Financial Market Contagion During the Global Financial Crisis: Evidence from the Moroccan Stock Market

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Financial Market Contagion During the Global Financial Crisis: Evidence from the Moroccan Stock Market *

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Abstract

In this paper, we aim at the study of the contagion of the global financial crisis (2007-2009) on Moroccan stock market. Our study focuses to examine whether contagion effects exist on Moroccan stock market, during the current financial crisis. Following Forbes and Rigobon (2002), we define contagion as a positive shift in the degree of comovement between asset returns. We use stock returns in MASI, CAC, DAX, FTSE and NASDAQ as representatives of Moroccan, French, German, British and U.S. markets respectively. To measure the degree of volatility comovement, time-varying correlation coefficients are estimated by flexible multivariate dynamic conditional correlation (DCC). We investigate empirical studies using the DCC-GARCH model to test the contagion hypothesis from U.S. and European markets to the Moroccan one.

Key-words : Multivariate GARCH model, financial crisis, contagion hypothesis, break identification, conditional volatility, volatility comovement.

JEL Classification : C5, C22, G1, G01, G15.

1 Introduction

The global financial crisis of 2007-2009 is generally recognized as one of the most severe since the Great Depression of 1929 and will be well-known in the books of history and finance. Stock market crash around the

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world during the crisis period demonstrated the financial contagion of recent global financial crisis. Notwithstanding the financial crisis firstly hit stock markets in the United States and other developed markets, it soon spread around the world to hit stock markets in emerging countries. Current studies on contagion offer many methods for measuring the propagation of international shocks across countries. Some of the more widely used processes include the cross-market correlation coefficient procedures (e.g., King and Wadhwani 1990), analysis with a cointegration relationship between markets (e.g., Longin and Solnik 1995), probit-logit models (e.g., Eichengreen, Rose, and Wyplosz 1996), and autoregressive conditional heteroskedasticity (ARCH) or GARCH models (e.g., Hamao et al. 1990). Forbes and Rigobon (2002) survey other prevailing contagion procedures used to measure how shocks are transmitted on different equity markets in the world.

The initial empirical literature on financial contagion was the simple comparative analysis of Pearson' correlation coefficients between markets in calm and in crisis periods. Contagion was found when significant increases in correlations occurred in periods of crisis. King and Wadhwani (1990), and Lee and Kim (1993) employed the correlation coefficient between stock returns to test for the impact of the U.S. stock crash in 1987 on the equity markets of several countries. Empirical findings show that the correlation coefficients between several markets significantly increased during the crash. Hamao and al. (1990) employed the conditional variance estimated under the GARCH model to test for correlations between market volatilities for the crisis of 1987. Edwards and Susmel (2001) used switching ARCH model. They found that many Latin American equity markets, during the times of high market volatility, were significantly correlated which proved the existence of contagion effects.

Many recent studies have dealt with the recent global financial crisis. Some of them tackle the specific issue of market contagion. Among them Guo et al (2011) and Longstaff (2010) study the cross-asset contagion between several asset classes in the US market. Kenourgios et al (2011) deal with the contagion in the BRIC emerging equity markets. Johansson (2011) examines equity market movements in East Asia and Europe during the global financial crisis. The issue with Johansson (2011) is that it uses a time period 2004-2008 and thus the time period ends in a period when the global financial markets enter the highest level of turmoil. Neaime (2012) examined the impact of the recent financial crisis in the MENA region, he found a higher correlation with the U.S. stock market during the crisis, the index of the place of Egypt, the CASE30, ended 2008 with a change of -56.43 %. All of these studies find evidence of contagion.

The current paper focuses to investigate empirically the comovements between the Moroccan stock market and the U.S., France, U.K. and Germany stock markets over the period of 2002-2012. Therefore, we contribute to the literature of contagion among the financial markets around the financial crisis of 2007-2009. We employ tow flexible multivariate GARCH models (CCC, and DCC) to measure conditional correlations between the stock markets under investigation. The aim is to examine the contagion effect from U.S., France, U.K and

Germany to Morocco.

In fact, DCC-GARCH model of Engle (2002) has been extensively used in the contagion literature, mainly because of its intuitive interpretation property and the fact that it involves a simpler estimation procedure than the VEC models described in Engle and Kroner (1995). In addition, it does not suffer from the simplistic assumption of constant correlation as is does the CCC-GARCH. Finally, being part of the GARCH family of models gives the DCC-GARCH the flexibility to be combined with any univariate GARCH model to capture asymmetric or long memory effects. On the other hand, the restrictive assumption of constant correlations (CCC) is employed to whether will be rejected by the data.

The rest of the paper is organized as follows. Section 2 describes the data used and provides the different used econometric tools. Section 3 is devoted to our empirical findings including their analysis and discussion. Finally, Section 4 provides conclusion.

2 Data and Methodology

In this section, we firstly present the description of the different data used in our analysis. Secondly, we present the econometric tools we use to develop our empirical analysis. We define shift contagion as a significant increase in correlations between stock returns during financial crisis period. Then, time-varying correlation coefficients are estimated by the Dynamic Conditional Correlation (DCC) Multivariate GARCH model. We use also its restriction CCC-GARCH model to test whether the assumption of constant correlations will be rejected by the data. In order to recognize the contagion effects, we test whether the mean of the DCC-GARCH estimated conditional correlation coefficients in post-crisis period differs from that in the pre-crisis period. This paper considers the same break point due to the financial crisis estimated previously in El Ghini and Saidi (2013) based on the structural break tests of Bai-Perron (1998, 2003) and Lee-Strazicich (2003, 2004).

