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Contagion Analysis of Islamic Financial Assets:
A DCC-GARCH approach

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Abstract

This thesis investigates the existence of financial contagion between Conventional Dow Jones and also between Islamic Dow Jones indices during the U.S subprime crisis. Daily stock prices for the period January 2th 2002 to November 20th 2015 are used for the analysis. The sample is divided into a pre-crisis, crisis and after crisis periods. The test for contagion is applied after the estimation of the VAR model following Forbes and Rigobon (2002), and also after the estimation of the DCC-GARCH model using a DCC means difference t-test. The later remains the main analysis. The obtained results show both an increase in cross-market correlations, i.e. contagion, in all considered DJ Islamic-Conventional indices and also herding behavior, except for the Japan DJ Islamic-Conventional indices which present only interdependency. Another finding is that Islamic indices are less contagious than Conventional indices. Finally, to understand the dynamic nature of financial contagion during the U.S subprime crisis, a rolling DCC means difference test of length m is adopted (the considered windows length 250 observations before the crisis and 250 observations after the crisis). The following results are of key interest for international investors and portfolio managers, government intervention.

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1 Introduction

Economic and financial systems have faced tremors and shocks during periods of crisis. The role played by the U.S. economy makes that these shocks acquires greater importance given its rapid influence in the financial world. The U.S. subprime financial crisis that started in August 2007 is seen as one of the most serious since the great depression of 1929. This crisis commenced in the U.S. financial sector has affected not only other economic sectors but also other countries, resulting in a collapse of the banking industry, stock market, high unemployment rate, and a reduction in international trade. However, the U.S. subprime crisis have questioned the stability of the global financial system.

Various definition of contagion can be found in the literature. In this thesis contagion is defined as a significant increase in the cross-market correlation during the period of crisis (Forbes and Rigobon, 2002) [1]. Using this approach it is possible to conclude that, if two markets are highly correlated before and after a shock, this does not mean the existence of contagion, but only interdependency, which indicate the presence of strong real linkages between the two countries (Forbes and Rigobon, 2002). While if two markets are mildly correlated during periods of stability, but highly correlated after a shock to one country, this would mean the existence of contagion.

In the early works the static measure of correlation between cross-country return series was used to determine the existence of contagion and therefore to make decisions about the construction of diversified portfolio. Over the years, the study of contagion has experienced a substantial development with the creation of new measures and the application of different econometrical techniques such as correlation analysis; ARCH and GARCH models; cointegration techniques; and principal component analysis[2]. As suggested by (Engle, 2002) correlation between stock markets are time-varying, i.e., they have a dynamic nature. And also in international financial markets, the transmission of shocks due to contagion is very quick and short lived. As a result, the simple static correlation is not compatible to measure the existence of contagion between stock return series, but it is must to resort to methods that take into account the dynamic nature of correlation and so of contagion. The DCC-GARCH model proposed by (Engle, 2002; Engle and Sheppard 2001) will be used in this paper to overcame this and all the limitations present in the literature. It belongs to the class of multivariate GARCH model and is characterized

[1] The very restrictive definition has been used for example by King and Wadhwani (1990), Favero and Giavazzi (2002) and Bekaert et al. (2003)

[2] See among others Lee and Kim (1993), Chou et al (1994), Longin and Solnik (1995) and Kaminsky nd Reinhart (1998)

by dynamic conditional variances and correlations, and consequently it takes into account the dynamic effect of contagion. Corsetti, Pericoli, and Sbracia, 2005; Bekaert and Harvey, 2000; Jeon and Moffett, 2010; Syllignakis and Kouretas, 2011; Suardi, 2012) have used the DCC-GARCH model to study contagion in emerging financial markets during the U.S. subprime crisis. In this paper, test for contagion has been applied first after the estimation of the VAR model, i.e., on the residuals of the VAR model. Then to refine the analysis after the estimation of the DCC-GARCH model. In the former case, the presence of contagion is determined by a Fisher z-transformation, while in the later the presence of contagion is determined by a mean differences t-test. The main analysis remains that of the DCC-GARCH model, while the other is only for comparison purpose. The literature on contagion of the U.S. subprime crisis is more focused on the study of conventional stock market returns. The objective of this paper is to test for contagion not only between conventional Dow Jones indexes, but also between Islamic Dow Jones indexes. The later indexes are expected to have different risk-return profile from the conventional stocks. Islamic's stock markets are constructed by filtering the conventional indexes using Shariah law, i.e. Islamic law. The filtering criteria exclude the firms which are considered unlawful (haram), like firms which operate in the liquor, gambling, hazard, etc.. markets, and only include firms which are considered lawful (halal). Consequently, Islamic stock indexes are generally characterized by a small number of firms, lower leverage, and under-diversification of the market compared to conventional stock indexes. Despite Islamic financial sector is developing at the rate of 15-20% on average per annum over the last decades (IIFM, 2010), empirical work in this field are scarce. Islamic stock indices are considered more resilient than conventional indices to a financial crisis (Sukmana and Kolid, 2012), so they can constitute a valid alternative to increase the benefits from international portfolio diversification. The smaller and less diversified universe may amplify the effect of the crisis on Islamic stocks indexes, while the lower leverage effects (due to their interest-debt limit) reduce the susceptibility of these indices to the shocks compared to the conventional counterparts. Consequently, perceiving the co-movements of Islamic stock indices is of great importance for investors and policy makers.

This thesis makes several contributions to the recent literature on financial contagion. First, it tests the presence of financial contagion not only between convention DJ indices, but also between Islamic DJ indexes during the U.S. subprime crisis. Second, the paper answers the following question: Are Islamic indexes more or less contagious than the conventional indexes.

This thesis is organized as follows. Section 2 presents the theoretical and empirical literature. Section 3 describes the data used. Section 4 presents

the methodology employed. Section 5 present the correlations test. Section 6 presents the empirical results. Section 7 summarizes and concludes.

2 Literature Review

After a number of economic and financial crises occured in the course of the years, the concern of researchers to understand the cause and different channels of contagion have been of great importance [3]. This is because financial contagion happens in periods of crises and has important aftermaths for the global economy in relation to monetary policy, optimal asset allocation, risk management, capital adequacy, and asset pricing. The effect and magnitude of financial contagion depends, first on the shared macroeconomic fundamentals, shocks are transmitted not only to countries connected by macroeconomic fundamentals but also to countries indirectly connected with these fundamentals. Secondly, it also increases in function of information asymmetry, so countries with high level of information asymmetry (ex: emerging markets) are more contagious.

A myriad of definitions of financial contagion have been used in the literature. However, with reference to the World Bank classification, contagion can be defined in three ways: broad, restrictive, and very restrictive definitions.

- Broad definition: contagion is identified with the general process of shock transmission across countries. The latter is supposed to work both in tranquil and crisis periods, and contagion is not only associated with negative shocks but also with positive spillover effects (Billio and Pelizzon, 2003).

