A Dynamic Conditional Correlation Analysis of Financial Contagion: The Case of the Subprime Credit Crisis

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Abstract

This paper uses a Dynamic Conditional Correlation Model to examine financial contagion phenomenon following the American subprime crisis. This model, which is developed by Engle (2001, 2002), Engle and Sheppard (2001) and Tse and Tsui (2002) as an original specification of multivariate models' conditional correlations, allows tracking correlation evolutions between two or more assets. Our sample consists of six developed countries, including the crisis-originating American market, and ten emerging countries. Data frequencies are on a daily basis reflecting the January 3rd 2006 to February 26th 2010 period. The obtained results seem to point to an amplification of dynamic conditional correlations during the crisis period which stretches from August 1st 2007 to February 26th 2010.

Keywords: Subprime crisis, International financial contagion, DCC GARCH, Stock market return

JEL classification: F30, G01, G12, G14, G15

1. Introduction

During these last few years, news about multiplication of financial crises is well covered along with the devastating effects incurred by financial markets worldwide. The most recent crisis, which is the American mortgage market crisis, resulted in catastrophic losses. Several studies have tried to explain the reasons of these financial setbacks and the mechanisms of their spread across the globe. In fact, one can see in the negative effects induced by the subprime crisis and incurred by financial markets worldwide a looming sign and may wonder about the existence of a contagion phenomenon across different financial markets worldwide.

To this effect, it is necessary to define the notion of contagion which, despite several and advanced studies, remains hard and complex to identify. Indeed, contagion may be defined as the spread of markets' turmoils from one country to other financial markets. Economics literature succeeded in identifying several possible mechanisms causing the spread of turmoils from one market to another. During these few years, studies on contagion phenomena are abundant; we can mention those of Allen and Gale (2000), kyle and Xiong (2001), kiyotaki and Moore (2002), Kaminsky, Reinhart and vedh (2003), Brunnermeier and Pederen (2005, 2009). Masson (1998, 1999) identifies three types of contagion. The first refers to an effect known as Moosonal where countries are simultaneously affected by crises caused by a common shock (for instance, increase in American interest rates), which in turn provokes a withdrawal of offshore funds. The second, known as spillovers, is linked to interdependencies between countries. In this case, a crisis hitting one country may provoke a substantial effect on the macroeconomic fundamentals of neighbour countries as inter-countries trade and financial transactions are already in place. Finally, the third type is known as pure contagion. Known for Forbes and Rigobon (2000) as shift contagion, this pure contagion is a panic movement, not justified by economic links, and which is triggered when agents withdraw their funds from other countries following a crisis in one country. In other words, contagion is not necessarily induced by economic fundamentals but rather it is a consequence of

investors' psychological behaviour. Indeed, several studies agree that correlations between markets and their transactions are at the heart of any international portfolios diversification strategy.

Calvo and Reinhart (1996) and Kaminsky and Reinhart (1999, 2000) consider fundamental contagion when induced by real and financial interdependencies between countries (referred to as *fundamentals-based contagion*). In this case, crisis propagation is caused by financial and trade links. According to Forbes and Rigobon (2000, 2002), trade and financial links are the main crisis-transferring mechanisms. These links are expected to be stable, i.e. they remain constant before, during or after the crisis. They are high whatever the circumstances. The works of Eichengreen, Rose and Wyplosz (1996), Glick and Rose (1999) illustrate that trade links are the main factors of transferring crisis across markets. However, Kaminsky and Reinhart (1999, 2000) underline that countries which have trade links should have as well significant financial links in order to facilitate exchange of goods and services. According to Kaminsky and Reinhart (1999, 2000) and Broner and Gelos (2003), the financial channel reflects connections between countries in terms of equities or loans portfolios. In this case, it is possible to consider banks' roles in inter-countries crisis propagation. Allen and Gale (2000) developed an inter-bank contagion model to illustrate how deposits' crossed detentions might trigger a first-order propagation of cash shocks across markets. Kaminsky and Reinhart (1999, 2000) and Sbracia and Zaghini (2001, 2003) highlighted the effect of banks' debts on transmission of shocks. Dornbush, Claessens and Park (2000) and Edwards (2000) distinguish between three propagation channels. These are the multiple equilibrium mechanism, liquidity/cash flow endogenous shocks and information asymmetry. As far as the multiple equilibrium mechanism is concerned, this latter is produced when a crisis in one country may badly affect economic equilibriums in other countries. Masson (1999), using multiple equilibrium-based macroeconomic auto models, showed that a crisis in one country may coordinate and stigmatize investors' expectations by making them move from a good to a bad equilibrium in another country. Change in investors' expectations and not in real economic links moderates the passage from a good to a bad equilibrium. In the case of liquidity endogenous shocks, a crisis in one country may provoke a decrease in investors' liquidity. In order for these investors to satisfy their cash needs, they are forced to compensate their portfolios by selling offshore assets. Calvo (1999) underlines that liquidity endogenous shocks intensify in situations of information asymmetry between agents. Indeed, in order to satisfy benefit margins following a liquidity shock in a given economy, informed agents may proceed to selling their assets in other countries. The uninformed agents who notice this behaviour are unable to accurately identify the cause of such behaviour. They tend to follow informed agents in their behaviour believing that such is a bad signal indicating a slackening of economic fundamentals in the given country. This mimetic behaviour resulting from an ill interpretation of informed agents' behaviour tends to amplify the initial crisis.