2.1 Data and Descriptive Statistics

The Casablanca Stock Exchange (CSE), which achieves one of the best performances in the region of the Middle East and North Africa (MENA), is Africa's third largest Bourse after Johannesburg Stock Exchange (South Africa) and Nigerian Stock Exchange in Lagos. Originally, CSE had the "Indice General Boursier" (IGB) as an index. IGB was replaced on January 2002 by two indices: MASI (Moroccan All Shares Index) and MADEX (Moroccan Most Active Shares Index). The Open Market Days are Monday-Friday and the financial market trading hours are 9:00 AM to 03:30 PM (GMT/GMT+1 in the summer).

In our empirical studies, we consider the stock market indices, namely, MASI (Morocco), NASDAQ 100 (Unites States), CAC 40 (France), FTSE 100 (United Kingdom), and DAX 30 (Germany). These indices are extensively based on financial and econometric literature and are considered as the most comprehensive index for the above countries. The sample set of data used are daily closing prices of the five indices from January 2002 to December 2012 excluding holidays (2869 observations).

We compute the returns (Stock return, R_{it} is measured as logarithmic difference of the price series, P_{it} as follows: $R_{it} = 100 * ln(P_{it}/P_{i(t-1)})$) for each index. Then we proceeded the pretreatment of the data by filtering method to remove the whole linear structure from the returns, which were present in the first moment of the series. Panel 1 displayed in the Appendix shows the dynamics of all return series.

Following El Ghini and Saidi (2013), we use the date September 26, 2008 as break point of NASDAQ due to the subprime crisis. The break point due to the subprime crisis is estimated using Lee-Strazicich (2003,2004) and Bai-Perron (1998, 2003) structural break tests. In the following, we divide the overall sample data into two sub-periods: the pre-crisis (January 2, 2002-September 26, 2008: 1758 observations) and the post-crisis (September 29, 2008 - December 31, 2012: 1111 observations). Following the NASDAQ crash, the MASI and the three other European markets indices, shown in the Panel 2 displayed in the Appendix, appears to decrease dramatically around September 26, 2008.

Table A.1 given in the Appendix contains the summary statistics of the market returns in the full and two defined sub-periods. The kurtosis of all return series is much larger than three. Further, the Jarque-Berra normality test ($p<0.0001$) reveals a statistically significant deviation of the data form normality. The Ljung-Box test Q statistics confirm the presence of autocorrelation on the return series. The Ljung-Box test for heteroscedasticity, Q^2 statistics, is significant ($p<0.0001$) for all squared returns, which confirm the presence of heteroscedasticity in all return sample series. The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test statistics for all return series are less than their critical values at the 1%.

2.2 Multivariate GARCH models

In conventional econometrics, the variance of the error terms is assumed to be constant (homoskedasticity) over time. But it is unlikely in the framework of financial time series. Many financial time series have exhibited the property of 'long-memory' (the presence of statistically significant correlations between observations that are a large distance apart), see e.g. Harris and Sollis (2003). Another distinguishing feature of the financial time series is known as 'volatility clustering', i.e large (small) volatility followed by large (small) volatility. In other terms, the current level of the volatility is positively related with its level during the immediately preceding periods (Brooks 2002).

Engle (1982) developed the ARCH (Autoregressive Conditional Heteroscedasticity) model that allows for the conditional variance to be time-varying. However there are some limitations for ARCH(q) model. Bollerslev extended the ARCH model to be more general one-GARCH (Generalized Autoregressive Conditional

Heteroscedasticity), which allows for the conditional variance to be dependent upon previous own lags. However, some researchers are interested in quantifying the interactions between the volatility of N different financial time series. In this context, the multivariate GARCH models are utilized instead of univariate counterparts.

In this section, we present the econometric tools we use to develop our empirical analysis. We define shift-contagion as a significant increase in correlations between stock returns during financial crisis period. Then, time-varying correlation coefficients are estimated by the Dynamic Conditional Correlation (DCC) Multivariate GARCH model. We use also its restriction CCC-GARCH model to test whether the assumption of constant correlations will be rejected by the data. In order to recognize the contagion effects, we test whether the mean of the DCC estimated conditional correlation coefficients in post-crisis period differs from that in the pre-crisis period.

2.2.1 DCC-GARCH model

In multivariate GARCH models, considering a stochastic vector series (X_t) with a dimension of $(N \times 1)$, the conditional mean of X_t is an $(N \times 1)$ vector μ_t and the conditional covariance of X_t is an $(N \times N)$ matrix H_t. Engle (2002) and Tse and Tsui (2002) attempted to model both variances and conditional correlations of several series using the DCC-GARCH process. To measure the degree of comovement time-varying correlation coefficients, we apply DCC-GARCH model of Engle (2002). The multivariate model is defined as follows:

$$X_t = \mu_t + H_t^{1/2}\epsilon_t \tag{1}$$

where

$$
\begin{aligned}
H_t &= D_t R_t D_t && (2)\\
R_t &= \Big(diag(Q_t)\Big)^{-1/2} Q_t \Big(diag(Q_t)\Big)^{-1/2} && (3)\\
D_t &= diag\big(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{NN,t}}\big) && (4)
\end{aligned}
$$

such that $X_t = \Big(X_{1t}, X_{2t}, \ldots, X_{Nt}\Big)$ is the vector of past observations, $\mu_t = \Big(\mu_{1t}, \mu_{2t}, \ldots, \mu_{Nt}\Big)$ is the vector of conditional returns, $\epsilon_t = \Big(\epsilon_{1t}, \epsilon_{2t}, \ldots, \epsilon_{Nt}\Big)$ is the vector of the standardized residuals, R_t is a $(N \times N)$ symmetric dynamic correlations matrix and D_t is a diagonal matrix of standard deviations for each of the returns series, obtained from estimating a univariate GARCH process in Equation 1:

$$h_{ii,t} = \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \tag{5}$$

Q_t is a $N \times N$ variance-covariance matrix of standardized residuals $\Big(u_t = \frac{\epsilon_t}{\sqrt{h_t}}\Big)$ which defined as follows :