- Restrictive definition: this is probably the most controversial definition. contagion is the propagation of shocks between two countries (or group of countries) in excess of what should be expected by fundamentals and considering the co-movements triggered by the common shocks. If we adopt this definition of contagion, we must be aware of what constitutes the underlying fundamentals. Otherwise, we are not able to appease effectively whether excess co-movements have occurred and then whether contagion is displayed (Billio and Pelizzon, 2003).

- Very restrictive definition: This is one adopted by F-R (2001a, 2001b). Contagion should be interpreted as the change in the transition mechanism that takes place during a turmoil period. For example, the latter can be inferred by a signifiant increase in the cross-market correlation (Billio and Pelizzon, 2003).

[3] see among others the East Asian crisis 1997, Mexican peso crisis 1994 and Brazilian devaluation 1999

Based on the chosen definition of contagion they may vary both, the conclusion regarding the existence or not of contagion, and also the econometrical approach to be used. As suggested by Rigobon (2001) the very restrictive definition is more neutral because it is not necessary to identify how the shift in coss-market linkages occurs. This definition of contagion is also helpful in: assessing the effectiveness of international diversification in reducing portfolio risk in periods of crises; justifying multilateral intervention; and differentiating between various propagation mechanisms (Forbes and Rigobon Chapter 3). Furthermore, using this definition allow to distinguish between theories that support contagion and theories that support only interdependecy. The theoretical analysis of financial contagion is very large, a more detailed explanation can be found in Forbes 2000b[4]. Mainly it can be divided in two class of theories: crisis-contingent and non-crises contingent theories. Crises-contingent theories claim that transmission mechanisms change significantly during a crisis and explain the structural shift of cross-market linkages after a shock. These theories indicate the presence of contagion. Three mechanism of how shocks are transmitted can be distinguished: multiple equilibria (Masson, 1998); endogenous liquidity (Valdés, 1996) ; and political economy (Drazen, 1998). These theories conclude the existence of new transmission mechanism different from these prevailing before the crisis, also they conclude that contagion is caused by investors's psychological behavior and not by economic fundamentals.

Non-crises contingent theories claim that transmission mechanisms does not change significantly after a crises. The cross market linkages are based on economic fundamentals and so any increase in the cross market correlation after a shock does not constitute a shift but a continuation of linkages in both periods. These theories do not indicate the presence of contagion, but only interdependency. Four mechanism of how shocks are transmitted can be found: trade ; policy coordination ; country reevaluation ; and random aggregate shocks.

The empirical literature which asses the existence of contagion is also vast. The first empirical paper on the study of contagion ascend to Sharpe (1964) and Grubel and Fadner (1971). Four econometrics thecniques have been applied: Analysis of cross-market correlation coefficients; ARCH and GARCH models; cointegration techniques; and probit models.

Lets start with the analysis of cross-market correlations and present the most relevant papers in this approach. The aim here is to compare the cross-market correlation coefficients during the stable and the turmoil periods and

[4]See also Claessens, Dornbusch and Park

test for a significant increase in the correlation coefficients. A significant increase in the cross-market correlation in the turmoil period means that the transmission mechanism between the two markets change and contagion exist. King and Wadhwani (1990) was the first paper who tested for the presence of contagion between the U.S, U.K and Japan and find a significant increase in the cross-market correlations after the 1987 U.S. crash. Lee and Kim (1993) add twelve major markets to the previews analysis of King and Wadhawani (1990) and found a significant increase in the average weekly cross-market correlations from 0.23 before the 1987 crash to 0.39 afterward. Calvo and Reinhart (1995) find the presence of contagion after the 1994 Mexican peso crises between Asian and Latin American emerging markets using stock prices and Brady bonds. Baig and Goldfajn (1998) found the presence of contagion for many emerging markets during the 1997-98 East Asian crisis using stock indices, sovereign spreads, interest rates, and currency prices, there analysis is considered as the most complete one.

The second approach to test for contagion estimates the variance-covariance transmission mechanism across countries using an ARCH or GARCH framework. This approach have been used by: Hamao et al. (1990) Chou et al. (1994) to study the co-movements across markets after the 1987 U.S. stock market crash. Edwards (1998) after the 1994 Mexican peso crises studied the propagation across bond market. He found that the transmission of volatility from one country to an other, but he does not test if this propagation changes significantly after a crisis.

The third approach uses co-integration techniques to test for contagion. the aim here is to test for changes in the co-integrating vector between stock market, i.e concentrate in long-run relationship variations between markets after a shock. Login and Solnik (1995) used this approach to study seven OECD countries during the period 1960 to 1990 and conclude that the average correlations between the U.S. stock market and the other countries increase by 0.36 over this period. This approach has important limitations such as assuming that the real linkages between the markets are constant over all the period. It could lose short periods of contagion, given that it concentrates on long periods (Rigobon chapter 3).

The fourth approach tests for contagion using exogenous events and simplifying assumptions to identify a model and directly measure changes in the propagation mechanism. Baig and Goldfajn (1998) studied the daily news effect in stock market of one country in the other countries market during the 1997-98 East Asian crisis. Their finding is that news in a country effect largely neighboring economies. Forbes(2000b) estimates the effect in single companies in the world of the Asian and Russian crises. This approach has been applied

also by Eichengreen, Rose and Wyplosz (1996) and Kaminsky and Reinhart (1998). They estimate a probit model to verify how a crisis in one country influence the probability that a crises happens in other countries.

However, the literature review comparing Islamic equities and conventional counterparts is scarse. Hassan and Tag el-Din (2005) studied bubble formation using the dependence tests of survival analysis to weekly and monthly returns of AMANX, AMAGX and DJIMI. They concluded the non existence of speculative bubbles among the studied returns. Al-Zoubi and Maghyereh (2006), studied the Dow Jones Islamic Market index by applying the Risk Matrices, skewed Student-t APARCH and Student-t APARCH. They concluded that The DJIM has lower risk than the conventional one. Atta (2000) studied the performances of the DJIMI using back-tested data. Other studies compared the performance of DJIMI to different conventional indexes Hassan (2001), Tilva and Tuli (2002) and Hakim and Rashidian (2002, 2004). Hakim and Rashidian (2004) compared the DJIM with the Wilshire 5000 index and the three-month treasury bills. They concluded no correlation between these indexes. Despite the filtring criteria adopted in the Islamic stock markets did not appear to wounding its diversification, but it may reduce its market risk. Girard and Hassan (2008) studied the Islamic and conventional groups of FTSE using a multivariate cointegration analysis. They conclude that these indexes are integrated, have similar return to risk and diversification benefits. Zhang and Zarina (2015) studied the effect of the U.S. subprime crisis on the short-long run relationship between selected Asia-Pacific Islamic stock markets and leading conventional stock markets, applying a VAR and VECM methods. They concluded the existence of benefits from portfolio diversification in both short-long run terms. Saiti, Bacha, and Masih (2015) tested the existence of contagion between conventional and Islamic stock indices after the U.S. subprime crisis. They concluded no existence of contagion in the outbreak of subprime crisis, while during the collapse of the Lehman Brothers the conventional indices displayed the existence of contagion and Islamic indices except Indonesia did not show the existence of contagion. As known contagion can be measured between interest rate, exchange rate, stock market return, or a linear combination of them. These indexes are affected by simultaneous equations, omitted variables, conditional and unconditional heteroschedasticity, serial correlation, nonlinearity, and non-normality problems. However, no econometric techniques can solve all these problems together, therefore, the literature has taken short cuts (Forbis and Rigobn 2002). Focusing on the three main limitations presented by the data, i.e. endogeneity, heteroschedasticity, and omitted variables, it is possible to notice that: Endogeneity is caused by the direct transmission of shocks across countries throughout real linkages.

