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Modeling interbank relations during the international financial crisis

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Abstract

This paper examines the effects of the current financial crisis on the correlations of four international banking stocks. We find that in the beginning of the crisis banks generally show a transition to a higher correlation followed by a dramatic decline towards the end of 2008. These findings are consistent with both traditional contagion theory and the more recent network theory of contagion.

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1. Introduction

Identifying the effects of crises and the way the shocks are transmitted from one market to the other is very important for both investors and policy makers. Under the context of contagion[1] many researchers identify the effects of stock market crises and generally found a significant increase in correlation in many countries (see Forbes and Rigobon, 2002 and Dungey and Martin, 2007, for more details).

Nevertheless, in contrast to the above, network theory of contagion associates contagion and crises with a reduction in linkages between banks. More specifically, it supports that the financial system can be viewed as a network of interrelated financial institutions and it emphasizes that a greater degree of interconnectedness between banks will result in a lesser probability of failure across the entire system (see Freixas, Parigi, Rochet and Krishnamurthy, 2000 for an earlier reference, and Allen and Babus, 2008 for a more recent contribution).

Therefore, motivated by the fact that although initially the contagion literature supported an increase in correlation between asset returns after a shock, whereas the network theory supports the opposite, this paper aims to contribute to the existing literature by providing a framework for examining the spread of the current global financial crisis. More specifically, it examines the evolution of the correlation coefficients between banking stocks for four major international banks which have been intrinsically caught up in the global financial crisis. These banks are Goldman Sachs (GS) for the US, Royal Bank of Scotland (RBS) for the UK, Societe Generale (SocGen) for France and Deutschebank (Deutsche) for Germany. Each has experienced problems during the crisis, but (so far) at least has survived.

The four different banks covered in this study hence cover a number of different aspects of the crisis as well as representing three of the main regions involved. RBS has received substantial government capital injection; Goldman Sachs has received far less but has also changed its status from investment bank to commercial bank holding company in order to qualify for assistance. Deutschebank has also moved to increase its exposure to retail activities, as opposed to concentrating on investment banking, although neither it or Societe Generale have had to receive government assistance. Finally, Societe Generale, has also suffered from an idiosyncratic shock associated with a rogue trader exposure. Using these stock returns from the Frankfurt stock exchange this paper considers how the relationships between these banks may have changed during the period of the global financial crisis.[2]

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[1] Contagion refers to a form of dependence that exists only during turbulent periods and occurs for large or extreme shocks to financial markets.

[2] Another aspect of these banks concerns the potential relationships between them. As major international banks, they clearly had interrelationships through client trading. An additional link has been the role of AIG. The US based international insurance giant provides insurance services not only to the general public, but also on a substantial amount of derivative trading, including such contracts as credit default swaps and instruments potentially based on assets which have declined massively in value since the crisis began. AIG itself has been given funding injections by the US Government on a number of occasions during the crisis, the first occurring on September 15, 2008, as it became evident that AIG would collapse in the wake of the bankruptcy of Lehman Bros. The contracts which AIG holds have meant that institutions such as Goldman Sachs and Societe Generale have received substantial payments from AIG - which would not have occurred if AIG had become insolvent. Thus the actions of the US Government in

The stock returns for the four multinational banks are collected from DataStream for the close of trading on the Frankfurt stock exchange.[3] The sample covers the period January 3, 2006 to February 27, 2009, a total of 824 observations. Returns are calculated as differenced log prices.

The rest of the paper is organized as follows. Section 2 provides a description of the empirical model. The results of the application are given in Section 3, which is followed by discussion and conclusions in Section 4.

2. The Modeling framework

2.1 Bivariate dynamic conditional correlation models

We first assume that the mean equation for the two-dimensional vector of stock returns is modelled as a VAR(1) model. Then, each conditional variance is assumed to follow a univariate GJRGARCH(1,1) process. The conditional correlations between the standardized errors is modeled using the dynamic conditional correlation (DCC) of Engle (2002) and the (Double) smooth transition conditional correlation (STCC) models of Berben and Jansen (2005) and Silvennoinen and Teräsvirta (2009) which allow correlations to be time-varying.