In this paper, we examine contagion phenomenon as induced by the subprime crisis that started in 2007 in the American risk-based mortgage market and which spread worldwide. To this effect, our empirical analysis attempts first at examining the simple correlation between the American market and other European and emerging markets before and after the crisis. Then, we refine our analysis through estimating the dynamic conditional correlation model developed by Engle (2002) and Engle and Sheppard (2001). The aim of this method is to show how market correlations vary in time and especially to point at their amplifications during the crisis. The correlation-based contagion test defines contagion as the significant increase of assets' price co-movements. Against this line of thinking, we try to test contagion by examining variations in conditional and unconditional correlations between the S&P 500 American stock index's returns and those of the other markets of our sample before and after the crisis. More specifically, the purpose of our empirical analysis is to study the correlation between the American market and the other markets which include 6 European markets and 10 emerging markets.

This paper is structured as follows. The second section presents the data used for the analysis as well as the descriptive statistics and the simple correlations output. Section three estimates the dynamic conditional correlation model. Section four presents the conclusions.

2. Data and descriptive statistics

The data used in this study are daily returns of stock-price indices from January 2, 2006, through February 26, 2010, for six developed market and ten emerging Markets that were seriously affected by the subprime crisis. The data set of developed markets consists of daily returns of the stock indices of United States (S&P 500), French (CAC 40), Germany (DAX), Netherlands (AEX), United Kingdom (FTSE 100) and Italy (MIB 30).The data set of the emerging markets consists of daily returns of the stock indices of India (BSE 30), Hong Kong (Hang seng), Malaysia (KLSE), Korea (KS11), China (Shang.comp), Singapore (STI), Brazilwood (Bovespa), Mexico (IPC), Argentina (MerVal) and Tunisia (Tunindex). All the national stock-price indices are in local currency. All the data were obtained from Datastream the web site: **http:// fr.finance.yahoo.comthe.**

We define two sub-periods: a stable period between January 3rd 2006 and July 31st 2007 including an average of 390 observations for each country and a crisis period starting August 1st 2007 and ends on February 26th 2010, i.e. a number of 684 observations for each country. The United Sates of America is noted as the crisis-originating country. The subprime crisis starting date is determined with reference to Horta, Carlos, Mendes and Vieira (2008).

Following is the descriptive analysis and graphics of the used data. Descriptives for stock indices' returns are run for the two country groups and over the two sub-periods; before and after the crisis. We shall complete our descriptive analysis by examining the simple correlations between the American market and the other markets before and after the subprime crisis. We present as well graphics on the different markets' returns in order to compare them with the American S&P 500 stock index.

[Insert Table 1 here]

With reference to these descriptives, we note that the variances of the different returns' series neatly increased during the subprime crisis. All the returns' series are not normally distributed (Skewness $\neq$ 0 and Kurtosis $\neq$ 3). We note as well high kurtosis values, generally superior to 3. These suggest that distributions of the different markets' returns are leptokurtic.

[Insert Table 2 here]

Tables 2 and 3 present the simple correlations, computed before and after the crisis. During the pre-crisis period (January 3rd 2006 and July 31st 2007), correlation coefficients of developed markets' returns with the American market are practically weak and non-significant. However, with the start of the crisis (August 1st 2007 to February 26th 2010), we note that the correlations between the different markets, both developed and emerging, and the American markets considerably increased during the subprime crisis and became significantly different from zero, except for the UK and the Netherlands. These results illustrate that the dependence of the developed markets (France, Germany, and Italy) on the American market has progressively intensified during the subprime crisis.

[Insert Table 2 here]

The descriptive statistics for the emerging economies indicate that the variances of the different series' returns neatly increased during the crisis, except for Tunisia. All series' returns are not normally distributed (Skewness $\neq$ 0 et Kurtosis $\neq$ 3). We note as well high kurtosis values, generally superior to 3. These suggest that the distributions of the different emerging markets' returns are leptokurtic.

[Insert Table 4 here]

Correlation results for the emerging markets with the American markets practically approximate those obtained for the developed economies. Indeed, during the pre-crisis period (January 3rd 2006 to July 31st 2007) correlation coefficients are low and non-significant. However, during the crisis period (August 1st 2007 to February 26th 2010), correlation coefficients increased significantly, notably for Brazil, Hong Kong, Korea and Argentina.