Heteroschedasticity is caused by the increase in market volatility during crisis period. Given that the correlation coefficient is positively correlated with the market volatility, the unadjusted correlation coefficients will be upward biased. Here, the increase in volatility is due to a large increase in the idiosyncratic shock of the market under crisis in a way that the other increases in variances are negligible. If the propagation mechanism remain constant, heteroschedasticity can mislead the presence of contagion. While omitted variable is caused by a large increase in the variance of the aggregate shock in a way that the other variance increases are negligible and correlation between the markets increases in absolute value. Consequently, most of the previous results which tested the existence of financial contagion in the literature are not consistent. To solve all the above limitations, Rigobon (1999) directly identified the model assuming that the variance of the disturbances in crisis period increases in only one market, i.e. assuming the knowledge of the country generating the crises, and the transmission mechanism is stable. Any shift in the transmission mechanism constitute contagion. Forbes and Rigobon(2002) applied this concept to the 1997 East Asian crisis, the 1994 Mexican peso collapse, and the 1987 U.S. stock market crash and the evidence of contagion drops to zero in most cases, indicating the presence of only interdependence. Corsetti, Pericoli and Sbracia(2005) applied their test to only 1997 East Asian crisis and find both the presence of contagion and interdependency. However, (Billio e Pelizzon, 2005) have also shown that the two mentioned tests for contagion are highly affected by the window selected, the presence of omitted variables, and the time zone. In addition to these limitation, it is also important to consider the dynamic nature of the correlation of stock markets. And also the fact that in international financial markets, the transmission of shocks due to contagion is very quick and short lived (Baig and Goldfajn 1999; Ait-Sahalia, Cacho-Diaz, and Laeven 2010).

Several recent studies have been adopted to overcame the limitations present in the literature. (Longing and Solnik (2001), Hartman et al (2001) Bae, Karolyi and Stulz (2003) have developed models based on extreme value theory. Rodriguez (2007), Horta et al (2008) used a copula approach to measure the dependence between asset return. While others have augmented multivariate GARCH models with asymmetry, Markov switching regime and time-varying correlations (Cappiello, Engle and Sheppard, 2006; Ang and Bekaert, 2002; Ang and Chen, 2002; Chiang et al., 2007). A pioneered model among the class of multivariate GARCH model is the DCC-GARCH. This model is characterized by dynamic conditional variances and correlations, and consequently it takes into account the dynamic effect of contagion. Also this model corrects for heteroskedasticity and no exogenous subsample assumptions have

to be made (Missio et al., 2011). The DCC-GARCH model has been used by Hwang et al. (2010), Naoui et al. (2010), and Bouaziz et al. (2012) to test the effect of U.S. subprime crisis (2007-08) in emerging and developed stock markets. All these studies conclude the existence of financial contagion not only in emerging but also in developed markets during this crisis. This model has been used also by Corsetti, Pericoli, and Sbracia, 2005; Bekaert and Harvey, 2000; Jeon and Moffett, 2010; Syllignakis and Kouretas, 2011; Suardi, 2012 to test contagion on emerging financial markets during the U.S. subprime crisis (2007-08).

3 Data

This paper analyze financial contagion between Dow Jone Indices including both Islamic and conventional indexes during the U.S. subprime crises. The indices are represented by:

- The Dow Jones United Kingdom U.S. Dollar Stock Index includes companies traded publicly on the London Stock Exchange. The index is price-weighted based on 9 different market sectors.
- The Dow Jones Islamic Market U.K. Index meet Islamic investment guidelines based on Shari'ah Law, it include stocks that in the United Kingdom satisfy these guidelines. The index is spread by the Dow Jones data feed of the Chicago Board of Trade.
- The Dow Jones Canada U.S. Dollar Stock Index, the selection used by this stock form indexes that cover 95% of free-float market capitalization at the country level and comprise large-cap, mid-cap and small-cap subindexes.
- The Dow Jones Islamic Market Canada Index, meet Islamic investment guidelines based on Shari'ah Law, it include stocks that in Canada satisfy these guidelines.
- The Dow Jones U.S. Index is a popular measure of the U.S. stock market. It is composed of 95% U.S stocks by float-adjusted market capitalization, roulling out the non relevant traded securities.
- The Dow Jones Islamic Market US Index tracks american companies that ?fulfill? Islamic Principles, it is suitable for people who wants to invest according these guidelines in U.S.
- The dow Jones Japan U.S. Dollar Stock Index includes companies traded publicly on the Tokyo, Osaka, and Nagoya Stock Exchange. The index is price-weighted based on 9 different market sectors.
- The Dow Jones Islamic Market Japan Index meet the Islamic investments guidelines based on Shari'ah Law, it is suitable for who wants to invest according these guidelines in Japan. The index is launched by the Dow Jones data feed of the Chicago Board of Trade.
- The Dow Jones Malaysia U.S. Dollar Stock Index includes companies traded publicly on the Kuala Lumpur Stock Exchange. The index is price-weighted based on 9 different market sectors.

- The Dow Jones Islamic Market Japan Index meet Islamic investment guidelines based on Shari'ah Law, it include stocks that in Malaysia satisfy these guidelines.

The daily closing last prices are obtained from Bloomberg, and range from 2nd January 2002 to 20th November 2015 for a total of 3610 observations. All the selected countries are among the developed countries, notably the U.S. economy which is considered as the largest economy in the world, and influence almost all the other economies creating dependence on its economy. Except Malaysia which belongs the developing countries, and can be seen as the biggest Islamic financial hub.