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 u_{t-1} u_{t-1}^{'} + \theta_2 Q_{t-1} \tag{6}$$

where $\overline{Q} = E(u_t u_t^{'})$ refers to $(N \times N)$ symmetric positively-defined matrix of the unconditional variance-covariance of standardized residuals. θ_1 and θ_2 are the unknown parameters to be estimated. The sum of these coefficients must be less than one in order to insure positivity of the matrix Q_t. Therefore, for a pair of markets i and j , their conditional correlation at time t can be written as :

$$\rho_{ij,t} = \frac{(1-\theta_1-\theta_2)\overline{q}_{ij} + \theta_1 u_{i,t-1}u_{j,t-1} + \theta_2 q_{ij,t-1}}{\Big((1-\theta_1-\theta_2)\overline{q}_{ii} + \theta_1 u_{i,t-1}^2 + \theta_2 q_{ii,t-1}\Big)^{1/2}\Big((1-\theta_1-\theta_2)\overline{q}_{jj} + \theta_1 u_{j,t-1}^2 + \theta_2 q_{jj,t-1}\Big)^{1/2}}, \tag{7}$$

where q_{ij} is the element on the i^{th} line and j^{th} column of the matrix Q_t.

The parameters are estimated using quasi-maximum likelihood method (QMLE) introduced by Bollerslev and Wooldridge (1992). This method permits to obtain, for each variable, the conditional variance and the conditional covariance. Under the Gaussian assumption, the likelihood function can be rewritten as:

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\Big(n\ln(2\pi) + 2\ln|D_t| + \ln|R_t| + u_t^{'}R_t^{-1}u_t\Big) \tag{8}$$

with $u_t = \frac{\epsilon_t}{\sqrt{h_t}} = D_t^{-1}\epsilon_t$.

2.2.2 CCC-GARCH model

The Constant Conditional Correlation multivariate GARCH model was introduced by Bollerslev in 1990 to primarily model the conditional covariance matrix indirectly by estimating the conditional correlation matrix. The conditional correlation is assumed to be constant while the conditional variances are varying. Obviously, this assumption is impractical for real financial time series. Then certain modifications were made grounded on this form, see Silvennoinen and Teräsvirta (2009) for more details.

3 Empirical results

In this part, we test the contagion effects of the U.S. subprime crisis on the Moroccan market by examining the variation in the time-varying conditional correlation coefficients estimated by using bivariate DCC-GARCH model.

In the Appendix, Tables A2-A3 give estimation results of the bivariate DCC-GARCH model in pre- and post-crisis periods for each pair: Morocco-U.S., Morocco-France, Morocco-UK and Morocco-Germany. The empirical results obtained from the CCC model presented in Tables A.4 and A.5, where it was found that the ARCH and GARCH estimated coefficients in the pre- and post-crisis periods are also statistically significant at 1% level, are so in accordance with the DCC estimation results. In order to investigate the contagion effects, using DCC-GARCH model, from the foreign stock markets to the Moroccan stock market, we propose in the forthcoming subsection to test, using Forbes and Rigobon (2002), the cross market contagion from the U.S., France, U.K. and Germany stock markets to Moroccan one. In the second, we present our discussion of the results.

3.1 Testing the contagion effect of the U.S. subprime crisis

The definition of the term contagion varies widely across the literature. Hence, the initial literature of this phenomenon has usually been divided as to whether transmission through real or financial channels constitutes contagion. The broad definition of the *World Bank* is : *"Contagion is the cross-country transmission of shocks or the general cross-country spillover effects. Contagion can take place both during 'good' times and 'bad' times. Then, contagion does not need to be related to crises. However, contagion has been emphasized during crisis times"*. During the past decades, there have been several empirical studies which seek to analyze the contagion and the cross-country economic comovement via real transmission channels or through a financial links or both.

By real sector channel, and as been identified by the theoretical and empirical literatures, shocks propagate through trade, foreign direct investment (FDI), policy coordination, country evaluation, and unexpected shocks in global economic. In addition, the correlated information, the correlated liquidity and the portfolio rebalancing are considered as the main channels of financial linkages through which cross-country shocks could affect an equity market (see Kodres and Pritsker, 1999).

In our paper we adopt the definition of contagion introduced by Forbes and Rigobon (2002) and we define the contagion as a significant increase in cross-market comovement after a shock occurred in one country. With respect to this definition, the condition for contagion is a significant increase in comovements as a result of a shock in one market. This implies, if two markets display a high degree of comovement during the stability period, even if they are highly correlated during a crisis, if this crisis-correlation shift is not significant it does not amount to contagion. In the absence of a significant correlation during the crisis-period, the term 'interdependence' is used to qualify the situation between the two markets.