To refine our analysis, it is fit to show how correlations evolved during the crisis. To this effect, we use the dynamic conditional correlation method (DCC-GARCH) developed by Engle (2001, 2002), Engle and Sheppard (2001) and Tse and Tsui (2002).

In order to check for the relevance of our approach to estimating dynamic correlations, we propose to analyse contagion phenomenon over the two sub-periods; the above-mentioned stable period and the crisis period.

3. The Dynamic Conditional Correlation Model

The DCC model is a dynamic specification based on conditional correlations within GARCH or multivariate ARCH models and is developed by Engle (2001, 2002), Engle and Sheppard (2001) and Tse and Tsui (2002) as noted above. It is a recent method allowing simultaneously modeling of variances and conditional correlations of several series. The estimation consists of two steps. First, we estimate the conditional variance of each variable using a univariate ARCH procedure. Second, we use the standardized regression residuals obtained in the first step to model those conditional correlations that vary through time.

3.1. Presentation of the model

Following Engle（2001), returns are assumed under the following process after filtration. (Note 1)

$$r_t \mid F_{t-1} \sim N(0, H_t) \qquad (1)$$

And
$$H_t \equiv D_t R_t D_t \qquad (2)$$

Where D_t is the k×k diagonal matrix of time-varying standard deviations from a univariate GARCH with $\sqrt{h_{it}}$ on the ith diagonal, and R_t is the time-varying correlation matrix. The log-likelihood of this estimator can be written :

$$
\begin{aligned}
L &= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+2\log|H_t|+r_t^{'}H_t^{-1}r_t\right)\\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+2\log|D_tR_tD_t|+r_t^{'}D_t^{-1}R_t^{-1}D_t^{-1}r_t\right)\\
&= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi)+2\log|D_t|+\log(|R_t|+\varepsilon_t^{'}R_t^{-1}\varepsilon_t\right)
\end{aligned}
\tag{3}
$$

Where $\varepsilon_t \sim N(0,R_t)$ are the residuals standardized on the basis of their conditional standard deviations.

First, the conditional variances for any individual asset can be obtained from the univariate GARCH model :

$$
h_{it}=\omega_i+\sum_{p=1}^{P_i}\alpha_{ip}r_{it-p}^2+\sum_{q=1}^{Q_i}\beta_{iq}h_{it-p} \quad for\ i=1,2,3...,k
\tag{4}
$$

With the usual GARCH restrictions of non-negativity and imposed stationarity, such as non-negativity of variances and $\sum_{p=1}^{P_i}\alpha_{ip}+\sum_{q=1}^{Q_i}\beta_{iq}<1$.

Then, the proposed dynamic correlation structure is :

$$
Q_t=(1-\sum_{m=1}^{M}\alpha_m-\sum_{n=1}^{N}\beta_n)\bar{Q}+\sum_{m-1}^{M}\alpha_m(\varepsilon_{t-m}\varepsilon_{t-m}^{'})+\sum_{n=1}^{N}\beta_nQ_{t-n}
\tag{5}
$$

$$
R_t=Q_t^{*-1}Q_tQ_t^{*-1}
\tag{6}
$$

Where $\bar{Q}$ is the unconditional covariance of the standardized residuals resulting from the univariate GARCH equation. And Q_t^* is a diagonal matrix composed of the square root of the diagonal elements of Q_t. That is

$$
Q_t^*=\begin{bmatrix}\sqrt{q_{11}} & 0 & \cdots & 0\\ 0 & \sqrt{q_{22}} & \cdots & 0\\ \vdots & \vdots & \vdots & 0\\ 0 & 0 & \cdots & \sqrt{q_{kk}}\end{bmatrix}
\tag{7}
$$

The typical element of R_t will be $\rho_{ijt}=\dfrac{q_{ijt}}{\sqrt{q_{ii}q_{jj}}}$, and the matrix R_t will be a positive definite/constant. The K assets' covariance matrix H_t is thus a positive definite/constant and can be written as $H_t\equiv D_tR_tD_t$

3.2. Interpretation of Results

The following graphs produce the evolution of conditional correlations during pre-crisis period.

[Insert Graph 1 here]

The graphs reporting evolutions of dynamic conditional correlations for the two markets, developed and emerging, with the American market seem to point to a weak correlation during the pre-crisis period. Indeed, during this period, conditional correlations of the six developed countries do not exceed 30%, with some up and down tendencies noticed. This conclusion is true for the emerging markets which record low dynamic correlation coefficients during the same period. Exceptions are China and Hong Kong where correlations approximate 60%.