2.2 DCC model

Engle (2002) specifies the bivariate DCC model through the GARCH(1,1)-type process

$$q_{ij,t} = \overline{\rho}_{ij} + \alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \overline{\rho}_{ij}) + \beta(q_{ij,t-1} - \overline{\rho}_{ij}) \qquad (1)$$

where $\overline{\rho}_{ij}$ is the (assumed constant) unconditional correlation between $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ (standardised residuals), α is the news coefficient and β is the decay coefficient. The quantity $q_{ij,t}$ is typically rescaled using

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \qquad (2)$$

in order to ensure a conditional correlation between -1 and +1.

2.3 STCC and DSTCC models

The STCC model assumes the presence of two regimes with state-specific constant correlations. These correlations are, however, allowed to change smoothly between the two regimes as a function of an observable transition variable s_t. More specifically, the conditional correlation $\rho_{ij,t}$ follows

$$\rho_{ij,t} = \rho_{ij}^{(1)}(1 - G_{ij}(s_t;\gamma,c)) + \rho_{ij}^{(2)}G_{ij}(s_t;\gamma,c) \qquad (3)$$

in which the transition function $0 \le G_{ij}(s_t;\gamma,c) \le 1$ is a continuous function of s_t, while γ and c are its parameters. A widely used specification for the transition function is the logistic

supporting AIG have also supported those international banks which have exposures through derivative product insurance.

[3] Martens and Poon (2001) provide evidence on the importance of simultaneous observation of asset prices in examining correlations.

function

$$G_{ij}(s_t;\gamma,c)=\frac{1}{1+\exp(-\gamma(s_t-c))},\quad \gamma>0 \tag{4}$$

where the threshold parameter c locates the midpoint between the two regimes. The parameter γ determines the smoothness of the change in G_t as a function of s_t When $\gamma\to\infty$, G_{ij} becomes a step function ($G_{ij}=0$ if $s_t<c$ and $G_{ij}=1$ if $s_t>c$) and the transition between the two extreme correlation states becomes abrupt. In that case, the model approaches a threshold model in correlations. Since we are interested in modeling temporal change, the transition variable is a time trend ($s_t=t/T$). By using time we are able to identify the exact point of change for the correlations of the banks.

The STCC model allows only for a single change in correlation between the assets. However, this may not be a sufficient description of the data. The double smooth transition conditional correlation (DSTCC) is a generalization of the single STCC and can be implemented by replacing equation (3) with

$$\begin{aligned}\rho_{ij,t}=&\rho_{ij}^{(1)}(1-G_{1ij}(s_t;\gamma_1,c_1))+\rho_{ij}^{(2)}G_{1ij}(s_t;\gamma_1,c_1)(1-G_{2ij}(s_t;\gamma_2,c_2))\\&+\rho_{ij}^{(3)}G_{1ij}(s_t;\gamma_1,c_1)G_{2ij}(s_t;\gamma_2,c_2)\end{aligned} \tag{5}$$

The second transition variable here is also a function of time, and hence (5) allows the possibility of a non-monotonic change in correlation over the sample.[4, 5]

3. Results

3.1 Descriptive Statistics and Specification tests

Table 1, presents the descriptive statics along with stationarity tests. All banks show negative average returns over our sample, with RBS possessing the lowest value at -0.524 percent per day and the remaining three between -0.16 and -0.04. On the other hand, GS and RBS have substantially higher (unconditional) volatility, at 40.1 and 29.8, compared with SG and DB, with values of 19.1 and 24.8 respectively. Furthermore, it may be noted that daily returns are negatively skewed for RBS and SG and positively for GS and DB. As usual, daily returns are highly leptokurtic with respect to the normal distribution. Finally, the Ljung-Box (LB) statistics for up to 10 lags, for returns and squared returns, indicate the presence of linear and non-linear dependencies, respectively, in the returns of all four banks. Linear dependencies may indicate possible market inefficiency while non-linear dependence may be due to autoregressive conditional heteroskedasticity. Furthermore, the LB statistic for the squared returns is, in all cases, several times that calculated for returns, indicating that second moment (nonlinear) dependencies are far more significant than first moment dependencies. Similar intuition is given

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[4] To ensure identification we require $c_1<c_2$ and hence that the two correlation transitions occur at different points of time.