Let X_t and Y_t be time series representing stock market returns following the relationship (cf. Forbes and Rigobon, 2002):

$$Y_t = \alpha + \beta X_t + \epsilon_t \tag{9}$$

where α and β are constants, ϵ_t represents the error terms. The correlation coefficient between X_t and Y_t is defined as :

$$\rho = \rho(X_t, Y_t) = \frac{Cov(X_t, Y_t)}{\sigma_x \sigma_y} := \frac{\sigma_{xy}}{\sigma_x \sigma_y} \tag{10}$$

Following Forbes and Rigobon (2002), the correlation coefficient is adjusted by the transformation defined by:

$$\rho^* = \frac{\rho}{\sqrt{1+\delta(1-\rho^2)}} \tag{11}$$

such that

$$\delta = \frac{\sigma_x^h}{\sigma_x^\ell} - 1 \tag{12}$$

where δ denotes the change in high-period volatility against low-period volatility, σ_x^h and σ_x^ℓ the conditional variances of stochastic variable X_t in the high- and low-period volatility respectively. For the purpose of the calculation of the adjusted correlation coefficient ρ^*, we assume that the turmoil-period is considered as high volatility period and the stable period as the low volatility period. In our empirical analysis, the variable Y_t represents Moroccan market returns data and X_t the foreign market returns data for each considered pair of countries in the previously estimated DCC-GARCH models.

To evaluate if there is significant increase in the unadjusted and adjusted correlation coefficients during the crisis-period [1], we use the hypothesis test :

$$\begin{cases} H_0 : \quad \rho_h = \rho_l \\ H_1 : \quad \rho_h > \rho_l \end{cases} \tag{13}$$

where H_0 is the null hypothesis of no-contagion (N), H_1 is the alternative hypothesis for the presence of contagion (C), and ρ_h and ρ_l represent the correlation coefficients in high and low volatility periods. The hypotheses are tested using the Collins and Biekpe (2003) t-test statistic defined by:

$$t = (\rho_h - \rho_l)\sqrt{\frac{n_h + n_l - 4}{1 - (\rho_h - \rho_l)^2}} \tag{14}$$

which is distributed as $t_{(\alpha, n_h+n_l-4)}$, n_l (n_h) indicates the number of observations during the low volatility (high) period. In Table 1 we report respectively the estimated unadjusted and adjusted correlation coefficients ($\rho_l; \rho_h; \rho$) for the pre-crisis (low volatility), post-crisis (high volatility) and full-period calculated using DCC bivariate-GARCH. The test statistics and results are reported on the right of table. According to the testing results, we find evidence of contagion from most of the countries except from Germany (see Table 1). Further, the tests with adjusted correlation coefficient give clear evidence of contagion from U.S., U.K. and France. The fundamental linkages (trade integration and financial connectivity) between Morocco and France/U.K. economies, and the effect of the collective behavior (herding and financial panics) after the occurrence of the last U.S. crisis can explain the shift-contagion under the DCC model.

[1] Based on our break test results, the crisis period considered is : September 26, 2008 to December 31, 2012.

Conditional Correlation	Country	Pre-Crisis		Post-Crisis		Full Period		Test Statistic	Contagion?
		ρ_l	S.E	ρ_h	S.E	ρ	S.E		
Unadjusted coefficients	U.S.	0.007	0.014	0.034	0.032	0.016	0.019	1.454*	C
	France	0.033	0.008	0.059	0.068	0.049	0.039	1.389*	C
	U.K.	0.022	0.019	0.069	0.044	0.044	0.040	2.532***	C
	Germany	0.036	0.017	0.045	0.063	0.042	0.036	0.457	N
Adjusted coefficients	U.S.	0.011	0.021	0.052	0.049	0.019	0.023	2.230**	C
	France	0.098	0.023	0.161	0.152	0.051	0.040	3.374***	C
	U.K.	0.033	0.029	0.104	0.063	0.042	0.037	3.778***	C
	Germany	0.069	0.032	0.083	0.108	0.043	0.038	0.728	N

t Critical one-tail (level of signf.) : (2.326) 1%; (1.645) 5%; (1.282) 10%.
"C"=contagion; "N"=no contagion.

Table 1: Contagion test in the Moroccan stock market during the global financial crisis

3.2 Discussions

This section discusses the results obtained from the implementation of the DCC model outlined in the methodology. We present at first the empirical results obtained by country and we conclude by providing a brief comparison of results (see Tables 1, A2-A3) according to the correlation corrected version of Forbes and Rigobon (2002).

Morocco-U.S.: The DCC-GARCH results provide evidence of contagion from the U.S. financial market to the Moroccan one. This consistent finding provides evidence in favor of volatility linkage between the Moroccan stock market and the U.S. stock Market.

Morocco-France: From the DCC-GARCH results we find evidence to the presence of a shift in comovement in stock market returns between France and Morocco in the crisis-period. Likewise here, we also find evidence of volatility linkage between the Moroccan stock market and the French one. The real and financial transmission channels as an explanation of the nature of contagion appears more relevant for this case.

Morocco-U.K.: The DCC-GARCH results indicate that the comovement of the Moroccan and the U.K. markets was higher after the subprime crisis. This can be explained by the significant impact of the subprime crisis on the U.K. market, and the increasing integration of the Moroccan and the U.K. stock markets.

Morocco-Germany: The DCC-GARCH results implies that there is no contagion from the German stock market to the Moroccan one. Thing to note about this result is that it can be related to fact that the financial contagion resulting from the U.S. subprime crisis was less important in Germany in comparison with the case of France and U.K.(see Horta et al. (2008)).