The contagion test, based on correlations, defines contagion as the significant increase of stock prices co-movements. We see it fit to examine stock indices series' returns after the crisis before estimating conditional correlations during the crisis.

[Insert Graph 2 here]

It is clear that during the crisis period the returns of developed and emerging countries' stock indices witness a high volatility, except for Malaysia. These results point to an increase in returns' correlations between the American market and the other markets of the sample. In order to better assess these interpretations, we thought it necessary to use a dynamic conditional correlation model to view correlation variation through time.

[Insert Graph 3 here]

Examining the graphic evolution of correlations between American market's returns with the other developed and emerging markets leads to the following observations:

✓ For the developed countries, all conditional correlations between the S&P 500 stock index's returns and the returns of the 5 developed countries are sometimes negative and sometimes positive. However, it is almost clear that by the end of the crisis correlations considerably increased to exceed 80% for all developed markets. Conditional correlation is much more pronounced since the start of the crisis in 2007. The coefficients are dynamic and reach a peak in 2009. We conclude that there is a contagion effect of the S&P 500 index on developed stock market indices. According to Kaminsky and Reinhart (1999, 2000) and Broner and Gelos (2003), it is possible to see that this contagion is triggered by the financial channel which reflects connections between developed countries in terms of equities or loans portfolios.

✓ For emerging countries, the obtained results allow us to classify these countries into three groups according to the level of correlation with the American market. The first group includes three countries with high conditional correlation with the American market during the crisis; Brazil, Mexico, and Argentina. Indeed, correlation levels for these countries reach 80%. The second group includes three countries with moderate conditional correlations approximating 50%; India, Malaysia and Singapore. The third group includes countries with weak conditional correlations with the American market. These are, China, Hong Kong, Korea and Tunisia, with correlations less than 20%. For the case of Tunisia, the correlation does not even exceed 12%.

4. Conclusion

The current international financial turmoils which started with the American risk-based mortgage crisis in 2007 have revealed a high interdependence between financial markets worldwide. In this paper, we set to test financial contagion between the American market and several other financial markets of 5 developed countries and 10 emerging countries. To this effect, we used stock indices daily returns of these markets observed over the January 3rd 2006-Febrauary 26th 2010 period. The application of the dynamic conditional correlation model seems to point to an increase in dynamic conditional correlations following the start of subprime crisis. More specifically, we noted that returns conditional correlations of the S&P 500 stock index and the five developed markets (France, Germany, Italy, Netherlands, United Kingdom) considerably increased during the crisis period with values sometimes exceeding 80%. In the case of emerging markets, the results show that conditional correlations allow us to divide these countries into three groups. The first group, including Brazil, Mexico and Argentina, is characterized by a high dynamic conditional correlation with the US market. The second group, composed of India, Malaysia and Singapore, presents correlations variable in time and do not exceed 50%. The third group, composed of China, Hong Kong, Korea and Tunisia, records weak dynamic conditional correlations with the US market and seems unaffected by the subprime crisis. Finally, it is sound to conclude that during the subprime crisis, contagion is strong between the US and the developed and emerging countries (notably for the first and second groups). These results corroborate the conclusions forwarded by Longstaff (2010).

Finally, we would like to signal that studying dynamic conditional correlations between markets is very rewarding at so many levels, notably with respect to international portfolios' diversification. Indeed, if correlation between markets is taken into consideration by international portfolio diversification models, it is convenient to add that this correlation varies through time.

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Notes

Note 1: The assumption of multivariate normality is not suggested for consistency and asymptotic normality of the estimated parameters. Following Engle (2002), when the returns have non-Gaussian innovations, the Dynamic conditional correlation estimator can be considered as quasi-maximum likelihood estimator.

Table (1). Descriptive Statistics (developed countries)

Before the subprime crisis (year 2006)

	S_P_500	AEX	CAC_40	FTSE_100	MIB_30	DAX
Mean	0.000353	0.000187	0.000167	0.000189	0.000277	0.000687
Median	0.000964	0.000900	0.000663	0.000364	0.000811	0.001503
Maximum	0.023864	0.025697	0.024225	0.029487	0.023539	0.026051
Minimum	-0.035343	-0.038228	-0.033109	-0.037845	-0.037905	-0.034633
Std. Dev.	**0.007259**	**0.009085**	**0.009792**	**0.008613**	**0.008419**	**0.009895**
Skewness	-0.674421	-0.557066	-0.491185	-0.506153	-0.586264	-0.430062
Kurtosis	6.009736	4.838139	3.929152	5.147242	4.535230	3.542497
Jarque-Bera	175.8591	74.69073	29.55871	91.10588	60.33002	16.71821
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000234

During the subprime crisis (the January 2007- February 2010 period)

