CORRCG_RBS	0,054***	0,872***	0,006**	0,802	0,064***	0,847***	0,002	**0,049*** **	0,822
CORRCG_SG	0,069***	0,847***	0,004	0,741	0,092***	0,797***	0,000	**0,051*** **	0,773
CORRCG_UBS	0,077***	0,815***	0,006**	0,706	0,098***	0,764***	0,002	**0,058*** **	0,747
CORRCG_BAR	0,070***	0,850***	0,005*	0,755	0,085***	0,82***	0,001	**0,045*** **	0,779
CORRCG_CS	0,069***	0,857***	0,001	0,732	0,091***	0,81***	-0,005	**0,053*** **	0,758

AR(1) Model GS	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRGS_JPM	0,105***	0,846***	0,001	0,721	0,123***	0,819***	-0,001	**0,025*** **	0,737
CORRGS_MS	0,110***	0,869***	0,003*	0,791	0,141***	0,833***	0,000	**0,027*** **	0,822
CORRGS_WF	0,094***	0,855***	0,003	0,762	0,133***	0,795***	0,001	**0,041*** **	0,794
CORRGS_BOA	0,080***	0,861***	0,006**	0,786	0,099***	0,829***	0,003	**0,042*** **	0,804
CORRGS_BNP	0,088***	0,810***	0,011**	0,764	0,116***	0,75***	0,007**	**0,062*** **	0,806
CORRGS_DB	0,070***	0,868***	0,008**	0,798	0,082***	0,846***	0,003	**0,055*** **	0,815
CORRGS_HSBC	0,062***	0,846***	0,011**	0,790	0,08***	0,804***	0,006	**0,068*** **	0,819
CORRGS_RBS	0,075***	0,829***	0,011**	0,766	0,096***	0,78***	0,006	**0,071*** **	0,801
CORRGS_SG	0,080***	0,837***	0,010**	0,787	0,112***	0,775***	0,006*	**0,069*** **	0,828
CORRGS_UBS	0,078***	0,837***	0,010**	0,766	0,102***	0,787***	0,005	**0,077*** **	0,806
CORRGS_BAR	0,073***	0,846***	0,008**	0,771	0,093***	0,805***	0,004	**0,056*** **	0,800
CORRGS_CS	0,076***	0,853***	0,007**	0,772	0,103***	0,802***	0,002	**0,068*** **	0,808

AR(1) Model JPM	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRJPM_MS	0,170***	0,746***	0,000	0,557	0,19***	0,716***	-0,003	**0,026*** **	0,584
CORRJPM_WF	0,070***	0,893***	0,004*	0,844	0,075***	0,884***	0,002	**0,026*** **	0,854
CORRJPM_BOA	0,058***	0,910***	0,004	0,858	0,061***	0,907***	0,002	**0,024*** **	0,863
CORRJPM_BNP	0,079***	0,840***	0,004	0,727	0,102***	0,792***	0,001	**0,041*** **	0,753
CORRJPM_DB	0,104***	0,824***	0,002	0,686	0,123***	0,792***	-0,001	**0,035*** **	0,707
CORRJPM_HSBC	0,088***	0,816***	0,006**	0,702	0,108***	0,775***	0,002	**0,047*** **	0,730
CORRJPM_RBS	0,058***	0,867***	0,004	0,775	0,071***	0,835***	0,001	**0,043*** **	0,792
CORRJPM_SG	0,075***	0,846***	0,004	0,738	0,105***	0,786***	0,000	**0,049*** **	0,769
CORRJPM_UBS	0,065***	0,844***	0,006*	0,745	0,091***	0,781***	0,002	**0,052*** **	0,777
CORRJPM_BAR	0,078***	0,848***	0,004	0,747	0,096***	0,814***	0,001	**0,035*** **	0,768
CORRJPM_CS	0,082***	0,843***	0,001	0,712	0,108***	0,793***	-0,004	**0,048*** **	0,743

AR(1) Model MS	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRMS_WF	0,085***	0,851***	0,004	0,753	0,119***	0,792***	0,000	**0,054*** **	0,794
CORRMS_BOA	0,104***	0,826***	0,006**	0,722	0,132***	0,779***	0,002	**0,043*** **	0,753
CORRMS_BNP	0,089***	0,819***	0,008**	0,735	0,121***	0,755***	0,003	**0,064*** **	0,787
CORRMS_DB	0,087***	0,844***	0,008**	0,761	0,103***	0,815***	0,003	**0,060*** **	0,788
CORRMS_HSBC	0,067***	0,840***	0,010**	0,761	0,088***	0,793***	0,004	**0,074*** **	0,797
CORRMS_RBS	0,070***	0,840***	0,010**	0,765	0,093***	0,787***	0,004	**0,081*** **	0,805
CORRMS_SG	0,077***	0,849***	0,007**	0,768	0,106***	0,792***	0,002	**0,072*** **	0,813
CORRMS_UBS	0,076***	0,838***	0,011**	0,773	0,102***	0,782***	0,005	**0,085*** **	0,819
CORRMS_BAR	0,083**	0,831***	0,007**	0,739	0,109***	0,777***	0,002	**0,063*** **	0,780
CORRMS_CS	0,087***	0,839***	0,008**	0,757	0,121***	0,777***	0,003	**0,072*** **	0,802

AR(1) Model WF	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRWF_BOA	0,091***	0,855***	0,009**	0,836	0,1***	0,842***	0,006**	**0,032*** **	0,849
CORRWF_BNP	0,091***	0,820***	0,004	0,699	0,135***	0,734***	0,000	**0,056*** **	0,748
CORRWF_DB	0,070***	0,863***	0,005	0,774	0,09***	0,824***	0,001	**0,050*** **	0,795
CORRWF_HSBC	0,068***	0,870***	0,004	0,782	0,097***	0,813***	0,000	**0,052*** **	0,815
CORRWF_RBS	0,070***	0,881***	0,002	0,777	0,076***	0,853***	-0,002	**0,049*** **	0,795
CORRWF_SG	0,085***	0,833***	0,003	0,713	0,132***	0,74***	-0,001	**0,064*** **	0,766
CORRWF_UBS	0,066***	0,848***	0,007**	0,740	0,099***	0,774***	0,002	**0,066*** **	0,780
CORRWF_BAR	0,077***	0,853***	0,004	0,758	0,104***	0,801***	0,000	**0,048*** **	0,790
CORRWF_CS	0,076***	0,855***	0,001	0,727	0,123***	0,767***	-0,007**	**0,067*** **	0,772

AR(1) Model BOA	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRBOA_BNP	0,073***	0,830***	0,008**	0,744	0,096***	0,776***	0,004	**0,055*** **	0,777
CORRBOA_DB	0,079***	0,833***	0,008**	0,734	0,091***	0,806***	0,004	**0,053*** **	0,753
CORRBOA_HSBC	0,071***	0,825***	0,010**	0,760	0,091***	0,777***	0,006**	**0,059*** **	0,791
CORRBOA_RBS	0,061***	0,853***	0,007**	0,777	0,077***	0,815***	0,003	**0,055*** **	0,801
CORRBOA_SG	0,080***	0,832***	0,006*	0,727	0,112***	0,768***	0,001	**0,059*** **	0,767
CORRBOA_UBS	0,057***	0,852***	0,009**	0,771	0,072***	0,812***	0,004	**0,064*** **	0,798
CORRBOA_BAR	0,056***	0,866***	0,007**	0,801	0,072***	0,83***	0,003	**0,050*** **	0,823
CORRBOA_CS	0,065***	0,857***	0,005	0,751	0,092***	0,799***	-0,001	**0,064*** **	0,787

AR(1) Model BNP	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRBNP_DB	0,097***	0,867***	0,003	0,773	0,112***	0,847***	0,000	**0,026*****	0,787
CORRBNP_HSBC	0,112***	0,848***	0,003	0,746	0,127***	0,827***	0,001	**0,024*****	0,759
CORRBNP_RBS	0,091***	0,863***	0,004	0,776	0,102***	0,848***	0,002	**0,0278*****	0,785
CORRBNP_SG	0,077***	0,906***	0,002	0,842	0,085***	0,897***	0,001	**0,014*****	0,847
CORRBNP_UBS	0,087***	0,859***	0,005**	0,787	0,117***	0,812***	0,003	**0,037*****	0,810
CORRBNP_BAR	0,128***	0,838***	0,003	0,735	0,138***	0,825***	0,002	**0,016*****	0,744
CORRBNP_CS	0,09327***	0,864***	0,004	0,777	0,118***	0,827***	0,001	**0,032*****	0,798

AR(1) Model DB	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRDB_HSBC	0,105***	0,841***	0,004	0,735	0,122***	0,816***	0,001**	**0,035*****	0,752
CORRDB_RBS	0,075***	0,877***	0,004	0,797	0,091***	0,852***	0,001	**0,040*****	0,814
CORRDB_SG	0,100***	0,856***	0,004	0,767	0,117***	0,832***	0,001	**0,033*****	0,783
CORRDB_UBS	0,075***	0,869***	0,005*	0,794	0,098***	0,83***	0,002	**0,050*****	0,820
CORRDB_BAR	0,010***	0,860***	0,003	0,759	0,117***	0,836***	0,000	**0,028*****	0,775
CORRDB_CS	0,073***	0,893***	0,003	0,815	0,092***	0,867***	0,000	**0,034*****	0,830