[5] Although, under the bivariate structure of the model we may lose useful information coming from other banks, it would be useful to modify the bivariate specification to a multivariate one. However, the addition of these equations resulted in convergence problems in estimation (for the STCC and DSTCC models) and hence they are excluded from our models. Therefore, the multivariate structure of the models and their estimations remain open for further research.

by the results of the ARCH-LM tests. As for the stationarity tests, the ADF results indicate that all four (return) series are stationary.[6]

Table 1. Descriptive Statistics

	Av. Returns	Variance	Skewness	Kurtosis	LB	LB^2	ARCH	ADF
GS	-0.037	40.087	1.129	22.617	14.077	586.56***	23.675***	-21.203***
RBS	-0.524	29.849	-9.694	151.937	35.395***	276.86***	16.504***	-24.247***
SG	-0.159	19.071	-0.389	9.410	19.358**	941.62***	30.859***	-26.792***
Deutshe	-0.154	24.831	0.333	15.692	60.539***	1071.3***	36.977***	-27.202***

Notes: *LB refers to Ljung Box statistic for the returns, while LB^2 , for the squared returns. ADF refers to the augmented Dickey Fuller unit root test while ARCH refers to Engle's ARCH LM test.* ***denotes significance at 5% and* *** *at 1% respectively.*

Table 2, reports the LM test developed by Silvennoinen and Teräsvirta (2009) which examines whether constant conditional correlation is more adequate. The test reveals that the null hypothesis of constant correlation in the co-movements between the stock returns of each bank is rejected at least at the 1% marginal level of significance. These results strongly support the notion of a regime switch in the correlations (or time varying correlations) of these returns should be employed.

Table 2: LM Tests for Constant Conditional Correlation

	LM test
GS-RBS	19.933***
GS-SocGen	21.425***
GS-Deutsche	23.561***
RBS-SocGen	18.352***
RBS-Deutsche	22.001***
SocGen-Deutsche	28.464***