	S_P_500	AEX	CAC_40	DAX	FTSE_100	MIB_30
Mean	-0.000744	-0.000977	-0.000819	-0.000775	-0.000519	-0.001194
Median	0.000495	-3.01E-05	5.74E-06	0.000178	8.62E-05	0.000233
Maximum	0.109572	0.100283	0.105946	0.107975	0.093842	0.107647
Minimum	-0.094695	-0.095903	-0.094715	-0.074335	-0.092646	-0.088168
Std. Dev.	**0.018235**	**0.018602**	**0.017832**	**0.016829**	**0.016613**	**0.016893**
Skewness	-0.249468	-0.093144	0.208065	0.371503	-0.030050	0.272652
Kurtosis	11.07379	11.29284	11.39646	13.05971	10.59746	11.64753
Jarque-Bera	1766.745	1857.760	1908.189	2747.245	1558.574	2027.083
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

Table(2). correlation between returns (developed countries) Before the subprime crisis (year 2006)

		Correlation	t-Statistic	Probability
AEX	S_P_500	0.001132	0.022240	0.9823
CAC_40	S_P_500	-0.032260	-0.634131	0.5264
FTSE_100	S_P_500	-0.032860	-0.645936	0.5187
MIB_30	S_P_500	0.045505	0.894957	0.3714
DAX	S_P_500	-0.021649	-0.425429	0.6708

During the subprime crisis (the January 2007- February 2010 period)

		Correlation	t-Statistic	Probability
AEX	S_P_500	-0.056729	-1.444181	0.1492
CAC_40	S_P_500	-0.093128**	-2.377329	0.0177
DAX	S_P_500	0.315915***	8.462872	0.0000
FTSE_100	S_P_500	-0.034898	-0.887529	0.3751
MIB_30	S_P_500	0.400699***	11.11576	0.0000

***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table (3). Descriptive Statistics for emerging countries

Before the subprime crisis (year 2006)

	S_P_500	BOVESPA	BSE_30	HANG_SENG	IPC	KLSE
Mean	0.000353	0.001160	0.001343	0.000864	0.001299	0.001076
Median	0.000964	0.001781	0.002177	0.001097	0.002573	0.001283
Maximum	0.023864	0.048455	0.066670	0.026567	0.065101	0.026012
Minimum	-0.035343	-0.068565	-0.070033	-0.040793	-0.059775	-0.047465
Std. Dev.	**0.007259**	**0.015267**	**0.015284**	**0.010060**	**0.013648**	**0.007336**
Skewness	-0.674421	-0.313217	-0.496999	-0.565632	-0.154715	-1.263294
Kurtosis	6.009736	4.632600	5.872785	4.324279	5.839372	10.02764
Jarque-Bera	175.8591	49.43448	149.3949	49.04111	131.8841	901.6376
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

During the subprime crisis (the January 2007- February 2010 period)

	S_P_500	BOVESPA	BSE_30	HANG_SENG	IPC	KLSE
	KS11	MERVAL	SHANG__COMP_		STI	TUNINDEX
Mean	0.000963	0.000771	0.003327		0.001069	0.001045
Median	0.001760	0.001285	0.003610		0.001714	0.001200
Maximum	0.034489	0.060860	0.046354		0.030573	0.360477
Minimum	-0.035112	-0.077866	-0.092562		-0.040367	-0.357687
Std. Dev.	**0.010916**	**0.013989**	**0.017910**		**0.009565**	**0.026277**
Skewness	-0.436154	-0.627810	-1.218164		-0.769944	0.036513
Kurtosis	3.843776	6.558177	7.439098		5.095116	180.6755
Jarque-Bera	23.81152	230.1682	414.5342		109.2990	510358.9
Probability	0.000007	0.000000	0.000000		0.000000	0.000000

Mean	-0.000744	-0.000167	-0.000465	-0.000496	-0.000413	-0.000404
Median	0.000495	0.000928	0.000000	0.000000	0.000372	0.000000
Maximum	0.109572	0.136766	0.079005	0.134068	0.104407	0.086253
Minimum	-0.094695	-0.120961	-0.116044	-0.135820	-0.072661	-0.099785
Std. Dev.	**0.018235**	**0.023288**	**0.020772**	**0.023031**	**0.016772**	**0.012219**
Skewness	-0.249468	0.050295	-0.290569	0.143297	0.315876	-0.801057
Kurtosis	11.07379	9.584500	6.269233	9.688227	9.565383	20.76651
Jarque-Bera	1766.745	1170.876	297.6914	1209.992	1174.591	8591.823
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000