AR(1) Model HSBC	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRHSBC_RBS	0,141***	0,806***	0,004*	0,694	0,16***	0,78***	0,002	**0,027*** **	0,711
CORRHSBC_SG	0,107***	0,854***	0,004	0,758	0,123***	0,832***	0,001	**0,027*** **	0,772
CORRHSBC_UBS	0,125***	0,801***	0,005*	0,678	0,166***	0,737***	0,001	**0,044*** **	0,719
CORRHSBC_BAR	0,114***	0,858***	0,002	0,750	0,123***	0,847***	0,001	**0,016*** **	0,757
CORRHSBC_CS	0,074***	0,894***	0,001	0,800	0,095***	0,864***	-0,002	**0,034*** **	0,816

AR(1) Model RBS	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRRBS_HSBC	0,141***	0,806***	0,0044*	0,694	0,16***	0,78***	0,002	**0,027*** **	0,711
CORRRBS_SG	0,117***	0,835***	0,004**	0,760	0,15***	0,79***	0,003	**0,029*** **	0,784
CORRRBS_UBS	0,095***	0,847***	0,002	0,721	0,14***	0,776***	-0,002	**0,050*** **	0,759
CORRRBS_BAR	0,107***	0,866***	0,002*	0,800	0,133***	0,834***	0,001	**0,019*** **	0,820
CORRRBS_CS	0,075***	0,863***	0,002	0,749	0,093***	0,83***	-0,003	**0,054*** **	0,767

AR(1) Model SG	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRSG_HSBC	0,107***	0,854***	0,004	0,758	0,123***	0,832***	0,001	**0,027*** **	0,772
CORRSG_RBS	0,117***	0,835***	0,004**	0,760	0,15***	0,79***	0,003	**0,029*** **	0,784
CORRSG_UBS	0,070***	0,890***	0,003	0,811	0,1***	0,842***	-0,001	**0,044*** **	0,836
CORRSG_BAR	0,119***	0,851***	0,003	0,757	0,123***	0,836***	0,002	**0,020*** **	0,766
CORRSG_CS	0,083***	0,875***	0,003	0,782	0,104***	0,843***	0,000	**0,040*** **	0,802

AR(1) Model UBS	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRUBS_BAR	0,113***	0,827***	0,003	0,707	0,098***	0,764***	0,002	**0,058*****	0,747
CORRUBS_CS	0,101***	0,847***	0,00**	0,786	0,118***	0,819***	0,005*	**0,040*****	0,806

AR(1) Model BAR	Model 1				Model 2				
Bank Correlation	Constant	Lag Correlation	Crisis	R Square	Constant	Lag Correlation	Crisis	**Lehman B. B**	R Square
CORRBAR_CS	0,090***	0,863***	0,002	0,754	0,113***	0,83***	-0,001	**0,035*****	0,774

Table 8: The significance of dummy crisis coefficient from the ADCC-AR regression.

This table shows the results of the effect of the GFC on banks pair correlations. On this table only are represented the significance level of the estimated coefficient associated with the dummy crisis.

** denotes the significance level at 5%, * denotes the significance level at 10%. ns denotes insignificant parameters.

	CG	GS	JPM	MS	WF	BOA	BNP	DB	HSBC	RBS	SG	UBS	BAR	CS
CG		ns	ns	ns	**	ns	ns	*	**	*	ns	**	*	ns
GS	ns		ns	*	ns	**	**	*	**	**	**	**	**	**
JPM	ns	ns		ns	*	ns	ns	ns	*	ns	ns	*	ns	ns
MS	ns	*	ns		ns	***	**	**	**	**	**	**	**	**
WF	**	ns	*	ns		**	ns	ns	ns	ns	ns	**	ns	ns
BOA	ns	**	ns	**	**		**	**	**	**	*	**	**	ns
BNP	ns	**	ns	**	ns	**		ns	ns	ns	ns	**	ns	ns
DB	*	**	ns	**	ns	**	ns		ns	ns	ns	*	ns	ns
HSBC	**	**	*	**	ns	**	ns	ns		*	ns	*	ns	ns
RBS	*	**	ns	**	ns	**	ns	ns	*		**	ns	*	ns
SG	ns	**	ns	**	ns	*	ns	ns	ns	**		ns	ns	ns
UBS	**	**	*	**	**	**	**	*	*	ns	ns		ns	*
BAR	*	**	ns	**	ns	**	ns	ns	ns	*	ns	ns		ns
CS	ns	**	ns	**	ns	ns	ns	ns	ns	ns	ns	*	ns	

Table 9: ***The dummy crisis coefficient from the ADCC-AR regression.***

This table shows the results of the effect of the GFC on banks pair correlations. The following equation is estimated (model 1) : $\rho_{ij,t} = \delta_0 + \sum_{j=1}^{p} \delta_1 \rho_{ij,t-j} \; + \; \xi_1 \, GFC \; + \; \nu_t$. On this table only are represented the estimated coefficient associated with the dummy crisis.

*** denotes the significance level at 1%, ** denotes the significance level at 5%, * denotes the significance level at 10%. The values in parenthesis are the standard deviations.

	CG	GS	JPM	MS	WF	BOA	BNP	DB	HSBC	RBS	SG	UBS	BAR	CS
CG		0,0028	0,0032	0,0022	0,0093**	0,0031	0,0049	0,0069*	0,0073**	0,0063*	0,0041	0,0064**	0,0053*	0,0008
		(0,0022)	(0,0021)	(0,0025)	(0,0030)	(0,0022)	(0,0030)	(0,0037)	(0,0032)	(0,0033)	(0,0029)	(0,0032)	(0,0030)	(0,0033)
GS	0,0028		0,0014	0,0027*	0,0033	0,0061**	0,0107**	0,0082**	0,0109**	0,0108**	0,0097**	0,0101**	0,0077**	0,0073**
	(0,0022)		(0,0021)	(0,0015)	(0,0023)	(0,0030)	(0,0034)	(0,0041)	(0,0041)	(0,0041)	(0,0036)	(0,0041)	(0,0034)	(0,0036)
JPM	0,0032	0,0014		-0,0003	0,0041*	0,0043	0,0041	0,0020	0,0061*	0,0044	0,0038	0,0055*	0,0039	0,0014
	(0,0021)	(0,0021)		(0,0020)	(0,0024)	(0,0028)	(0,0027)	(0,0027)	(0,0032)	(0,0032)	(0,0028)	(0,0030)	(0,0025)	(0,0028)
MS	0,0022	0,0027*	-0,0003		0,0041	0,0055**	0,0075**	0,0084**	0,0095**	0,0096**	0,0071**	0,0106**	0,0072**	0,0077**
	(0,0025)	(0,0015)	(0,0020)		(0,0027)	(0,0027)	(0,0031)	(0,0039)	(0,0041)	(0,0042)	(0,0034)	(0,0042)	(0,0034)	(0,0035)
WF	0,0093**	0,0033	0,0041*	0,0041		0,0089**	0,0041	0,0053	0,0042	0,0019	0,0032	0,0071**	0,0040	0,0006
	(0,0030)	(0,0023)	(0,0024)	(0,0027)		(0,0028)	(0,0027)	(0,0034)	(0,0027)	(0,0036)	(0,0029)	(0,0034)	(0,0027)	(0,0030)
BOA	0,0031	0,0061**	0,0043	0,0055**	0,0089**		0,0076**	0,0081**	0,0103**	0,0073**	0,0055*	0,0088**	0,0071**	0,0048
	(0,0022)	(0,0030)	(0,0028)	(0,0027)	(0,0028)		(0,0032)	(0,0041)	(0,0036)	(0,0036)	(0,0032)	(0,0039)	(0,0033)	(0,0034)
BNP	0,0049	0,0107**	0,0041	0,0075**	0,0041	0,0076**		0,0027	0,0032	0,0043	0,0018	0,0053**	0,0031	0,0036
	(0,0030)	(0,0034)	(0,0027)	(0,0031)	(0,0027)	(0,0032)		(0,0022)	(0,0022)	(0,0030)	(0,0016)	(0,0024)	(0,0019)	(0,0022)
DB	0,0069*	0,0082**	0,0020	0,0084**	0,0053	0,0081**	0,0027		0,0044	0,0042	0,0042	0,0055*	0,0028	0,0030
	(0,0037)	(0,0041)	(0,0027)	(0,0039)	(0,0034)	(0,0041)	(0,0022)		(0,0029)	(0,0030)	(0,0026)	(0,0030)	(0,0022)	(0,0025)
HSBC	0,0073**	0,0109**	0,0061*	0,0095**	0,0042	0,0103**	0,0032	0,0044		0,0044*	0,0036	0,0047*	0,0022	0,0011
	(0,0032)	(0,0041)	(0,0032)	(0,0041)	(0,0027)	(0,0036)	(0,0022)	(0,0029)		(0,0024)	(0,0024)	(0,0025)	(0,0020)	(0,0023)
RBS	0,0063*	0,0108**	0,0044	0,0096**	0,0019	0,0073**	0,0043	0,0042	0,0044*		0,0044**	0,0015	0,0024*	0,0022
	(0,0033)	(0,0041)	(0,0032)	(0,0042)	(0,0036)	(0,0036)	(0,0030)	(0,0030)	(0,0024)		(0,0021)	(0,0026)	(0,0013)	(0,0040)
SG	0,0041	0,0097**	0,0038	0,0071**	0,0032	0,0055*	0,0018	0,0042	0,0036	0,0044**		0,0028	0,0034	0,0031
	(0,0029)	(0,0036)	(0,0028)	(0,0034)	(0,0029)	(0,0032)	(0,0016)	(0,0026)	(0,0024)	(0,0021)		(0,0024)	(0,0021)	(0,0027)
UBS	0,0064**	0,0101**	0,0055*	0,0106**	0,0071**	0,0088**	0,0053**	0,0055*	0,0047*	0,0015	0,0028		0,0034	0,0081**
	(0,0032)	(0,0041)	(0,0030)	(0,0042)	(0,0034)	(0,0039)	(0,0024)	(0,0030)	(0,0025)	(0,0026)	(0,0024)		(0,0025)	(0,0030)
BAR	0,0053*	0,0077**	0,0039	0,0072**	0,0040	0,0071**	0,0031	0,0028	0,0022	0,0024*	0,0034	0,0034		0,0023
	(0,0030)	(0,0034)	(0,0025)	(0,0034)	(0,0027)	(0,0033)	(0,0019)	(0,0022)	(0,0020)	(0,0013)	(0,0021)	(0,0025)		(0,0025)
CS	0,0008	0,0073**	0,0014	0,0077**	0,0006	0,0048	0,0036	0,0030	0,0011	0,0022	0,0031	0,0081**	0,0023	
	(0,0033)	(0,0036)	(0,0028)	(0,0035)	(0,0030)	(0,0034)	(0,0022)	(0,0025)	(0,0023)	(0,0040)	(0,0027)	(0,00295)	(0,0025)	