Otherwise, we provide empirical evidence from the countries pairs considered that contagion effects are better captured by adjusted estimated conditional correlation coefficient. Our results are in line with the evidence of Collins and Biekpe (2002) and Lagoarde-Segot and Lucey (2009) concerning contagion in Morocco.

4 Conclusion

The current international financial crisis which started in U.S. has revealed a high interdependence between financial markets worldwide. The aim of this paper focuses to investigate empirically the comovements between the Moroccan stock market and the France, Germany, U.K. and U.S. stock markets over the period of 2002-2012. The paper contributes to the literature of contagion among the financial markets around the financial crisis of 2007-2009. Then, tow flexible multivariate models were applied (CCC, and DCC) to examine the contagion from U.S., France, U.K and Germany to Morocco. The restrictive assumption of constant correlations (CCC) was rejected by the data.

The empirical results of our paper suggest that it is important to highlight the correlation of the Moroccan stock market with those of U.S., U.K. and France. The presence of a significant comovements between the considered economic partners and Morocco was pointed. Furthermore, we find that bad news about economic partners of Morocco can in fact generate contagion in the local stock market.

Given these latter findings, it is apparent that the recent global financial crisis leads to increase the financial linkages between Moroccan market and the other considered markets. This rising integration can be usefully considered by the international investors in their trading strategy which consists of taking a position in one market following the signals given by the volatility of another market. A good understanding of the contagion effect is an important ingredient for designing trading and hedging strategies and optimizing portfolios.

Some promising issues to develop in our future research concern the assessment of integration degree of Moroccan financial market within International markets using the co-integration techniques. Other interesting perspectives concern the detecting of changing regime in the Moroccan stock index volatility using other extended GARCH models.

References

[1] Baillie, R.T. and Bollerslev, T. (1991). Intra-Day and Inter-Market Volatility in Foreign Exchange Rates. *Review of Economic Studies* Vol. **58**, 565-585.

[2] Bhar, R. and Hamori, S. (2003). New Evidence of Linkages among G-7 Stock Markets. *Finance Letters*, Vol. **1**, 35–40.

[3] Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, Vol. **31**, 307–327.

[4] Bollerslev, T. and Wooldridge, M. (1992). Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Reviews*, Vol. **11**, 143-172.

[5] Collins D., and Biekpe, N. (2003). Contagion: a fear for African equity markets?. *Journal of Economics and Business*, Vol. **55**, 285–297.

[6] Edwards S. and Susmel, R. (2001). Volatility dependence and contagion in emerging equity markets. *Journal of Development Economics*, Vol. **66**(2), 505-532.

[7] Eichengreen, B, Rose, AK & Wyplosz, C. (1996). Contagious currency crises. *NBER Working Paper*, 5681.

[8] El Ghini, A. & Saidi, Y. (2013). Return and Volatility Spillovers in the Moroccan Stock Market During The Financial Crisis. *Working Paper.*

[9] Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, Vol. **50**(4), 987–1007.

[10] Engle, R.F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics*, Vol. **20**, 339–350.

[11] Engle, R. F. and Kroner F. K. (1995). Multivariate Simultaneous Generalized ARCH. *Econometric Theory*, Vol. **11**, 122–150.

[12] Forbes, K, & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market comovement. *The Journal of Finance*, Vol. **57**, 2223-2261.

[13] Guo, F., Chen, C.R., Huang, Y.S. (2011). Markets contagion during financial crisis: A regime-switching approach. *International Review of Economics and Finance*, Vol. **20**, 95–109

[14] Hamao, Y., Masulis, R. & Ng, V. (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies*, Vol. **3**, 281–307.

[15] Harris, R. and R. Sollis (2003). Applied Time Series Modelling and Forecasting. *Wiley.*

[16] Horta, P., Mendes, C., Vieira, I (2008). Contagion effects of the US Subprime Crisis on Developed Countries. *CEFAGEUE Working Paper*, 2008.

[17] Kenourgios, D., Samitas, A., Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money*, Vol. **21**, 92–106.

[18] King, M, & Wadhwani S. (1990). Transmission of volatility between stock markets. *The Review of Financial Studies*, **3**, 5–33.

[19] Kodres, L.E., and Pritsker, M. (1999). A Rational Expectations Model of Financial Contagion. *FEDS Working Paper 1998-48, The Federal Reserve Board*.

[20] Johansson, A.C. (2011). Financial Markets in East Asia and Europe during the Global Financial Crisis. *The World Economy, 2011*, 1088–1105.

[21] Lagoarde-segot T., Lucey B.M. (2009). Shift-contagion vulnerability in the MENA stock markets. *The World Economy*, Vol. **32(10)**, 1478–1497.

[22] Lee, S. B., & Kim, K. J. (1993). Does the October 1987 crash strengthen the co-movements among national stocks markets? *Review of Financial Economics*, **3**, 89–102.

[23] Longin, F. & Solnik, B. (2001). Extreme correlation of international equity markets. *The Journal of Finance*, Vol. **56 (2)**, 649–676.

[24] Longstaff, F.A. (2011). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics*, **97**, 436–450.