	KS11	MERVAL	SHANG__COMP_		STI	TUNINDEX
Mean	-0.000704	-0.000656	-0.000937		-0.000907	0.000625
Median	0.000555	0.000303	0.000145		-9.98E-05	0.000411
Maximum	0.112844	0.104316	0.090343		0.075305	0.036133
Minimum	-0.111720	-0.129516	-0.080437		-0.092155	-0.050037
Std. Dev.	**0.018387**	**0.020691**	**0.020556**		**0.016375**	**0.005784**
Skewness	-0.538897	-0.885222	-0.057022		-0.399647	-0.686231
Kurtosis	10.55896	10.94704	6.029655		8.419808	19.45919
Jarque-Bera	1574.086	1789.829	248.1790		810.3562	7365.293
Probability	0.000000	0.000000	0.000000		0.000000	0.000000

Table (4). Correlations of emerging economies returns
Pre-subprime crisis period (January 3rd 2006 to July 31st 2007)

		Correlation	t-Statistic	Probability
BOVESPA	S_P_500	0.006296	0.123700	0.9016
BSE_30	S_P_500	0.050003	0.983639	0.3259
HANG_SENG	S_P_500	0.063896	1.257926	0.2092
IPC	S_P_500	-0.008513	-0.167253	0.8673
KLSE	S_P_500	0.170536	3.400313	0.0007
KS11	S_P_500	-0.042213	-0.830096	0.4070
MERVAL	S_P_500	-0.016067	-0.315700	0.7524
SHANG__COMP_	S_P_500	-0.021115	-0.414930	0.6784
STI	S_P_500	0.039915	0.784830	0.4330
TUNINDEX	S_P_500	-0.034656	-0.681292	0.4961

During the subprime crisis (the January 2007- February 2010 period)

		Correlation	t-Statistic	Probability
BOVESPA	S_P_500	0.616869***	19.92038	0.0000
BSE_30	S_P_500	0.001134	0.028815	0.9770
HANG_SENG	S_P_500	0.203957***	5.295172	0.0000
IPC	S_P_500	0.558858***	17.12874	0.0000
KLSE	S_P_500	-0.060821	-1.548718	0.1219
KS11	S_P_500	0.162917***	4.196848	0.0000
MERVAL	S_P_500	0.265147***	6.989284	0.0000
SHANG__COMP	S_P_500	-0.009639	-0.244998	0.8065
STI	S_P_500	0.041906	1.066037	0.2868
TUNINDEX	S_P_500	-0.045693	-1.162560	0.2454

Appendix: Note on the processing of daily data

In so far as our data is daily-based and in order to facilitate its processing, we substituted the dates with observations. This allowed us to resolve the problem of quotations' unavailability (weekends, holidays, etc ..)

Period	Observations	Corresponding year
Pre-crisis period **(390 observations)**	1 to 245	2006 (January 3rd till December 28th)
	246 to389	2007 (January 2nd till July 31st
Post-crisis period **(648 observations)**	1 to 101	2007 (August 1st till December 28th
	102 to 350	2008 (January 2nd till December 30th
	351 to 607	2009 (January 5th till December 3rd)
	608 to 648	2010 (January 4th till February 26th)
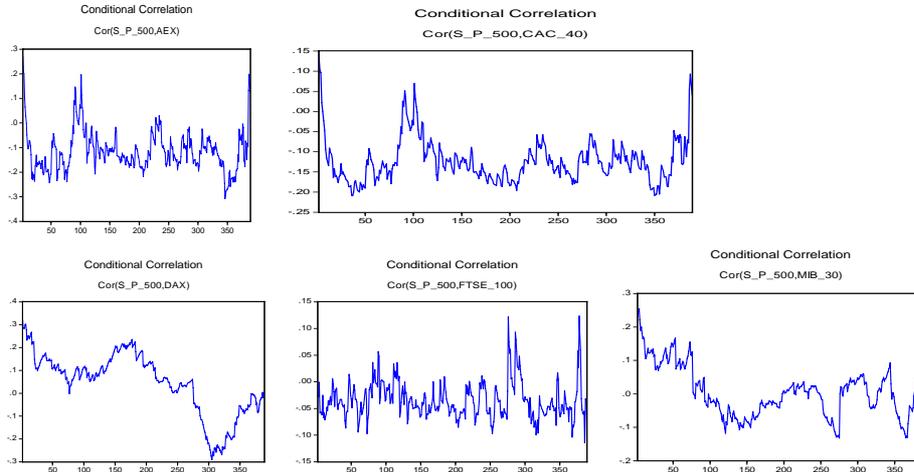
Emerging Economies
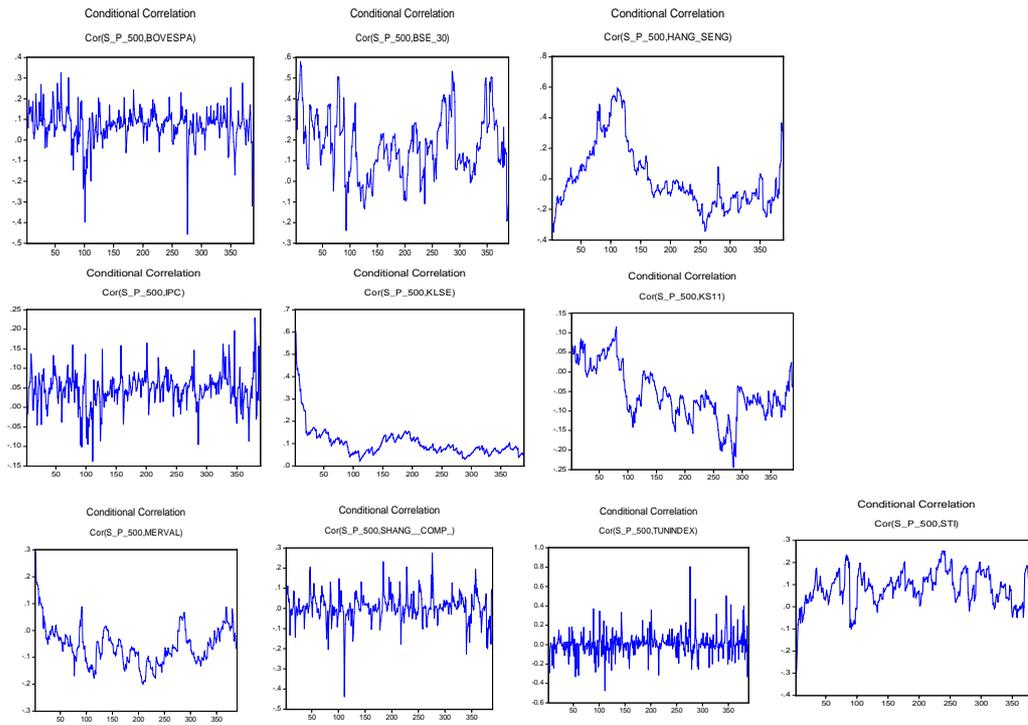
Graph (1). Dynamic Conditional Correlation during the pre-crisis period