Table 12: ***Subprime writedowns and credit losses and capital raised in billions of dollars announced by the G14 banks from January 2007 to August 2008 (source: Bloomberg).***

Financial Institutions	Writedown & Loss	Capital Raised
Citigroup	55.1	49.1
UBS	44.2	28.3
HSBC	27.4	3.9
Bank of America	21.2	20.7
Royal Bank of Scotland	14.9	24.3
Morgan Stanley	14.4	5.6
JPMorgan Chase	14.3	7.9
Deutsche Bank	10.8	3.2
Credit Suisse	10.5	2.7
Wells Fargo	10	4.1
Barclays	9.1	18.6
Societe Generale	6.8	9.8
BNP Paribas	4	-
Goldman Sachs	3.8	0.6

Figure 1: CDS premiums for the G14 banks.

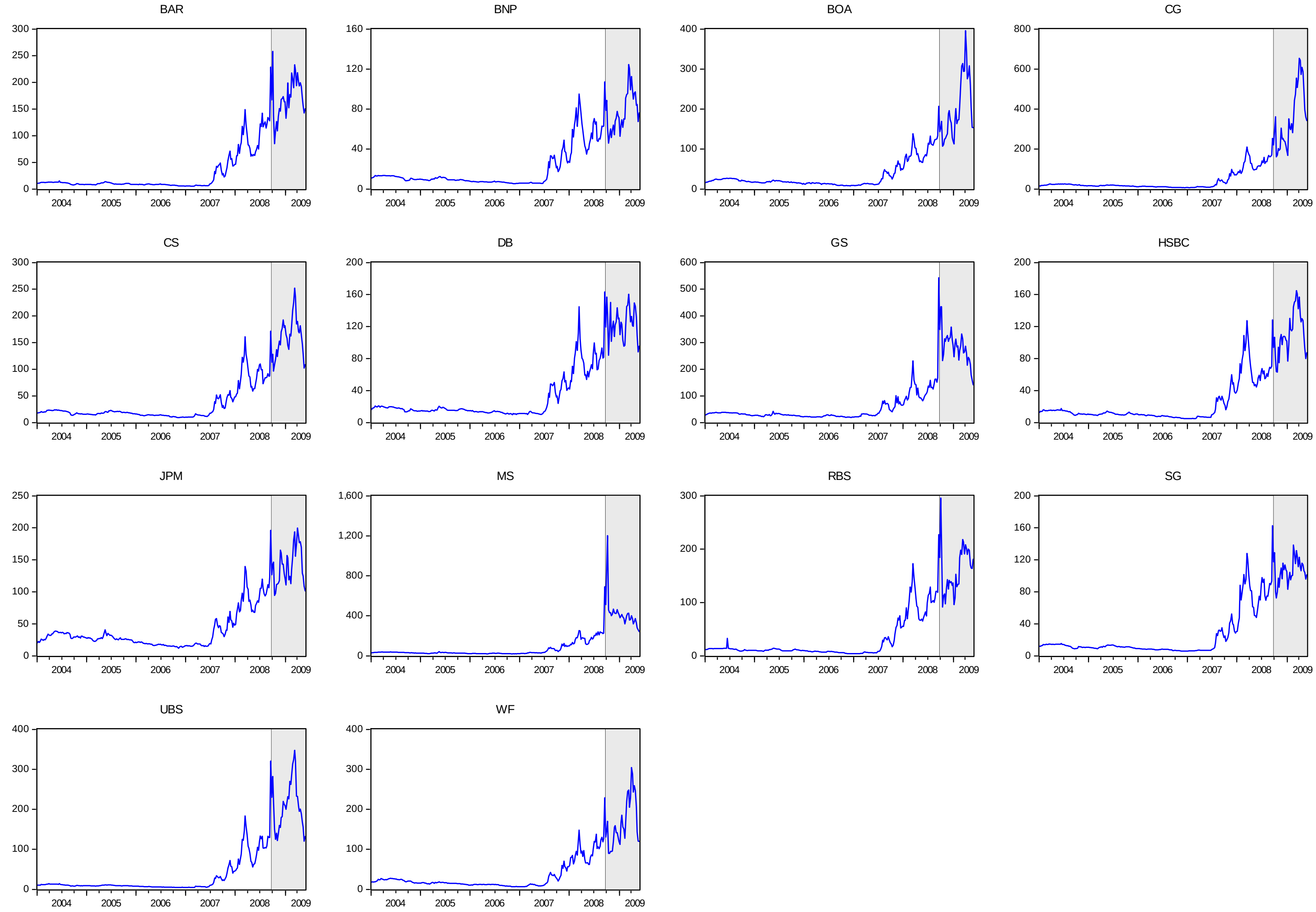


Figure 2: CDS returns for the G14 banks.

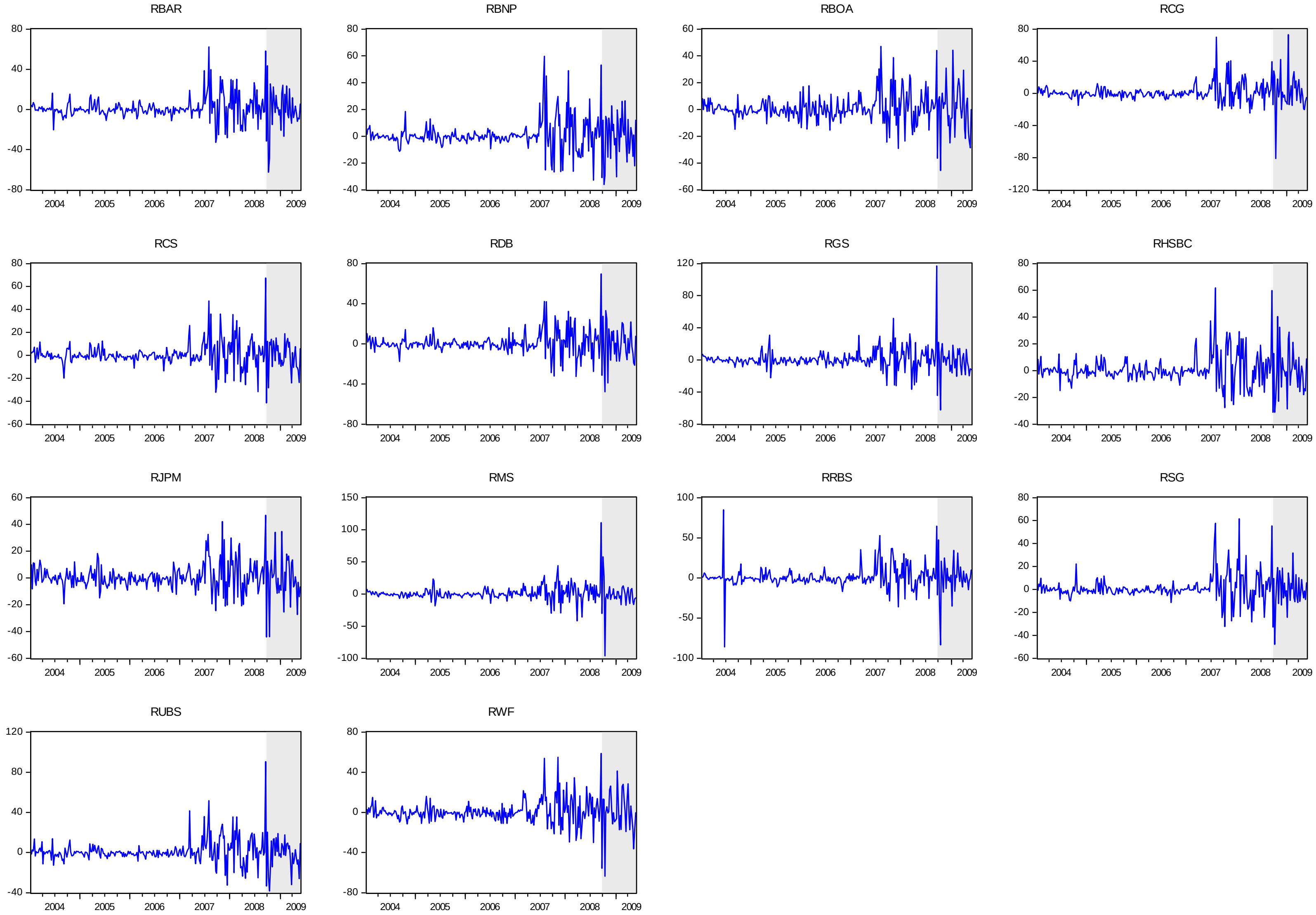


Figure 3: ***Weekly Asymmetric Dynamic Conditional Correlation between pairwise of banks.***