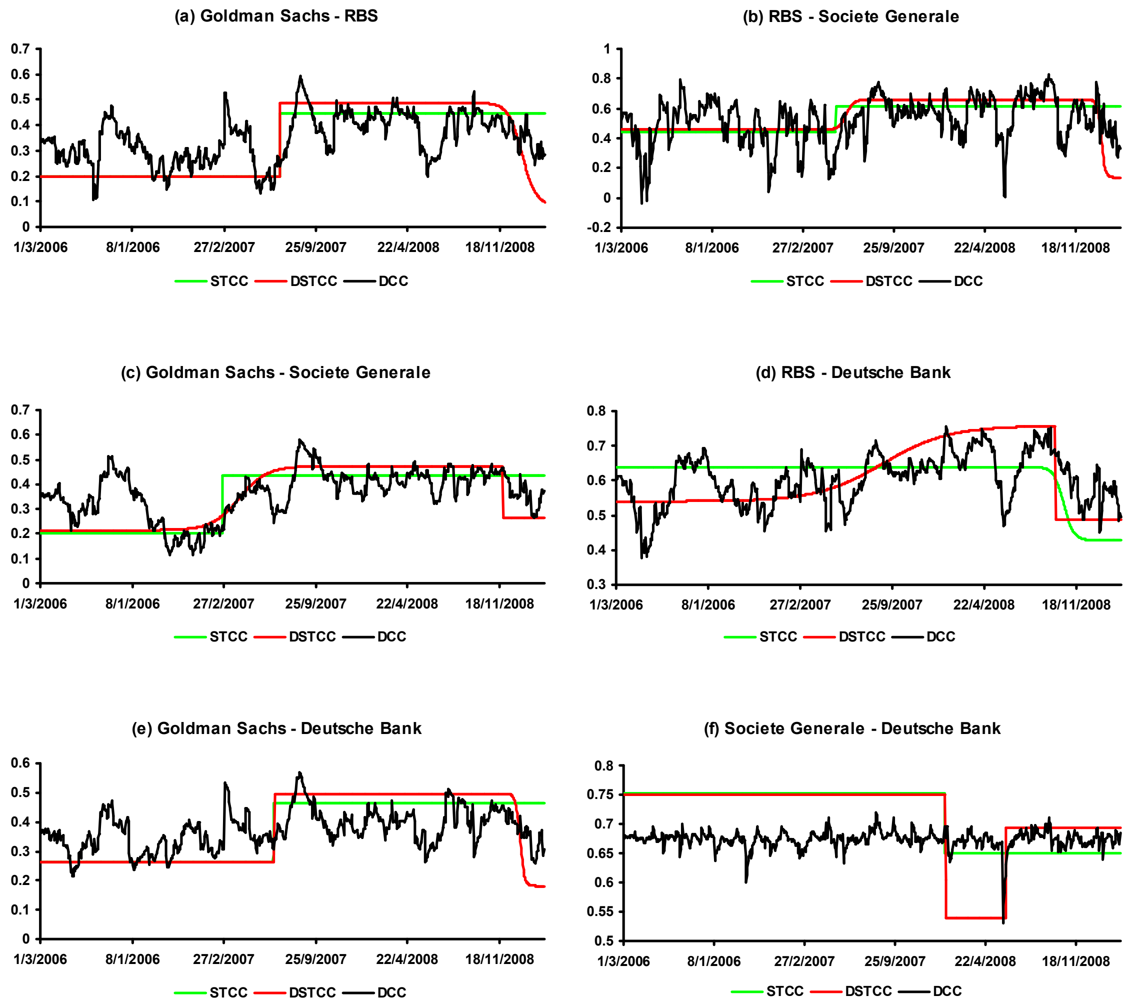
Notes: ****denotes significance at 1%*

3.2 Empirical Findings

Three different models of the potentially time varying correlation between the pairs of bank stock returns are estimated (DCC, STCC and DSTCC). The results for the VAR, volatility models and DCC are very close to those found elsewhere and are hence omitted for brevity. The resulting estimates of the correlation coefficients for each model and each pair of bank stock returns are shown in Figure 1. It is immediately clear that the general shape of the DCC estimates are retained in the STCC and DSTCC estimates. Tables 3 and 4 report the parameter estimates and estimated correlation change dates for the STCC and DSTCC version of the model respectively.

[6] Similar results obtained using a number of stationarity tests (such as Phillips Perron, KPSS tests). These results are available from the author upon request.

Figure 1: Estimated correlations between bank returns using the STCC, DSTCC and DCC



3.3 Single transition model

The results for the STCC version of the model demonstrate that the dominant change in the correlation occurs between February and July 2007 for the majority of cases. In all those cases, the estimates show an increase in correlation. The earliest break is for the pair GS-SocGen in February 2007 and the latest for the GS-RBS pair in July 2007. However, the latest occurring break is for RBS-Deutsche, which is centered on October 2, 2008 (implying a substantial drop in correlation), in the mid of the aftermath of the bankruptcy of Lehman Bros and rescue of AIG. Notably, this is the only pair in the single transition model which does not display an abrupt transition between the correlations.

Moreover, a particularly interesting result is obtained for the SocGen-Deutsche pair, where the break occurs on January 17, 2008, which aligns with the discovery of the rogue trader position at SocGen. Here it is clear that the problems with SocGen dominate the linkage between the two returns series, as opposed to other pairs involving SocGen which occur in the first half of 2007.

Table 3. STCC estimates

	$\rho^{(1)}$	$\rho^{(2)}$	γ	Date
GS-RBS	0.195	0.446	500	05/07/2007
GS-SocGen	0.201	0.435	500	23/02/2007
GS-Deutsche	0.264	0.465	500	03/07/2007
RBS-SocGen	0.446	0.618	500	14/05/2007
RBS-Deutsche	0.639	0.428	29.68	02/10/2008
SocGen-Deutsche	0.752	0.649	500	17/01/2008

Notes: The table presents maximum likelihood estimates of the parameters of STCC models; standard errors are available upon request.