To have a synchronic data set, days of no trading were eliminated, so the effective sample is composed of 2571 observations. All the indexes have the same currency (USD dollar) to avoid any exchange rate variation's problem. As suggested by Forbes et Rigobon (2002) the differences in operating hours and time zone have no significant effect on the test for contagions[5]. The analysis is made considering firstly the full sample period, followed by the analysis of the stable and crisis periods. The determination of the stable and turmoil periods is made with reference to:

- Dungey (2009) where the stable period begins in January 03rd 2002 and ends July 16th 2007 for an average of 399 observations for every stock return, and the crisis begins July 17th 2007 and ends on December 31st for an average of 642 observations for every stock return, while the rest of the sample represents the after crisis period;

- Horta, Carlos, Mendes and Vieira (2008) where the stable period begins in January 03rd 2002 and ends July 31st 2007 for an average of 405 observations for every stock return, and the crisis begins August 1st 2007 and ends on December 31st for an average of 636 observations for every stock return, while the rest of the sample represents the after crisis period ;

- Using the above two references the crisis period is determined looking at the conditional variances of the country generating the crisis, i.e. the Dow Jones return index provided by the DCC analysis [6]. From

[5]Forbis and Rigobon (2002) used a two-day moving average return to solve the problem of operating-hour and time zone in the test for contagion, and they conclude no significant difference

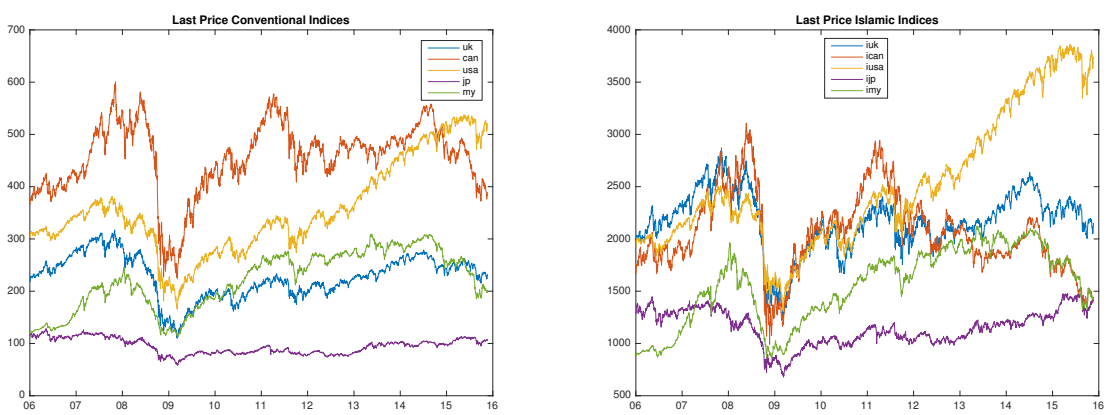
[6]some studies determines endogenously the crisis period using a Markov regime switching model, while others uses the Bai and Perron's test

table (1) it is possible to observe that the conditional variance increases significantly after the July 23th. According to this the stable period begins in January 03rd 2002 and ends July 31st 2007 for an average of 411 observations for every stock return, and the crisis begins August 1st 2007 and ends on December 31st for an average of 630 observations for every stock return, while the rest of the sample represents the after crisis period;

This is useful to understand the difference in behavior of stylized facts between the samples, and in order to further implement the Forbis and Rigobon (2002) test for contagion where the U.S is considered as the source country of the crisis.

Figure (1)[7] shows the plot of the considered Dow Jones Indices in the full sample period, All the indices present almost the same random walk like behavior, i.e. they exhibit the same trend direction, where mean and variance change over the time, these characteristics are typical of non-stationary time series.

Figure 1: Last Price Indices



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[7]Figure(8) shows the plot of each single stock price index can be find in appendix

Important attention must be given at the pair of indices, Islamic and conventional relative to the same country. It is possible to observe that all the pair of indices have almost the same plot. However, this is due to the fact that Islamic indices are obtained filtering the conventional indices including only companies that meet Shariah Law in their business activities, debt level, expenses and interest income [8].

Looking at the autocorrelation functions Figure(9), all the autocorrelation functions are characterized by an infinite extension with a slow linear decay, these autocorrelation functions are typical of non-stationary series. The most predominant tool to test for stationarity is the Augmented Dickey Fuller (ADF) test, the null hypothesis indicates that the indices are difference stationary $\mathbf{I(1)}$ and so they present a stochastic trend, while the alternative hypothesis indicates that they are trend stationary $\mathbf{I(0)}$. If the p-value is higher than the critical value of 5%, so the null hypothesis of non-stationarity is accepted. The results of the test are given in table(2), using 5 % as a critical value, for all the indices, the null hypothesis of non-stationarity can not be rejected given that the p-values are higher than 5 %. To obtain stationarity, returns are calculated by using a conventional approach, i.e. as the first difference of the natural log of every stock price index. Denoting with $\mathbf{r_t}$ the return index at time $\mathbf{t}$, $\mathbf{p_t}$ the corresponding closing stock price for day $\mathbf{t}$ and $\mathbf{p_{t-1}}$ the closing stock price for day $\mathbf{t-1}$,

$$\mathbf{r_t = ln(\frac{p_t}{p_{t-1}})}$$

To confirm that the return indices are stationary, the ADF test has been performed on the return indices. The results of the test are given in Table(3), using a 5% critical value, all return series in this case are stationary since the p-values are smaller that 5

Figure(2)[9] shows the plot of the Islamic and conventional return indices in the sample period.

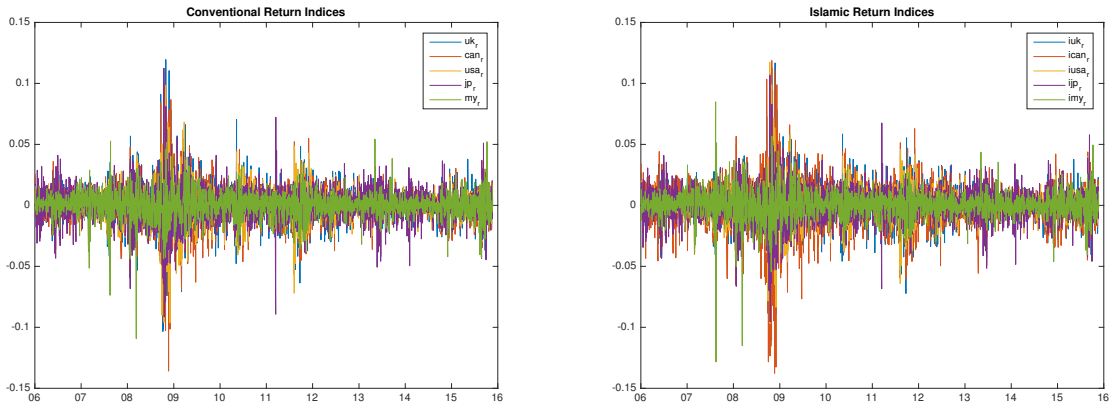
Conversely to the stock prices, the return indices present a mean-reverting behavior with a constant daily mean close to zero. However, the covariance stationarity assumption of the mean seems to be satisfied.