These are the graph of the asymmetric dynamic conditional correlation. The shadow area represents the GFC period starting on September 17th, 2008.

Figure 3.1: ADCC between CG and other banks

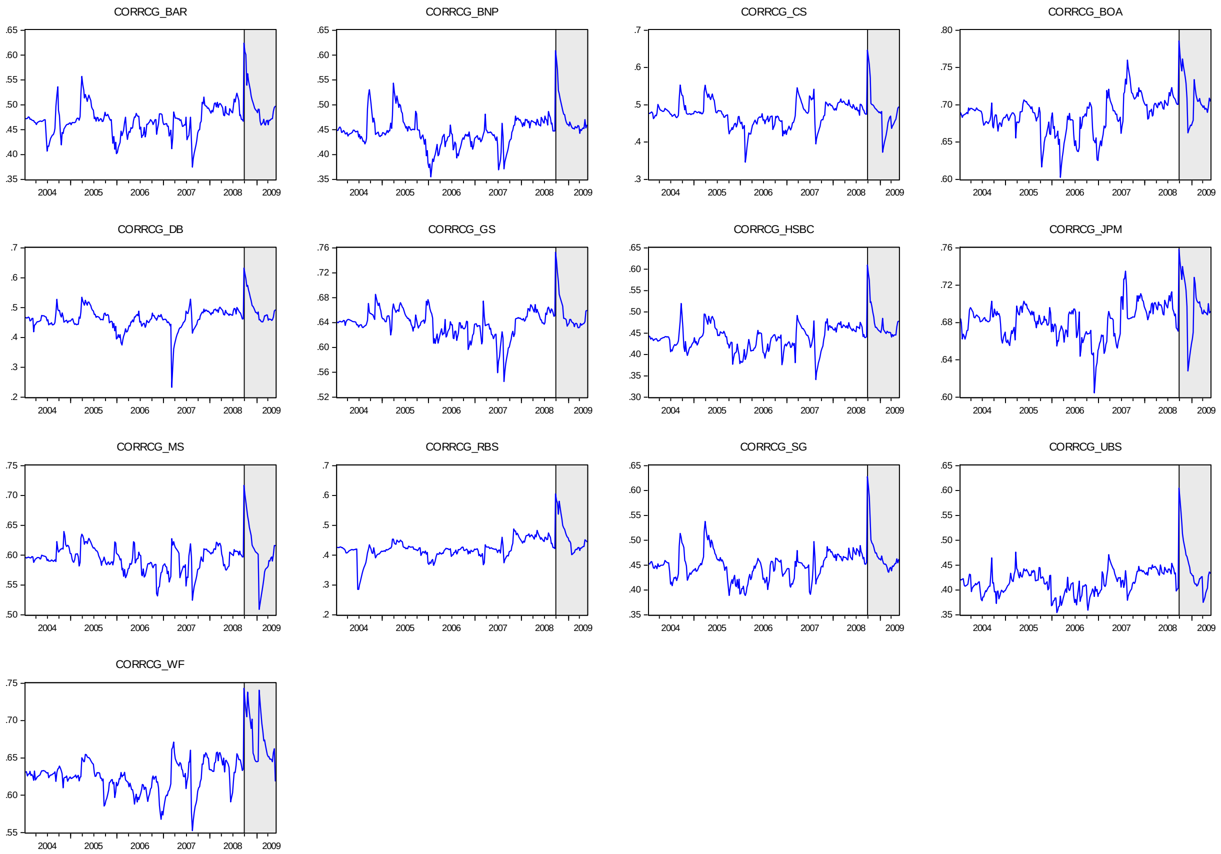


Figure 3.2: ADCC between GS and other banks