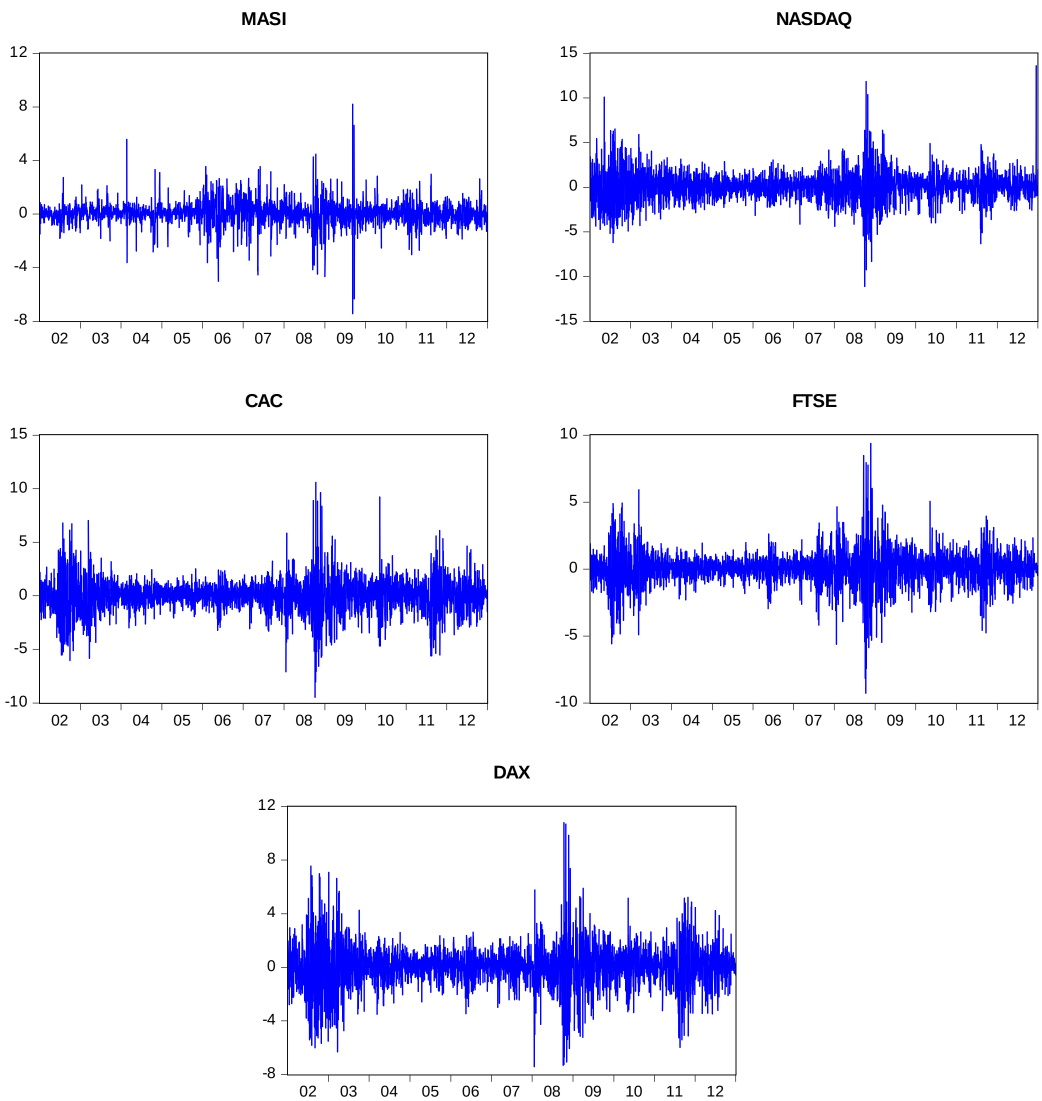
[25] Neaime, S. (2012). The global financial crisis, financial linkages and correlations in returns and volatilities in emerging MENA stock markets. *Emerging Markets Review*, 268–282.

[26] Silvennoinen, A. & Teräsvirta, T. (2009). Modeling Multivariate Autoregressive Conditional Heteroskedasticity with the Double Smooth Transition Conditional Correlation GARCH Model. *Journal of Financial Econometrics, Society for Financial Econometrics*, Vol. **7(4)**, 373–411.

[27] Tse, Y. K., Tsui, A. K. C., 2002. A multivariate generalized autorregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business and Economic Statistics*, Vol. **20 (3)**, 351–362.