The volatility of the return indices changes during the time, indicating a time varying behavior of the variance, this phenomena is called intermittency. The volatility clustering -periods of low volatility are followed by periods of low volatility and periods of high volatility are followed by periods of high

[8]The data regarding the components of the DJ indices has been provided by SP Dow Jones Indices

[9]Figure (10) shows the plot of each single stock return index can be find in appendix

Figure 2: Islamic Return Indices



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volatility- is clear, meaning that the volatility of returns present some time dependence[10]. Finally, it can be seen that the 2008 is characterized by high volatility for all the return indices due to the financial crisis.

Table(4) present the descriptive statistics and stochastic properties for each daily return index. The average return range from (-6.04e-05) assumed by the Dow Jones Islamic return index Canada and (2.59e-04) assumed by the Dow Jones Islamic return index U.S. All the returns are small and positive, except the Dow Jones Islamic return index Canada and the Dow Jones return index Japan which are negative, indicating a disadvantage for these return indices. The minimum (-0.1377) is assumed by Dow Jones return index Canada, while the maximum (0.1195) is assumed by Dow Jones return index United Kingdom. Looking at the standard deviations, which are used to measure the uncertainty associated with the return indices, the less risky return is the Dow Jones return index Malaysia with a standard deviation of (1.02%), while the more risky return is Dow Jones Islamic return index Canada with a standard deviation of (1.87%). Note that the Dow Jones Islamic return index Canada has the worst performance in terms of return and risk.

As in the case of all financial time series, looking at the value of kurtosis, it can be seen that the return indices are leptokurtic (Fama 1965, Blattberg and Gonedes 1974, Bookstaber and McDonald 1987, Eberlein and Keller 1995, etc.), i.e. the empirical distributions return series have fat tails relative to the normal distribution and high peaks around the mean suggesting a broad

[10]The of the squared residuals presents volatility clustering, and also the ACF shows clearly the presence of autocorrelation on squared residuals, these are indicators of autoregressive conditional heteroschedasticity.

possibility of movements. Along with this all the return indices are negatively skewed denoting a long left tail of the distribution, i.e. the risk of negative losses[11]. From the frequency histograms the leptokurtic effect is more clear, the histograms figure(11) present the non-normal characteristics of financial time series, this result is reinforced by the Jarque-Bera test statistic (JB) which strongly rejects the null hypothesis of normal distributed returns table(5). The tests present a p-value equal to zero, and indicate that for these markets negative and positive shocks are more likely to be present.

Figure (12) shows the autocorrelation functions for the return indices, the blue dotted lines on the plots test the null hypothesis that the autocorrelations are equal to zero at 5% critical value, if more than 5% of the autocorrelations exceeds the blue line and make a pattern, than there is evidence of autocorrelation. The daily return indices present a lack of autocorrelation, i.e. there is little evidence of linear time dependence. This does not exclude the presence of time dependence on the squared returns. Figure(13) shows the autocorrelation functions of the squared returns. The squared autocorrelations decay slowly and are significantly positive for many lags, highlighting the presence of non linear time dependence (see Granger et al 1993). In other words they indicate the presence of correlation in the volatility of returns. Since the return indices are uncorrelated, but dependent a GARCH type modeling can be used (Bolleslev et al., 1992).

Table (6) shows the correlations between the return indices. It can be seen that the correlations between the return indices are all high and positive, exception for Japan, indicating a high dependence between these markets. The highest correlation (98.28) is between The Dow Jones U.S. return index and the Dow Jones U.S. Islamic return index, while the smallest correlation (1.61) is between the Dow Jones U.S. return index and Dow Jones Japan return index . The high value of correlation between the return indices indicate that are not complementary, limiting the possibility of gaining advantages diversifying between these return indices (Ling and Dhesi, 2010). However, a DCC-GARCH model developed by Engle (2002) is more suitable to analyze the dynamics of the correlations and the contagion phenomenon.

Table(7-9) present the descriptive statistics of the daily return indices in the pre-crises, crises, and after crisis periods. In the pre crises period all the average returns are positive, and present values different than the standard value of 0. They are negatively skewed denoting the asymmetry of the distribution. Another important statistic of the return indices is the high value of kurtosis which exceeds the standard value of 3 denoting a leptokurtic distribution.

[11]The standard normal distribution has a value of kurtosis=3 and skewness=0

These values indicate that the return indices may not be normally distributed. In the crisis period all the average returns present a high values of kurtosis, and are negatively skewed except ICAN, UK, IUK, and JP. This may indicate the non normal distribution of the return indices. While in the after crisis period the average return is negative for CAN, ICAN, and IUSA, and positive for the other return indices. Similarly to the other two periods, all the return indices are negatively skewed and present a high values of kurtosis, indicating the non normal distribution of the return indices. A comparison between the pre-crises and the crises periods shows that all the means in the pre-crises period are higher than these in the crises period, while all the standard deviations in the crises period are higher than these in pre-crises period.

4 Methodology

4.1 The VAR model

A flexible and simple to use extension of the univariate Autoregressive model to dynamic multiple time series is given by the vector autoregressive model. The VAR model, which constitute an alternative to simultaneous equation (Sims 1980) is used to describe the co-movements and the interactions between multiple time series, i.e. to explain the dynamic evolution of economic and financial time series from their common history and for forecasting. It is also applied in policy analysis and structural inference. Here each variable is explained by past values of itself plus current and past values of the other variables, it is also possible to comprise exogenous variables like trends or seasonal dummies in the VAR model without adding additional equations to explain them. Three kinds of VAR model are available in the literature: reduced, recursive, and structural form.

Reduced-VAR model: This model represent the VAR model in the pure form. Every variable is expressed as a linear function of lagged values of itself and lagged values of all other variables, i.e is a function of past values of predetermined variables. In the reduced VAR model the OLS estimator can be used to estimate each equation in the system, providing consistent and asymptotically efficient estimates. This model present a drawback, since the number of parameters in the original VAR model is higher than the one in the reduced-VAR, it is not possible to recuperate the parameters of the original VAR model from the estimated parameters of the reduced-VAR model, so the original VAR model is not exactly identified. To resolve this problem it is necessary to impose n^2 additional restrictions.

Recursive-VAR model: It states a priority of influence between the dependent variables. In the recursive VAR model the error term of each equation is uncorrelated with the error in the previous equations, so it is possible to estimate and exactly identify the parameters of the original VAR model. The additional restriction in the recursive var model are based on the Choleski decomposition:

- The variance-covariance matrix of the error term is a diagonal matrix, it imposes $\frac{\mathbf{n^2-n}}{2}$ restrictions.

- The matrix of the coefficients is a triangular matrix with one along the diagonal, it imposes $\frac{\mathbf{n^2+n}}{2}$ restrictions.

Structural-VAR model: it can be represented by an exactly identified var model, where the restrictions on the matrix of coefficients is based on economic theory.