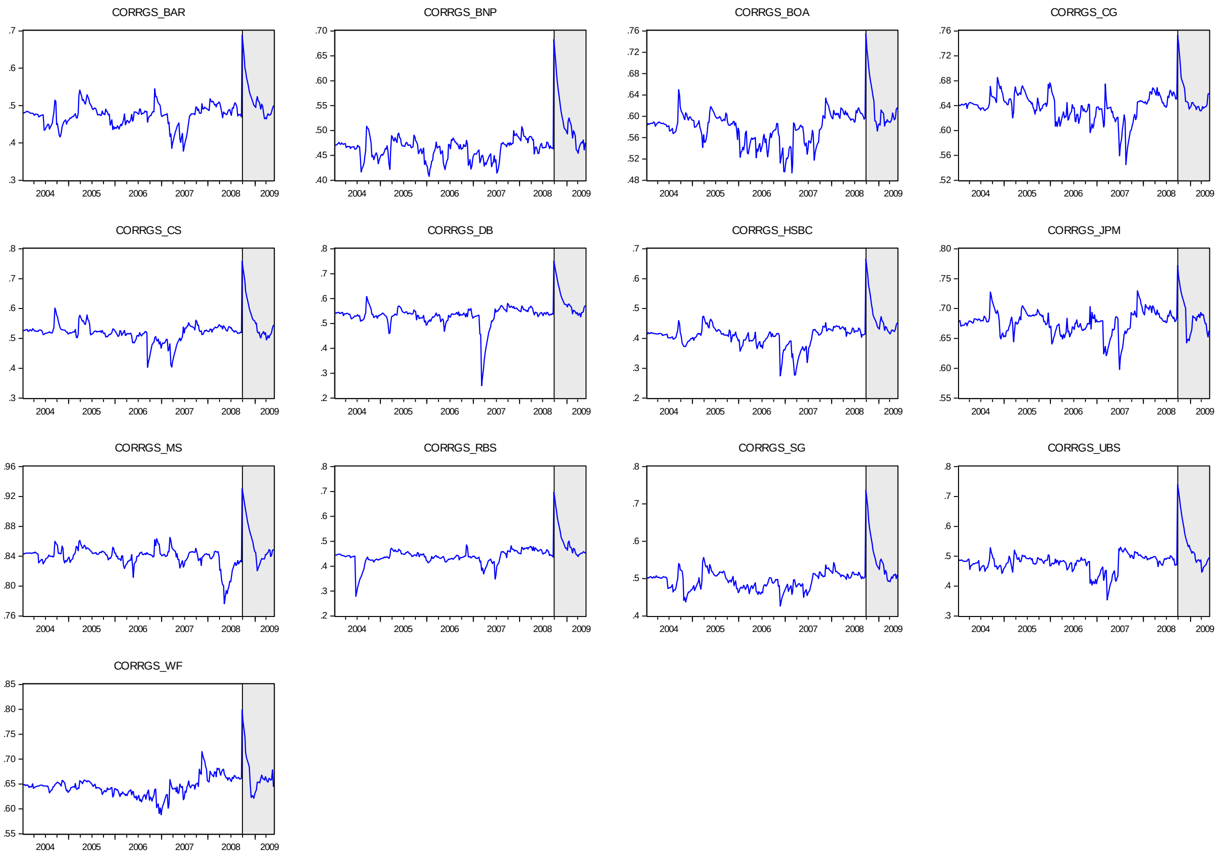


Figure 3.3: ADCC between JPM and other banks

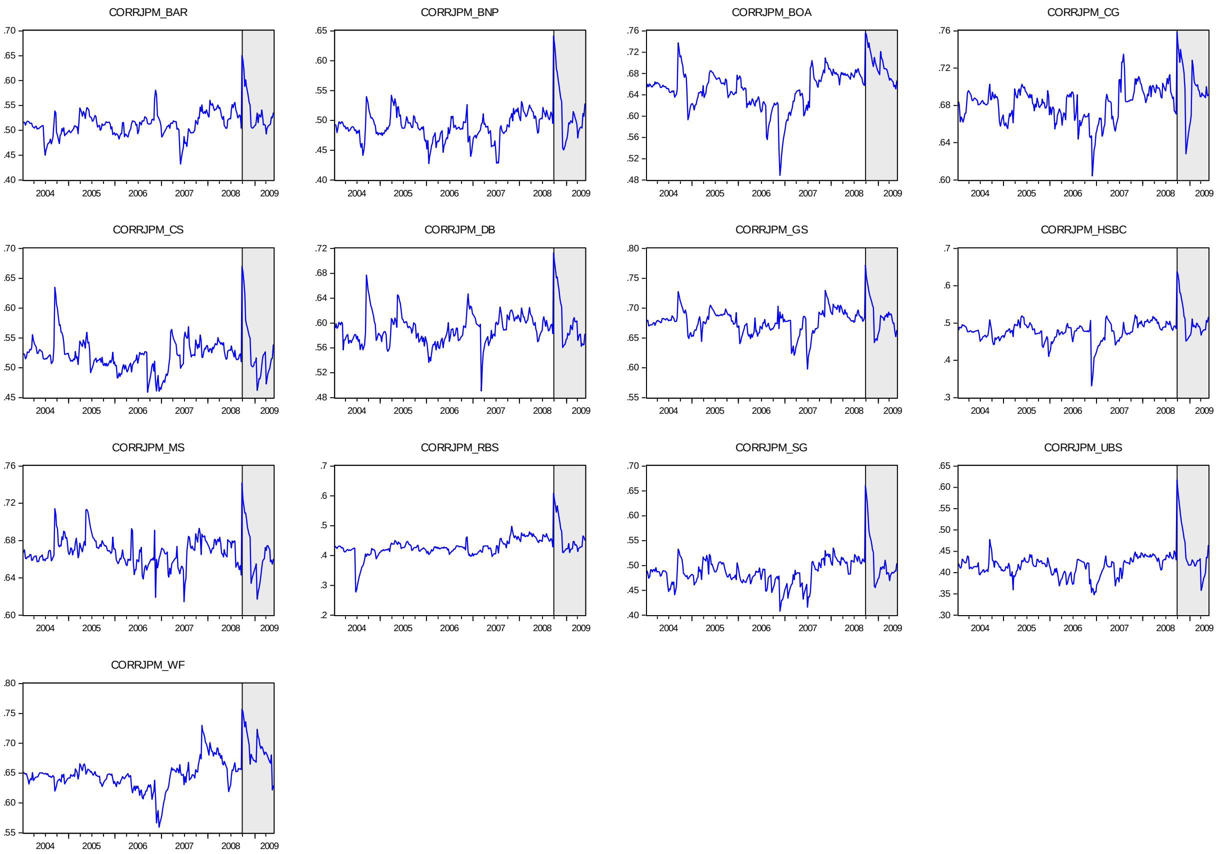


Figure 3.4: ADCC between MS and other banks

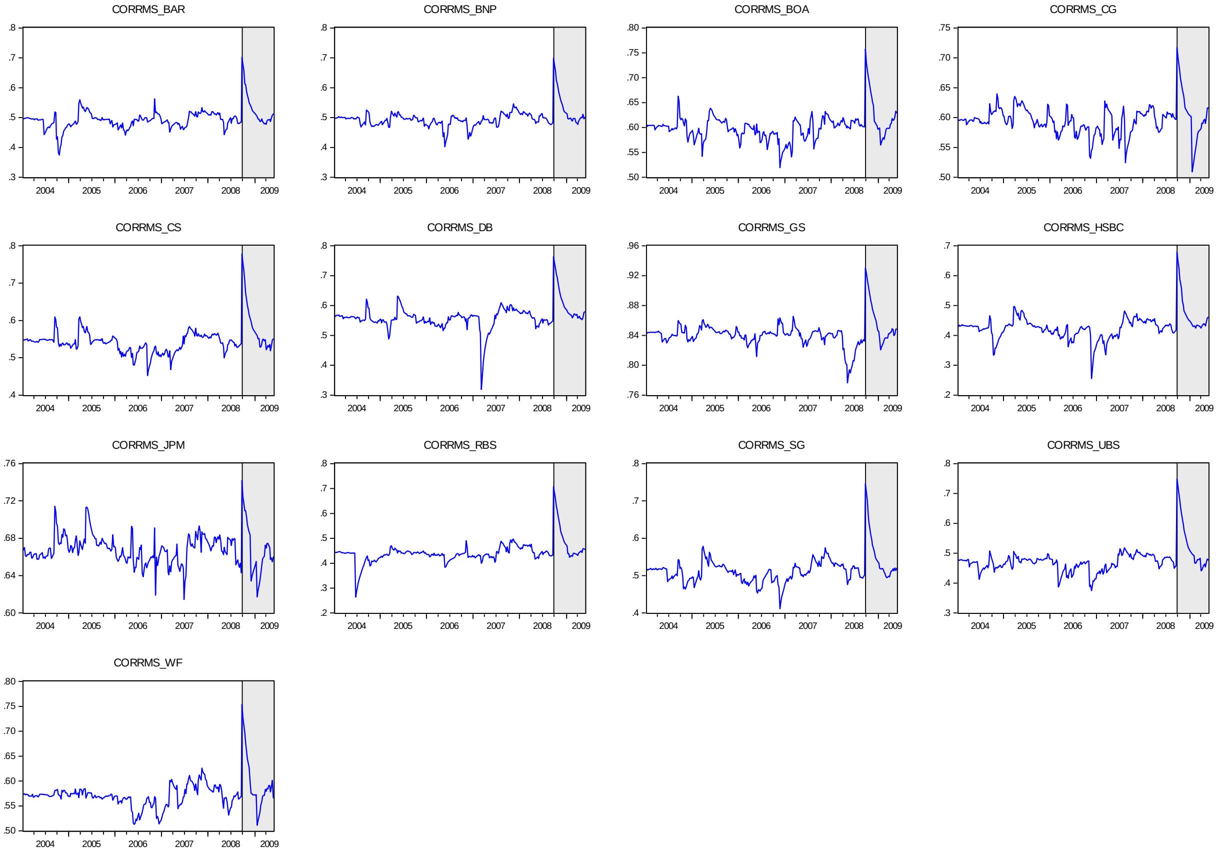


Figure 3.5: ADCC between WF and other banks