Developed countries
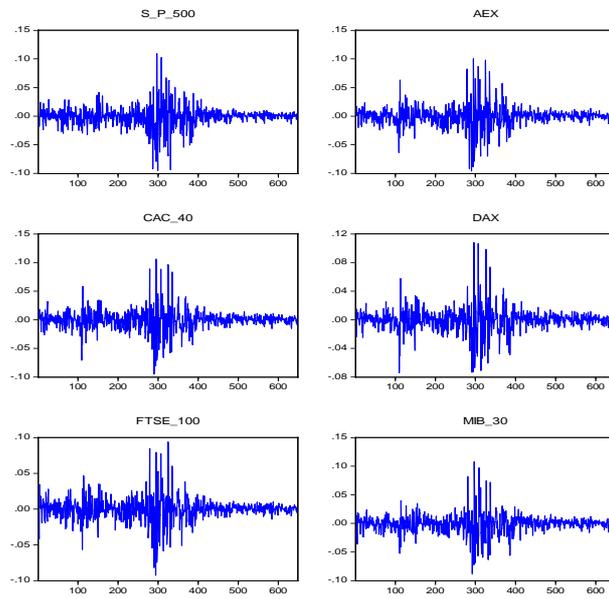
Emerging countries
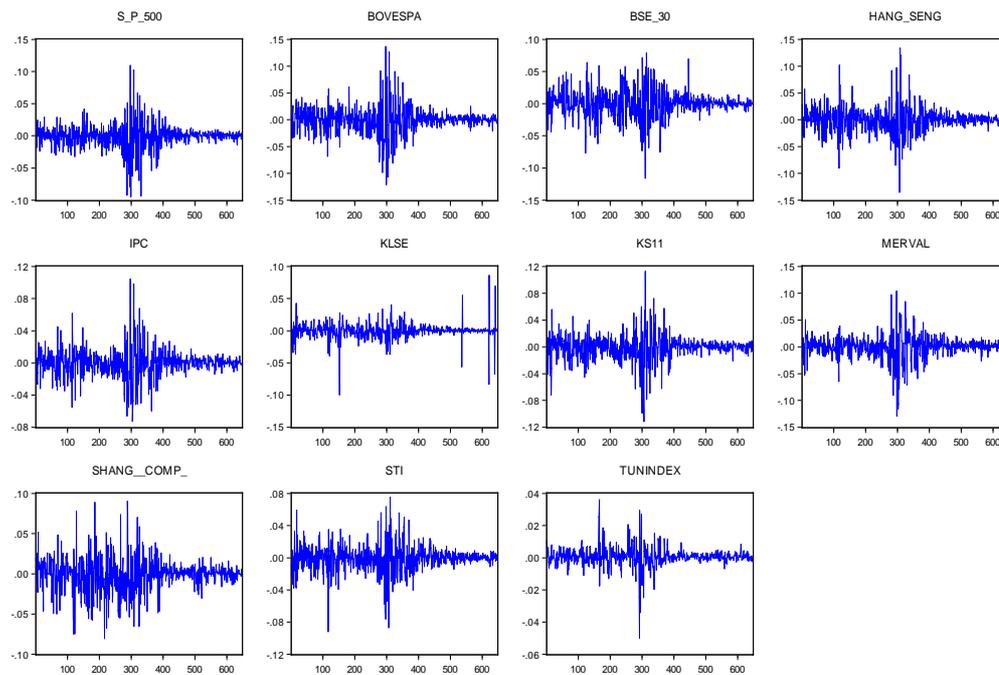
Graph (2). returns evolution during subprime crisis