3.4 Double transition model

With the exception of SocGen-Deutsche, the DSTCC results are generally consistent with the single transition estimates in that there is some form of transition in the first half of 2007. The SocGen-Deutsche pair reflects again the actions of the rogue trader, retaining the initial abrupt drop in correlation on January 17, 2008, from 0.75 to 0.54, but returning to an increased level of correlation (although lower than that prevailing prior to January 2008 at 0.69) in June 2008, not long after the resignation of the CEO of SocGen.

The 2007 breakpoints for the remaining 5 stock return pairs all show an increase in correlation. In the cases of GS-RBS and GS-Deutsche the abrupt correlation changes observed in the single transition model are centered on the same dates, July 5, 2007 and July 3, 2007 respectively. They both show increases in correlation from about 0.20 to around 0.50. However, the value added of the DSTCC model is shown with a move to a lower correlation coefficient in early January 2009 (0.08 for GS-RBS and 0.18 for GS-Deutsche which are both lower than the correlations prevailing prior to mid 2007). The drop in correlation in January 2009 may well be associated with the return to profitability of GS in that quarter.

The change dates for the GS-SocGen and RBS-SocGen differ slightly because in the double transition model the estimates produce a smooth transition path to the new higher correlation, taking approximately 9 months for the GS-SocGen correlation to rise from 0.22 to 0.47 and about one month for the RBS-SocGen correlation to rise from 0.46 to 0.66. As before, the DSTCC estimates imply a substantial drop in correlation, which occurred in the last period of the sample. Another new feature of the DSTCC results is the long transition of 2007 in the RBS-Deutsche pair. This is not captured by the single transition model, while the transition in late September-early October 2008 has been retained and become abrupt, reducing to 0.49. As a whole, in most of the estimates the 2007 break was evident in the single transition model, while the events of late 2008 were not.

Table 4. DSTCC estimates

	$\rho^{(1)}$	$\rho^{(2)}$	$\rho^{(3)}$	γ_1	γ_2	Date1	Date2
GS-RBS	0.196	0.488	0.084	500	21.23	05/07/2007	06/01/2009
GS-SocGen	0.214	0.473	0.262	10.6	500	29/03/2007	25/11/2008
GS-Deutsche	0.264	0.497	0.182	500	67.5	03/07/2007	06/01/2009
RBS-SocGen	0.458	0.658	0.137	40.12	74.17	05/06/2007	14/01/2009
RBS-Deutsche	0.540	0.758	0.488	4.43	500	23/08/2007	30/09/2008
SocGen-Deutsche	0.750	0.539	0.693	500	500	17/01/2008	06/062008

Notes: The table presents maximum likelihood estimates of the parameters of DSTCC models; standard errors are available upon request.

4. Discussion – Conclusions

Our results can be summarized as follows. First, the correlation between Societe Generale and Deutsche Bank stocks is less affected by the financial crisis and more by the idiosyncratic shock to Societe Generale in the form of the rogue trader write down. This event dramatically reduced the correlation link between the two banks, which was subsequently partially repaired later in 2008. Second, the other banking stock pairs all show a transition to a higher correlation during 2007. In some cases the transition was quite abrupt; often dating in the middle of the year, in others it was more gradual - with the increase in correlation being about 0.20-0.30 in each case. Such an increase in correlation is consistent with the literature on contagion, where crisis events manifest themselves in changes in correlation coefficients, and are often associated with increased correlation (or decreased diversification opportunities). Third, the correlations then decline dramatically in the period from the third quarter of 2008 to early 2009. This decline, abrupt in some cases or more extended in others, is also evidence of contagion effects, but in this case is also consistent with contagion via the network theory.

Thus, the paper finds evidence of both traditional contagion as represented by a significant increase in correlation after a shock, and evidence consistent with the breakdown of network linkages put forward in the more recent network theory of contagion as overviewed by Allen and Babus (2008). In this direction, the results in Idier (2008) are interesting as they document that in volatile periods the resilience to a shock may be different between stocks and, therefore, a decrease in correlation could even be observed after an initial sudden rise.

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