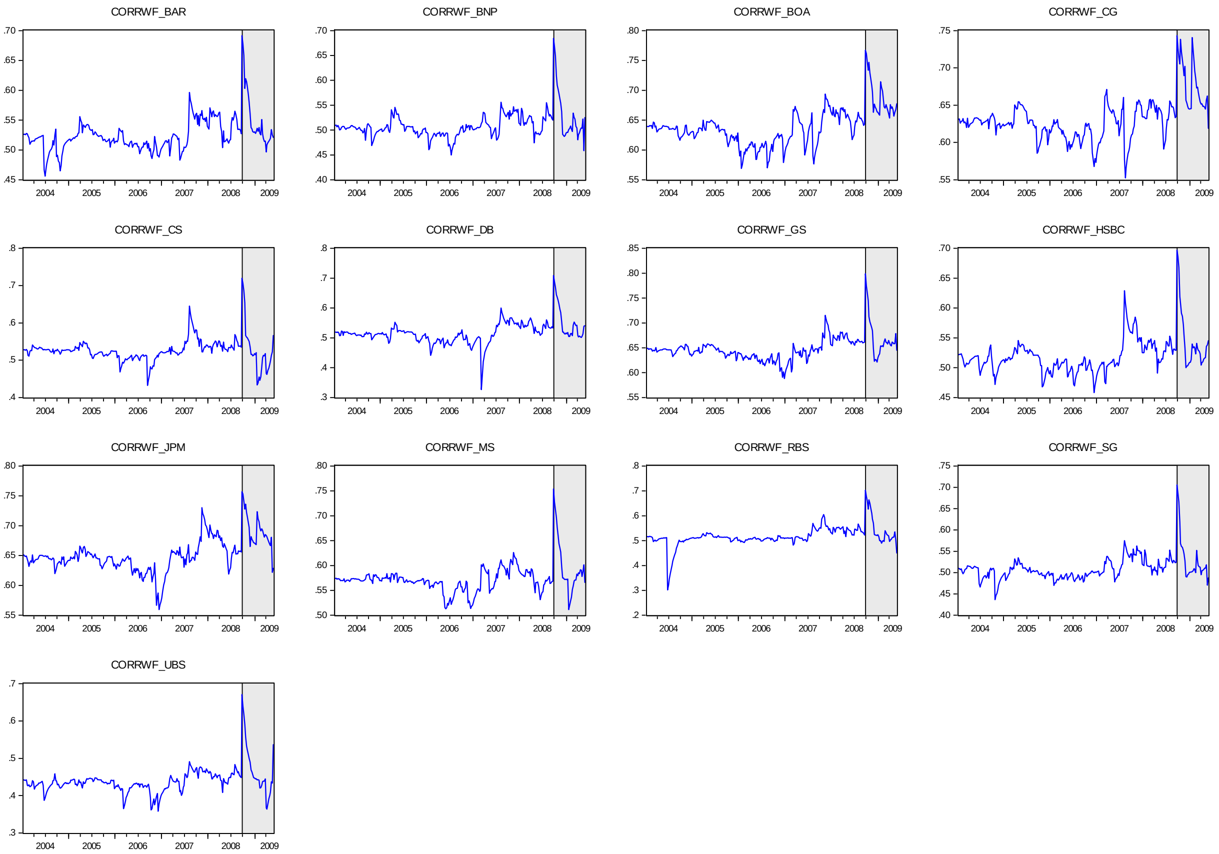


Figure 3.6: ADCC between BOA and other banks

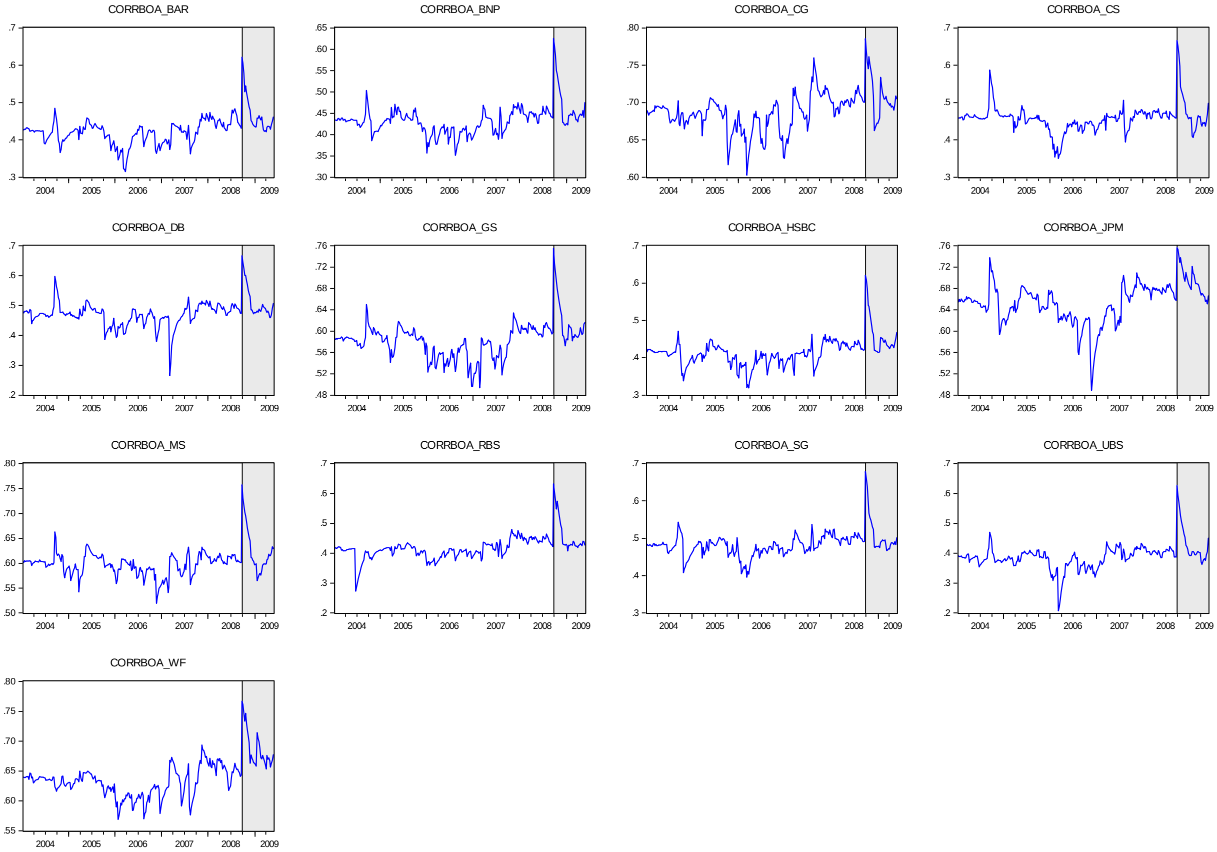


Figure 3.7: ADCC between BNP and other banks

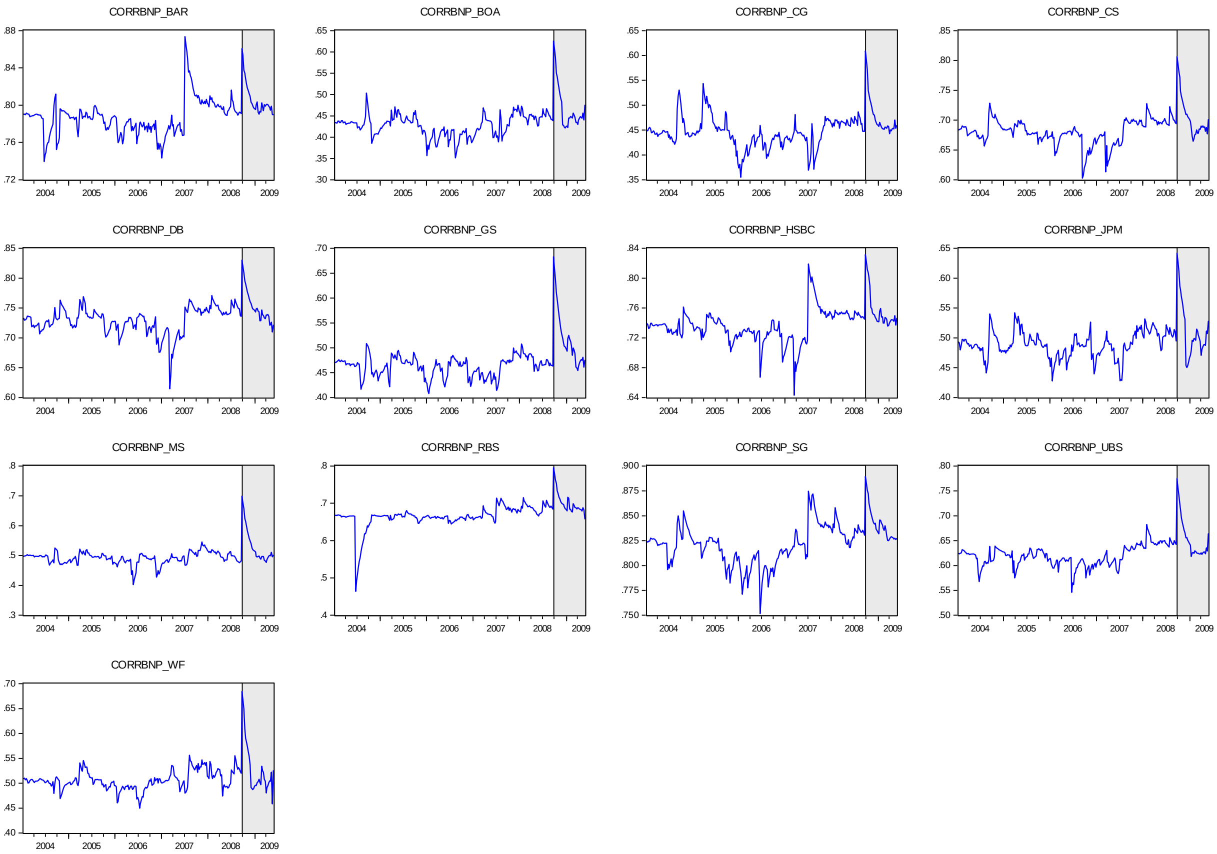


Figure 3.8: ADCC between DB and other banks