If only two variables $\mathbf{x_t}$ and $\mathbf{y_t}$ are considered, the first order VAR(1) model consists of only two equations, and they are given by:

$$\mathbf{x_t} = \boldsymbol{\beta_{10}} - \boldsymbol{\beta_{12}}\boldsymbol{y_t} + \boldsymbol{\gamma_{11}}\boldsymbol{x_{t-1}} + \boldsymbol{\gamma_{12}}\boldsymbol{y_{t-1}} + \boldsymbol{\epsilon_{xt}}$$

$$\mathbf{y_t} = \boldsymbol{\beta_{20}} - \boldsymbol{\beta_{21}}\boldsymbol{x_t} + \boldsymbol{\gamma_{21}}\boldsymbol{x_{t-1}} + \boldsymbol{\gamma_{22}}\boldsymbol{y_{t-1}} + \boldsymbol{\epsilon_{yt}}$$

where
$\boldsymbol{\beta_{12}}$ is the coefficient of $\mathbf{y_t}$ in the equation of $\mathbf{x_t}$, while $\boldsymbol{\beta_{21}}$ is the coefficient of $\mathbf{x_t}$ in the equation of $\mathbf{y_t}$, so this system include a feedback where:

- $\boldsymbol{\beta_{12}}$ is the direct contemporaneous effect of y_t an x_t
- $\boldsymbol{\beta_{21}}$ is the direct contemporaneous effect of x_t an y_t

  and also include an indirect contemporaneous effect which occur when:

- $\boldsymbol{\beta_{12}} \neq \mathbf{0}$, so $\boldsymbol{\epsilon_{yt}}$ has an indirect contemporaneous effect on x_t.
- $\boldsymbol{\beta_{21}} \neq \mathbf{0,}$ so $\boldsymbol{\epsilon_{xt}}$ has an indirect contemporaneous effect on y_t.

$\boldsymbol{\epsilon_{xt}}$ and $\boldsymbol{\epsilon_{yt}}$ are serially uncorrelated white noise process where $\mathbf{Var}(\boldsymbol{\epsilon_{xt}}) = \boldsymbol{\sigma_x^2}$, $\mathbf{Var}(\boldsymbol{\epsilon_{\mathrm{yt}}}) = \boldsymbol{\sigma_y^2}$, and $\mathbf{Cov}(\boldsymbol{\epsilon_{xt}}, \boldsymbol{\epsilon_{yt}}) = \boldsymbol{\sigma_{xt}} = \boldsymbol{\sigma_{yt}} = \mathbf{0}$.

Since $\mathbf{x_t}$ and $\mathbf{y_t}$ are interdependent, it is not possible to estimate the VAR model because of the endogeneity problem. A solution to this problem is the use of reduced-VAR model, so the system became:

$$\mathbf{x_t} + \boldsymbol{\beta_{12}}\mathbf{y_t} = \boldsymbol{\beta_{10}} + \boldsymbol{\gamma_{11}}\mathbf{x_{t-1}} + \boldsymbol{\gamma_{12}}\mathbf{y_{t-1}} + \boldsymbol{\epsilon_{xt}}$$

$$\mathbf{y_t} + \boldsymbol{\beta_{21}}\mathbf{x_t} = \boldsymbol{\beta_{20}} + \boldsymbol{\gamma_{21}}\mathbf{x_{t-1}} + \boldsymbol{\gamma_{22}}\mathbf{y_{t-1}} + \boldsymbol{\epsilon_{yt}}$$

In a more compact form:

$$\mathbf{BX_t} = \boldsymbol{\Omega_0} + \boldsymbol{\Omega_1}\mathbf{X_{t-1}} + \boldsymbol{\epsilon_t}$$

assuming that $\boldsymbol{\beta_{12}\beta_{21}} \neq \mathbf{1}$, it is possible to multiply both side by $\mathbf{B^{-1}}$, as a result the reduced-VAR model is given by:

$$\mathbf{B^{-1}\ BY_t} = \ \mathbf{B^{-1}}\boldsymbol{\Omega_0} + \mathbf{B^{-1}}\boldsymbol{\Omega_1}\mathbf{Y_{t-1}} + \ \mathbf{B^{-1}}\boldsymbol{\epsilon_t}$$

or:

$$\mathbf{Y_t} = \mathbf{C_0} + \mathbf{C_1}\mathbf{Y_{t-1}} + \mathbf{E_t}$$

where
$\mathbf{C_0} = \ \mathbf{B^{-1}}\boldsymbol{\Omega_0}$
$\mathbf{C_1} = \ \mathbf{B^{-1}}\boldsymbol{\Omega_1}$
$\mathbf{E_t} = \ \mathbf{B^{-1}}\boldsymbol{\epsilon_t}$

The reduced form intercept coefficient vector is given by:

$$\mathbf{C_0} = \frac{\mathbf{1}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \begin{bmatrix} \mathbf{1} & -\boldsymbol{\beta_{12}} \\ -\boldsymbol{\beta_{21}} & \mathbf{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta_{10}} \\ \boldsymbol{\beta 20} \end{bmatrix} = \begin{bmatrix} \frac{\boldsymbol{\beta 10 - \beta 12\beta 20}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \\ \frac{\boldsymbol{\beta 20 - \beta 10\beta 21}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\omega_{10}} \\ \boldsymbol{\omega 20} \end{bmatrix}$$

The reduced form lagged matrix is given by

$$\mathbf{C_1} = \frac{\mathbf{1}}{\mathbf{1} - \boldsymbol{\beta 12\,\beta 21}} \begin{bmatrix} \mathbf{1} & -\boldsymbol{\beta_{12}} \\ -\boldsymbol{\beta_{21}} & \mathbf{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{\delta_{11}} & \boldsymbol{\delta 12} \\ \boldsymbol{\delta_{21}} & \boldsymbol{\delta 22} \end{bmatrix} = \begin{bmatrix} \frac{\boldsymbol{\delta 11 - \beta 12\delta 21}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} & \frac{\boldsymbol{\delta 12 - \beta 12\delta 22}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \\ \frac{\boldsymbol{\delta 21 - \beta 21\delta 11}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} & \frac{\boldsymbol{\delta 22 - \beta 21\delta 12}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\omega_{11}} & \boldsymbol{\omega 12} \\ \boldsymbol{\omega_{21}} & \boldsymbol{\omega 22} \end{bmatrix}$$

While, the reduced form error vector is:

$$\mathbf{E_t} = \frac{\mathbf{1}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \begin{bmatrix} \mathbf{1} & -\boldsymbol{\beta_{12}} \\ -\boldsymbol{\beta_{21}} & \mathbf{1} \end{bmatrix} \begin{bmatrix} \boldsymbol{\epsilon_{xt}} \\ \boldsymbol{\epsilon_{yt}} \end{bmatrix} = \begin{bmatrix} \frac{\boldsymbol{\epsilon_{xt}} - \boldsymbol{\beta_{12}\epsilon_{yt}}}{\mathbf{1} - \boldsymbol{\beta 12\beta 21}} \\ \frac{\boldsymbol{\epsilon_{yt}} - \boldsymbol{\beta_{10}\epsilon_{xt}}}{\mathbf{1} - \boldsymbol{\beta_{12}\beta_{21}}} \end{bmatrix} = \begin{bmatrix} \mathbf{e_{xt}} \\ \mathbf{e_{yt}} \end{bmatrix}$$