Developed countries
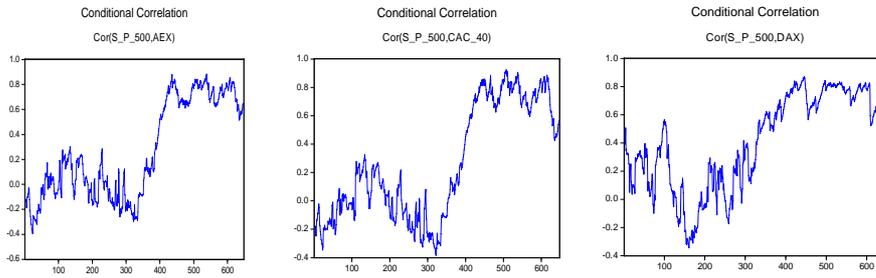
Emerging countries
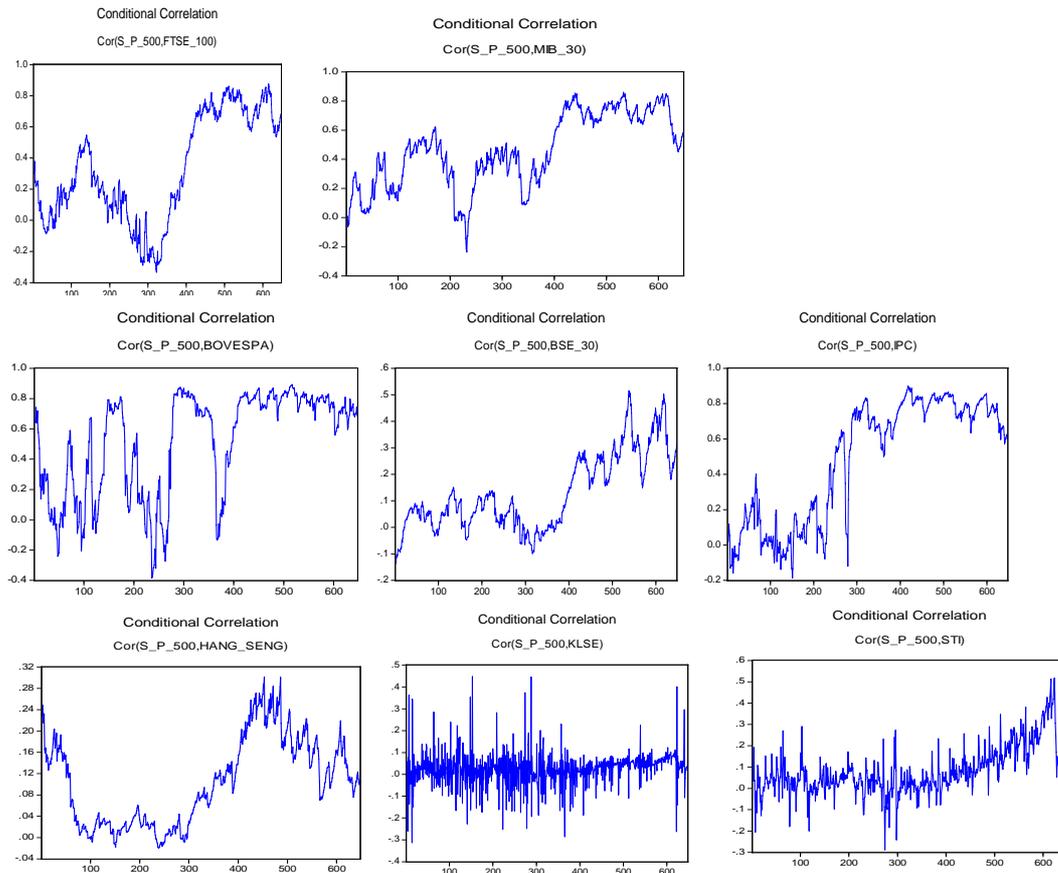
Graph (3). dynamic conditional correlation of the S&P 500 index with the other currencies