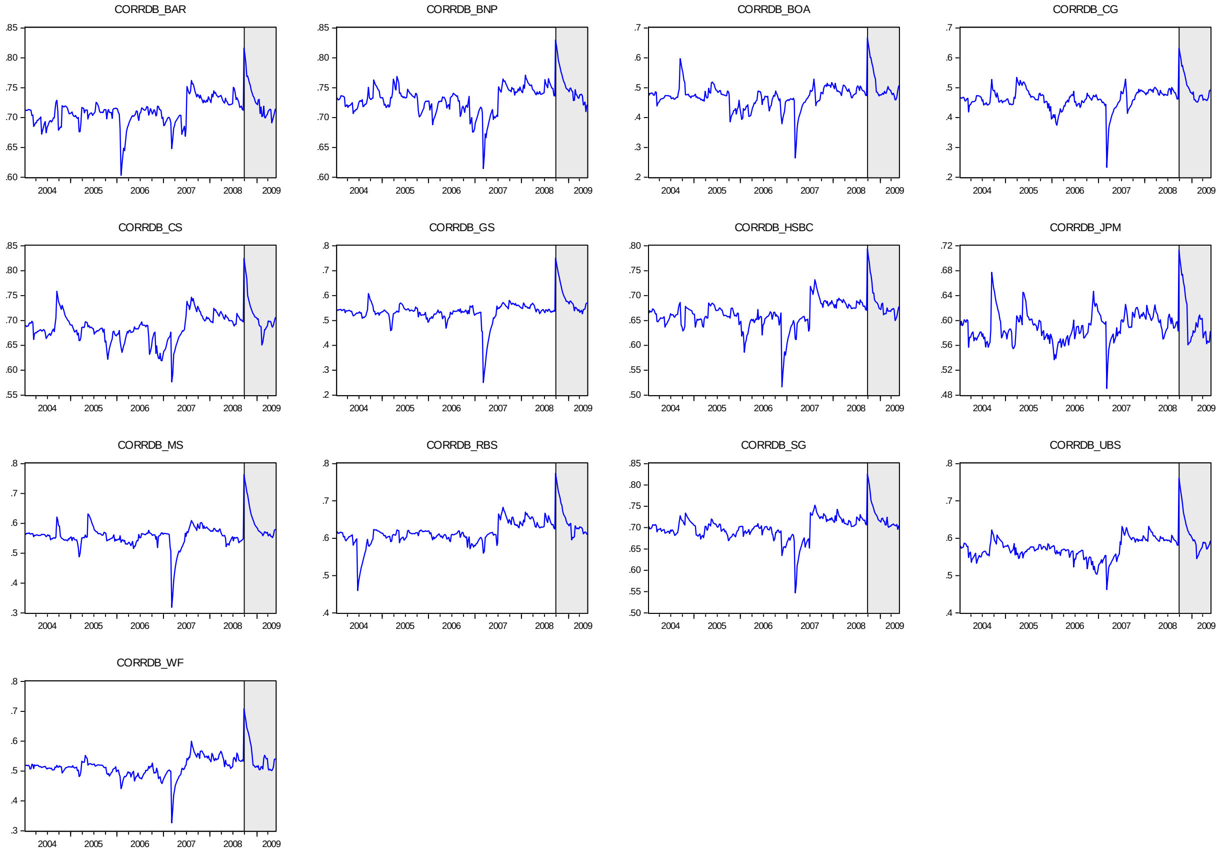


Figure 3.9: ADCC between HSBC and other banks

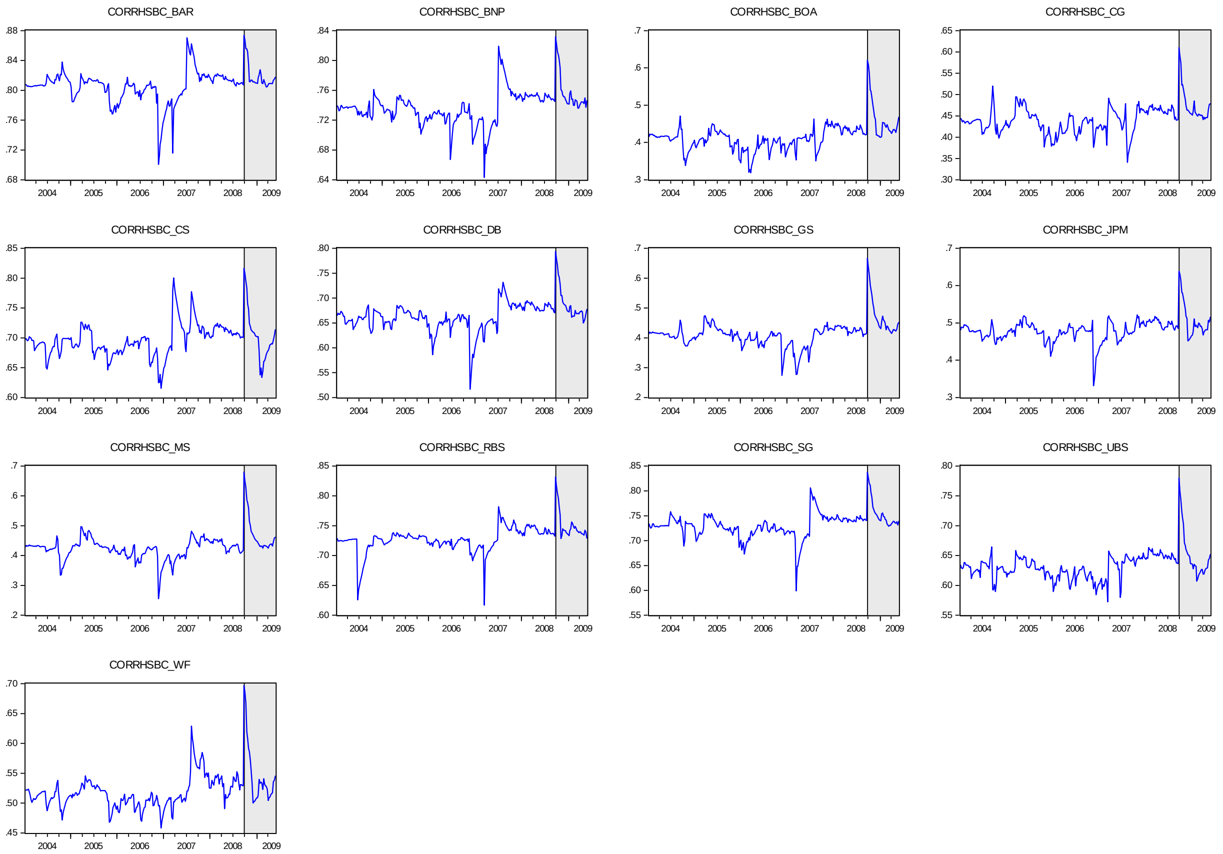


Figure 3.10: ADCC between RBS and other banks

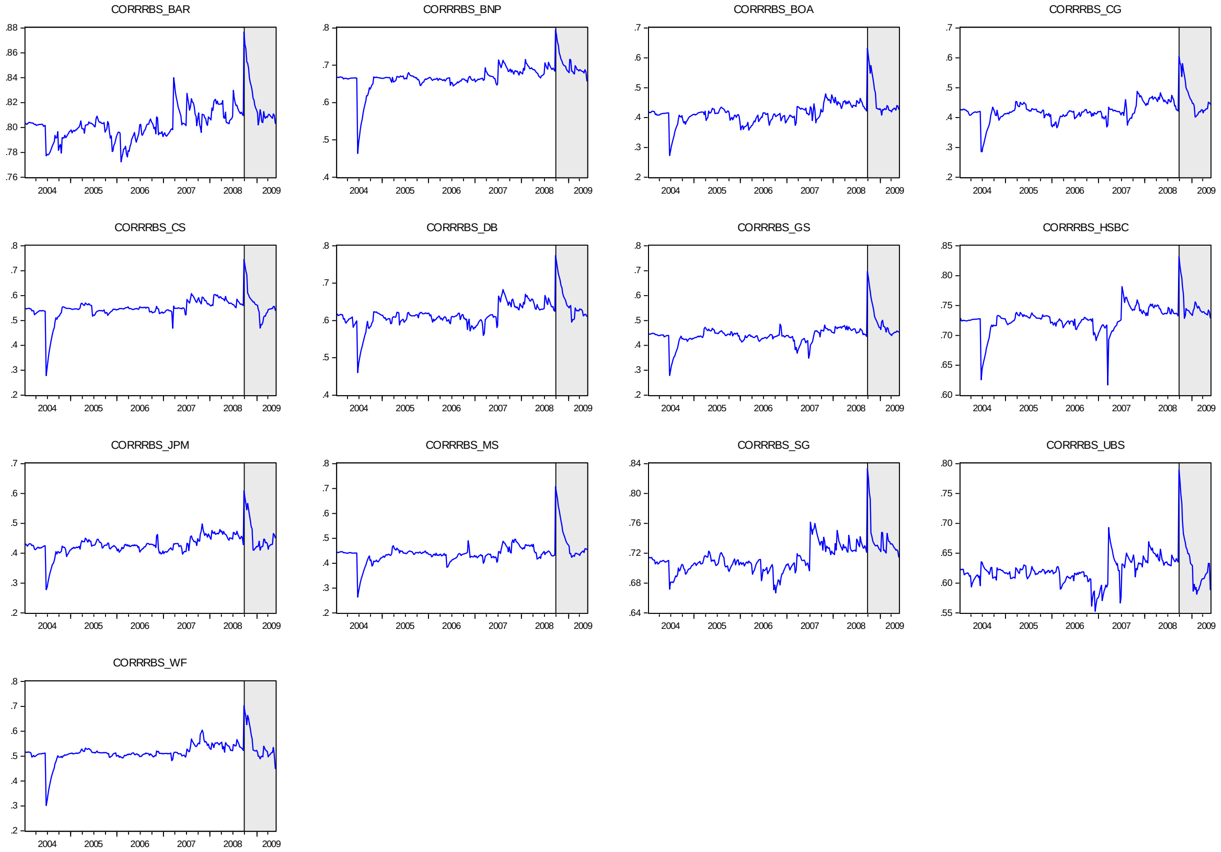


Figure 3.11: ADCC between SG and other banks