6 Appendix

Panel 1 : Stock Index returns



Panel 2 : Daily Stock Market Indices

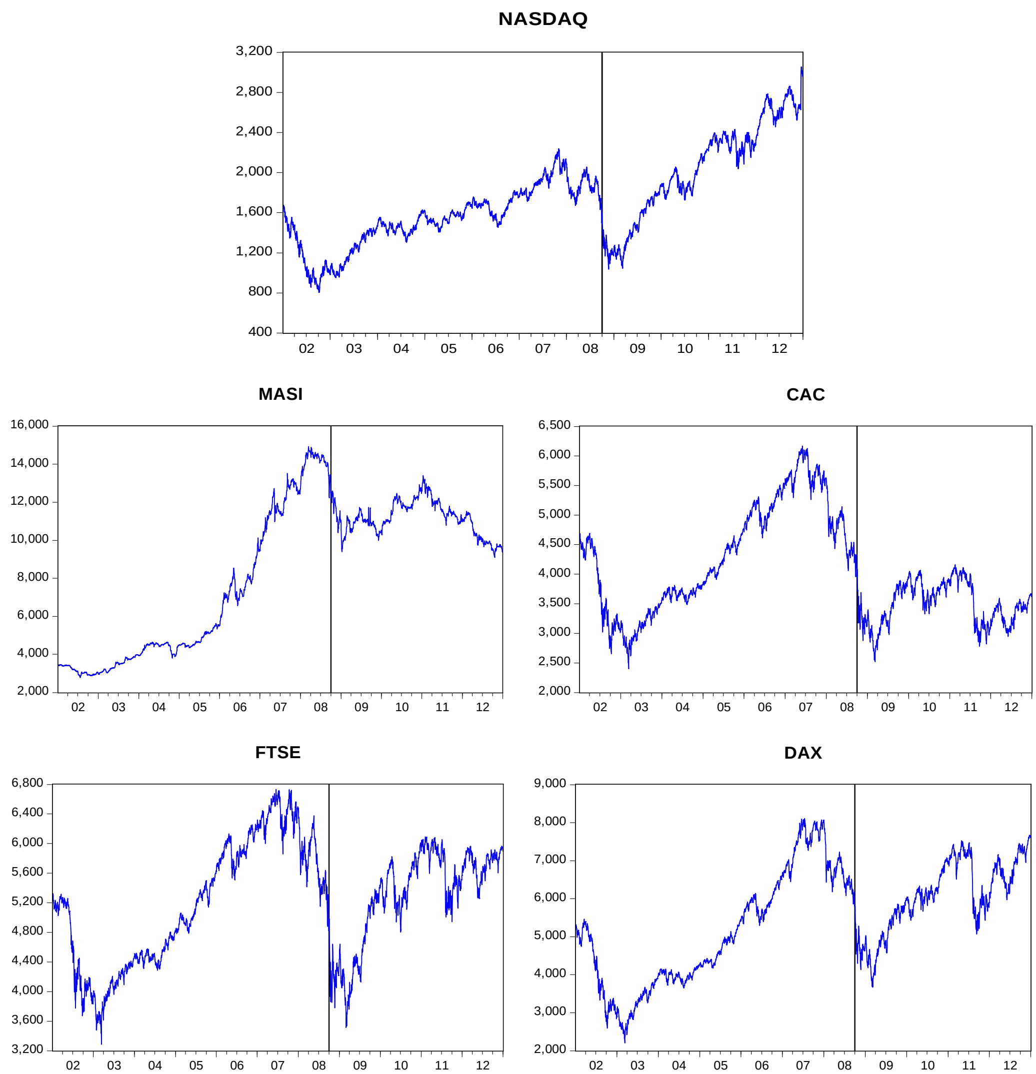


Table A.1 : Descriptive statistics of return series

	Full Period (January 3, 2002 to December 31, 2012)				
	MASI	**NASDAQ**	**CAC**	**FTSE**	**DAX**
Mean	0.035	0.022	-0.008	0.004	0.014
Median	0.019	0.044	0.000	0.000	0.044
Maximum	8.192	13.588	10.595	9.384	10.797
Minimum	-7.435	-11.115	-9.472	-9.265	-7.433
Std. Dev.	0.859	1.617	1.556	1.280	1.595
Skewness	-0.163	0.259	0.084	-0.122	0.059
Kurtosis	14.235	9.392	8.275	9.864	7.688
Jarque-Bera	15096.8***	4914.3***	3328.9***	5637.3***	2627.4***
Ljung-Box Q(24)	169.1***	47.8***	70.4***	92.0***	35.6*
Ljung-Box Q^2(24)	820.4***	1991.7***	2856.7***	3702.1***	3118.2***
ADF	-42.6***	-58.5***	-26.8***	-26.0***	-54.9***
PP	-42.3***	-58.9***	-56.4***	-57.1***	-55.1***
(Observations : 2868)	Significance level: *** 1%, ** 5%, *10%				

	Pre-Crisis Period (January 3, 2002 to September 26, 2008)				
	MASI	**NASDAQ**	**CAC**	**FTSE**	**DAX**
Mean	0.076	0.002	-0.005	-0.001	0.009
Median	0.054	0.022	0.000	0.000	0.045
Maximum	5.564	10.097	8.868	8.469	7.553
Minimum	-5.017	-6.191	-7.077	-5.637	-7.433
Std. Dev.	0.824	1.544	1.379	1.148	1.498
Skewness	-0.268	0.191	0.093	0.041	-0.049
Kurtosis	9.459	5.579	7.366	8.058	6.684
Jarque-Bera	3075.0***	497.5***	1397.9***	1873.1***	994.5***
Ljung-Box Q(24)	199.2***	41.3**	78.5***	102.9***	57.4***
Ljung-Box Q^2(24)	634.5***	1605.1***	1950.4***	1394.7***	2815.4***
ADF	-30.2***	-45.8***	-44.2***	-27.8***	-44.7***
PP	-30.0***	-46.0***	-44.9***	-47.1***	-44.8***
(Observations : 1757)	Significance level: *** 1%, ** 5%, *10%				

	Post-Crisis Period (September 29, 2008 to December 31, 2012)				
	MASI	**NASDAQ**	**CAC**	**FTSE**	**DAX**
Mean	-0.031	0.052	-0.013	0.011	0.019
Median	0.000	0.062	0.000	0.001	0.041
Maximum	8.192	13.588	10.595	9.384	10.797
Minimum	-7.435	-11.115	-9.472	-9.265	-7.336
Std. Dev.	0.908	1.725	1.801	1.466	1.738
Skewness	-0.001	0.324	0.078	-0.247	0.167
Kurtosis	19.310	13.033	7.904	10.019	8.243
Jarque-Bera	12325.4***	4683.5***	1115.4***	2293.9***	1278.8***
Ljung-Box Q(24)	39.6**	28.3	41.8**	52.6***	26.8
Ljung-Box Q^2(24)	318.1***	626.1***	785.2***	1269.1***	893.9***
ADF	-30.1***	-36.3***	-34.0***	-16.1***	-25.2***
PP	-29.9***	-36.5***	-34.5***	-34.1***	-32.6***
(Observations : 1111)	Significance level: *** 1%, ** 5%, *10%				