So the reduced form VAR(1) model where $\mathbf{x_t}$ and $\mathbf{y_t}$ depends only in past values of itself can be written as:

$$\begin{bmatrix} \mathbf{x_t} \\ \mathbf{yt} \end{bmatrix} = \begin{bmatrix} \boldsymbol{\omega_{10}} \\ \boldsymbol{\omega_{20}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\omega_{11}} & \boldsymbol{\omega_{12}} \\ \boldsymbol{\omega_{21}} & \boldsymbol{\omega 22} \end{bmatrix} \begin{bmatrix} \mathbf{x_{t-1}} \\ \mathbf{y_{t-1}} \end{bmatrix} + \begin{bmatrix} \mathbf{e_{xt}} \\ \mathbf{e_{yt}} \end{bmatrix}$$

Given that $\boldsymbol{\epsilon_{xt}}$ and $\boldsymbol{\epsilon_{yt}}$ are white noise processes, consequently $\mathbf{e_{xt}}$ and $\mathbf{e_{yt}}$ have both, zero means, constant variances, and may be correlated. The variance-covariance matrix of $\mathbf{e_{xt}}$ and $\mathbf{e_{yt}}$ is given by:

$$\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\sigma_x^2} & \boldsymbol{\sigma_{xy}} \\ \boldsymbol{\sigma_{yx}} & \boldsymbol{\sigma_y^2} \end{bmatrix}$$

Where
$\mathbf{Var}(\mathbf{e_{xt}}) = \boldsymbol{\sigma_x^2}$ and $\mathbf{Var}(\mathbf{e_{yt}}) = \boldsymbol{\sigma_y^2}$, and generally $\mathbf{Cov}(\mathbf{e_{xt}}, \mathbf{e_{yt}}) = \boldsymbol{\sigma_{12}} = \boldsymbol{\sigma_{21}} \neq \mathbf{0}$.

A general extention of the VAR(1) model to Var(P) model is given by:

$$\mathbf{Y_t} = \mathbf{C_0} + \mathbf{C_1 Y_{t-1}} + \mathbf{C_2 Y_{t-2}} + ... + \mathbf{C_p Y_{t-p}} + \mathbf{E_t}$$

in a more compact form:

$$\mathbf{Y_t} = \mathbf{C_0} + \sum_{\mathbf{j=1}}^{\mathbf{p}} \mathbf{C_i Y_{t-i}} + \ \mathbf{E_t}$$

where
$\mathbf{Y_t}$ is $(k \times 1)$ vector of variables in the VAR model
$\mathbf{C_0}$ is $(k \times 1)$ vector of intercept coefficients
$\mathbf{C_i}$ is $(k \times k)$ matrix of autoregressive coefficients
$\mathbf{E_t}$ is$(k \times 1)$ vector of white noise terms

The VAR model has many advantages, it can be easily estimated applying ordinary least squares at each equation which is consistent and asymptotically efficient. It is possible to obtain more parsimonious models that have a small number of lags. Finally it is possible to obtain more accurate forecasting because the information set includes lagged variables of interest.

4.2 The DCC-GARCH model

One of the most important topics in financial econometrics is modeling of volatility of financial assets which is considered today as the most representative way of measuring the level of risk. Volatility plays an important role in areas such as risk management, portfolio optimization and asset pricing. An

univariate model and for the volatility is the ARCH, i.e. autoregressive conditional heteroskedasticity model introduced by Engle (1982). ARCH models have been extended in many directions. Bollesrslev (1986) proposed GARCH, i.e. generalized autoregressive conditional heteroskedasticity models. ARCH model, the one based on squared residuals, wherein the next period variance depends only in the last period squared residuals. On the other hand, GARCH model can be seen as an ARMA model on squared residuals with declining weight that never goes completely to zero. According to it, the next period conditional variance depends on the last period conditional variance and the last period squared residuals. ARCH/GARCH models are widely applied to analyse financial time series to forecast the mean, i.e. the return on asset or portfolio, and the variance, i.e. a volatility or risk level on the asset. In finance, squared-returns are positively autocorrelated and we define it as volatility clustering. In other words, periods of high volatility are followed by periods of high volatility and periods of low volatility are followed by periods of low volatility. Though ARCH/GARCH models are symmetric models, in many markets, specifically equity markets, the impact of positive price changes are different from that of the negative. To account for this, a number of asymmetric models like EGARCH and TARCH are available, see for example Engle Bollerslev, and Nelson (1994), Shephard (1996), Palm (1996).

Since most of realistic applications in financial econometrics are multivariate i.e. they involve $\mathbf{n} > \mathbf{2}$ assets, we need to develop useful multivariate time series methods for modeling and forecasting variables of interest and, among them, dynamic covariances and correlations to understand the co-movements of financial returns, which enable more relevant empirical models than working with separate univariate models and better decision tools in various areas of finance.

Let $\boldsymbol{\epsilon_t}$ be a stochastic vector process such that $\boldsymbol{\epsilon_t} \mid \boldsymbol{\Im_{t-1}} \sim \boldsymbol{N(0, \Sigma_t)}$ where $\boldsymbol{\Im_{t-1}}$ represents past information set generated by the observed series till time $\mathbf{t-1}$, the CC-GARCH models can be defined as follows Nakatani and Teräsvirta (2008):

$$\mathbf{y}_t = \boldsymbol{\eta}_t + \boldsymbol{\epsilon}_t$$
$$\boldsymbol{\epsilon}_t = \boldsymbol{\Sigma}_t^{-1/2}\mathbf{z}_t$$

where:

- $\mathbf{y_t}$: $n \times 1$ vector of log returns of n assets at time t.

- $\boldsymbol{\eta_t}$: $n \times 1$ vector of expected value.

- $\boldsymbol{\epsilon_t}$: $n \times 1$ vector of mean-corrected returns of n assets at time t, the dependence in $\boldsymbol{\epsilon_t}$ is non linear.

- $\boldsymbol{\Sigma_t}$: $n \times n$ time-varying conditional covariance matrix of $\boldsymbol{\epsilon_t}$ at time t. $\boldsymbol{\Sigma}^{\frac{1}{2}}$ can be obtained using Cholesky factorization of $\boldsymbol{\Sigma_t}$.