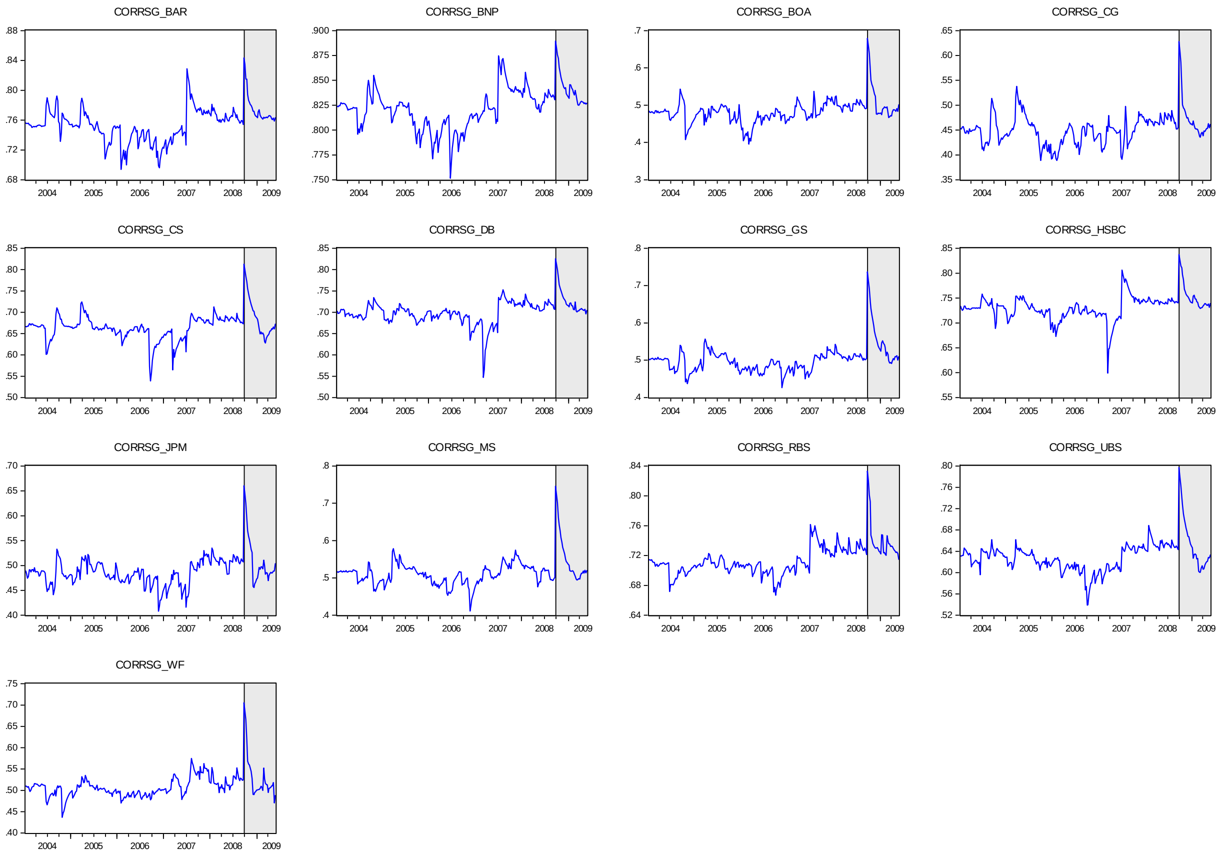


Figure 3.12: ADCC between UBS and other banks

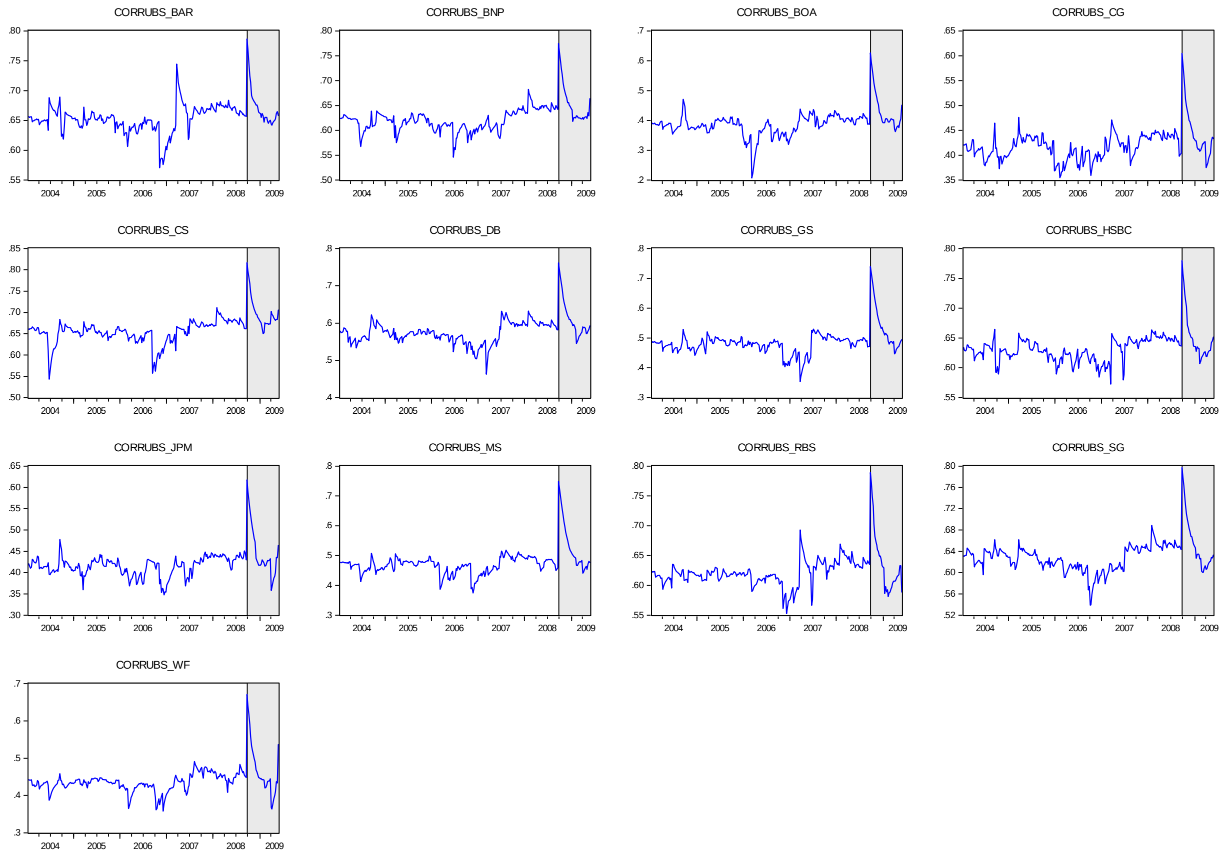


Figure 3.13: ADCC between BAR and other banks

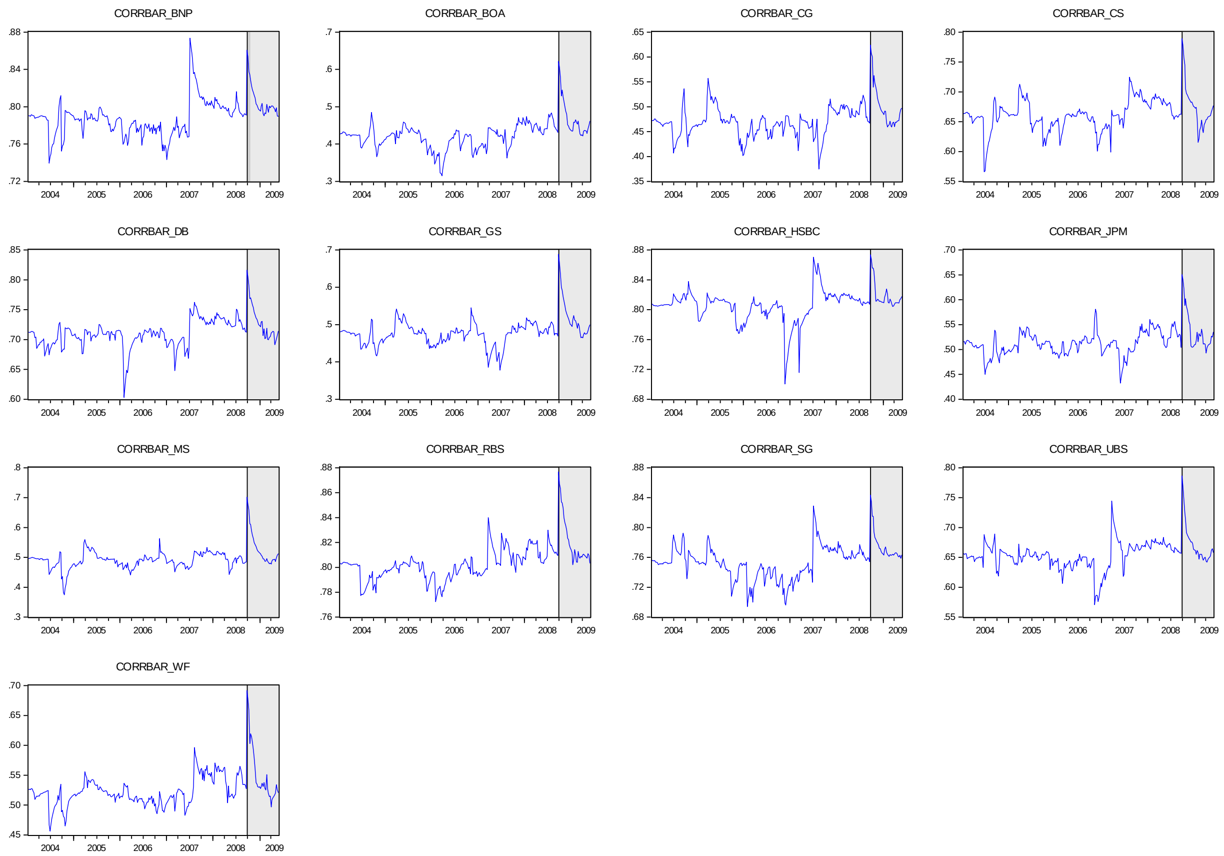


Figure 3.14: ADCC between CS and other banks