Table A.2 : Bivariate DCC-GARCH model estimations - Pre-Crisis Period

	Morocco-U.S.		Morocco-France		Morocco-U.K.		Morocco-Germany	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean(1)	-0.019*	(0.011)	-0.018	(0.011)	-0.019*	(0.011)	-0.018	(0.011)
Mean(2)	0.037	(0.028)	0.055**	(0.024)	0.034**	(0.018)	0.076***	(0.025)
C(1)	0.050***	(0.005)	0.049***	(0.005)	0.005***	(0.005)	0.050***	(0.005)
C(2)	0.006**	(0.003)	0.019***	(0.005)	0.011***	(0.003)	0.021***	(0.005)
A(1)	0.444***	(0.024)	0.442***	(0.024)	0.443***	(0.024)	0.443***	(0.024)
A(2)	0.036***	(0.007)	0.099***	(0.011)	0.111***	(0.013)	0.089***	(0.011)
B(1)	0.572***	(0.017)	0.574***	(0.017)	0.572***	(0.017)	0.573***	(0.017)
B(2)	0.962***	(0.007)	0.893***	(0.012)	0.883***	(0.013)	0.901***	(0.012)
DCC(1)	0.005	(0.012)	0.003	(0.009)	0.007	(0.010)	0.014	(0.029)
DCC(2)	0.947***	(0.194)	0.941**	(0.413)	0.935***	(0.170)	0.694	(0.819)

Table A.3 : Bivariate DCC-GARCH model estimations - Post-Crisis Period

	Morocco-U.S.		Morocco-France		Morocco-U.K.		Morocco-Germany	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean(1)	0.016	(0.019)	0.016	(0.019)	0.015	(0.019)	0.016	(0.019)
Mean(2)	0.152***	(0.037)	0.067	(0.041)	0.057*	(0.031)	0.092**	(0.038)
C(1)	0.062***	(0.006)	0.062***	(0.006)	0.062***	(0.006)	0.062***	(0.006)
C(2)	0.070***	(0.015)	0.047***	(0.015)	0.021**	(0.008)	0.022**	(0.009)
A(1)	0.303***	(0.020)	0.303***	(0.020)	0.301***	(0.020)	0.303***	(0.020)
A(2)	0.087***	(0.015)	0.100***	(0.013)	0.098***	(0.014)	0.087***	(0.012)
B(1)	0.667***	(0.013)	0.667***	(0.013)	0.668***	(0.013)	0.667***	(0.013)
B(2)	0.886***	(0.019)	0.884***	(0.015)	0.890***	(0.014)	0.905***	(0.012)
DCC(1)	0.008	(0.014)	0.017	(0.014)	0.048	(0.038)	0.015	(0.011)
DCC(2)	0.937***	(0.114)	0.939***	(0.048)	0.034	(0.709)	0.936***	(0.058)

Table A.4 : Bivariate CCC-GARCH model estimations - Pre-Crisis Period

	Morocco-U.S.		Morocco-France		Morocco-U.K.		Morocco-Germany	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean(1)	-0.019	(0.012)	-0.019	(0.012)	-0.019	(0.012)	-0.018	(0.012)
Mean(2)	0.037	(0.027)	0.055**	(0.022)	0.040**	(0.017)	0.076***	(0.022)
C(1)	0.049***	(0.009)	0.049***	(0.009)	0.049***	(0.009)	0.049***	(0.008)
C(2)	0.006***	(0.001)	0.019***	(0.005)	0.011***	(0.003)	0.021***	(0.004)
A(1)	0.443***	(0.051)	0.441***	(0.052)	0.442***	(0.046)	0.441***	(0.051)
A(2)	0.036***	(0.001)	0.098***	(0.004)	0.111***	(0.005)	0.089***	(0.004)
B(1)	0.573***	(0.039)	0.574***	(0.040)	0.573***	(0.038)	0.574***	(0.039)
B(2)	0.962***	(0.001)	0.893***	(0.005)	0.884***	(0.003)	0.901***	(0.003)
R(2.1)	-0.005	(0.024)	0.021	(0.024)	0.003	(0.024)	0.037	(0.024)

Table A.5 : Bivariate CCC-GARCH model estimations - Post-Crisis Period

	Morocco-U.S.		Morocco-France		Morocco-U.K.		Morocco-Germany	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Mean(1)	0.015	(0.019)	0.015	(0.019)	0.015	(0.019)	0.014	(0.019)
Mean(2)	0.149***	(0.036)	0.061	(0.039)	0.056*	(0.031)	0.089**	(0.036)
C(1)	0.062***	(0.009)	0.062***	(0.010)	0.062***	(0.010)	0.062***	(0.010)
C(2)	0.069***	(0.002)	0.050***	(0.006)	0.022***	(0.004)	0.023***	(0.004)
A(1)	0.303***	(0.018)	0.303***	(0.019)	0.303***	(0.019)	0.303***	(0.019)
A(2)	0.085***	(0.002)	0.103***	(0.004)	0.100***	(0.004)	0.089***	(0.003)
B(1)	0.667***	(0.009)	0.667***	(0.010)	0.667***	(0.010)	0.666***	(0.010)
B(2)	0.888***	(0.001)	0.881***	(0.003)	0.888***	(0.003)	0.903***	(0.003)
R(2.1)	0.028	(0.027)	0.001	(0.029)	0.005	(0.030)	-0.007	(0.029)