- $\mathbf{z_t}$: $n \times 1$ i.i.d vector error process such that $\mathbf{E}(\mathbf{z_t} \mid \Im_{\mathbf{t-1}}) = \mathbf{0}$ and $\mathbf{E}(\mathbf{z_t'}\mathbf{z_t} \mid \Im_{\mathbf{t-1}}) = \boldsymbol{\Gamma_t}$

Based on the way the covariance matrix $\boldsymbol{\Sigma_t}$ is specified, we have four categories of multivariate GARCH models:

1. The first model in this class is the VEC-GARCH model of Bollerslev, Engle, and Wooldrige(1988), where every conditional variance and covariance is a function of lagged squared errors and cross- products of errors and lagged conditional variances and covariances. This model is a very general one where flexibility represent an advantage, but at the same time it presents disadvantages such as, the conditions for the positive definetness of the covariance matrix for all t are very restrictive(Gourièroux 1997), the number of parameters to be estimated is large unless **n** is small, the estimation of the parameters is demanding.

   A simplification of the original VEC-GARCH model which reduce the number of parameters is given by the "diagonal VEC" model. In this model the elements of the conditional covariance matrix depend on past values of itself and past values of squared error . Here, each equation can be estimated separately which simplify the estimation procedure and it is easiest to set the conditions for the positive definetness of the conditional covariance matrix for all t, see Bollerslev, Engle, and Nelson(1994). This model does not provide the interactions between the conditional covariances and variances and the estimation of large-scale systems is still difficult.

   Since positive definetness of the conditional covariance matrix in the VEC parametrization requires strong restrictions on the parameters, other models in this class have been developed, see Engle and Kroner(1995). The BEKK model (Baba, Engle, Kraft and Kroner) can be seen as a restricted version of the original VEC model, the diagonal

BEKK can be seen as a restricted version of the diagonal VEC model and the scalar BEKK model can be seen as the restricted version of the diagonal BEKK.

In all the BEKK models the positive definetness of the covariance matrixes is ensured by construction or by imposing sufficient conditions, the number of parameters to be estimated is less than the respective VEC models, even thought the estimation of the model parameters remain difficult due to the high number of parameters and the matrix inversions. This explains why the VEC and BEKK models are not used when the number of series exceed 3 or 4 series.

As we have already mentioned the BEKK model is a restricted version of the VEC model, for each BEKK model it is possible to have an equivalent VEC model, but the converse is not true, see Engle and Kroner (1995) for proportions and proofs.

Kawakatsu(2006) Proposed an extension of the univariate exponential GARCH model of Nelson (1991) called matrix exponential GARCH model, the structure of the model imply that the conditional covariance matrix is positive definite and there is no need to impose further restrictions. This model is characterized by a high number of parameters.

2. Factor models: These models are justified by economic theory. The first factor GARCH model was introduced by Engle, Ng and Rothschild (1990), the original observations are assumed to be generated by unobserved conditionally heteroschedastic factors. The parsimonious conditional covariance matrix is assumed to be generated by $\mathbf{K}$, even correlated factors that are smaller than the number of assets $\mathbf{n}$, these factors are assumed to follow a first order GARCH type model. When the number of factors is smaller than the number of assets the dimensionality of the problem reduces making the model feasible also for a high number of assets. While a drawback of the model is represented by the fact that the factors are correlated so they capture similar characteristics of the data. To overcame this limitation, different factor models with uncorrelated factors have been developed. These models are based on the following idea, factors and the return observations are related through a linear invertible transformation. Based on the way the linear invertible transformation is specified and if the number of factors is smaller or greater than the number of assets, it is possible to have different factor models. Van der Weide (2002) proposed the GO-GARCH model which

represent a generalization of the O-GARCH model of Alexander and Chibumba(1997), the factors are assumed to have a GARCH type process, and normalized to have a unit unconditional variance. The transformation matrix must be invertible but not orthogonal. The estimation of the parameters is easy and needs to use conditional information, solving in this way possible identification problems. A similar model the Full Factor(FF-) GARCH model was proposed by Vrontos, Dellaportas and Politis(2003). This model can be used with high dimensional time series data, it has a zero idiosyncratic variance, the covariance matrix is always positive definite and it present a small number of parameters. A restriction of the model is given by the assumption that the linear transformation is triangular, which can neglect some relations between the factors and the returns. Another model was proposed by Lanne and Saikkonen (2007), this model include the advantages of the factor ARCH model and the orthogonal models. Here the transformation matrix is decomposed using a polar decomposition. The GOF-GARCH models it is possible to have both homoschedastic and heteroschedastic factors, which enable the model to enclose also idiosyncratic risk. In all the models where the factors are uncorrelated, the number of factors is relatively smaller than the case where the factors are correlated. This class of models are justified by economic theory.

3. This class belongs to models that can be seen as nonlinear combinations of univariate GARCH models. Here the conditional covariance matrix can be decomposed into conditional standard deviations and correlations. The simplest model in this class is the CCC-GARCH model introduced by Bollerslev(1990), where the conditional correlation matrix is constant -time invariant-. The conditional variance matrix is a diagonal matrix where the elements are derived using any univariate GARCH model, while the conditional correlation matrix is a symmetric positive definite matrix with one along the diagonal. Jeantheau(1998) proposed an extension to the CCC-GARCH model called the ECCC-GARCH model, in this model the squared returns have a rich autocorrelation structure. The assumption that the conditional correlation matrix is time invariant simplify the estimation because it reduces the number of parameters to $\mathbf{n(n+5)/2}$, at the same time it represents a disadvantages because it may seem too restrictive as suggested by many empirical studies. The CC-GARCH model can be generalized assuming the conditional correlation matrix time-varying, see Christodoulakis and Satchell (2002),

Engle (2002) and Tse and Tsui (2002). Lets start with the model of Christodoulakis and Satchell (2002) which is a bivariate model, it uses a fisher transformation for the correlation coefficient, this fisher transformation implies the positive definetnes of the correlation matrix which makes it easy to estimate. In the DCC-GARCH model of Engle (2002) and Tse and Tsui(2002) the conditional variances are calculated as in the case of the CCC-GARCH model using any univariate GARCH model, the conditional correlation matrix in Tse and Tsui (2002) is calculate as a weighted sum of past correlations, while Engle (2002) uses an ausiliary variable that follow a GARCH equation to compute the correlation dynamics. Both models present a limitation, the conditional correlation is restricted to have the same dynamics. To overcame this limitation, different variant of the DCC-GARCH models have been proposed. Billio and Caporin (2006) proposed the Quadratic Flexible DCC-GARCH model, which introduces a block structure in parameter matrices that with a reduce number of parameters consent for interdependence. see also Silvennoinen and Teräsvirta(2005) for the STCC-GARCH model, Cappiello,Engle and Sheppard (2006) for the AG-DCC-GARCH model, Silvennoinen and Teräsvirta(2005) for the STCC-GARCH model and Silvennoinen and Teräsvirta(2007) for the DSTCC-GARC model.

4. When the errors are not multivariate normal distributed, the quasi-maximum likelihood estimator is not consistent, relevant efficiency losses in finite sample occur. An alternative to the parametric approach is given by non- and semi parametric approaches, where no particular structure on the data must be imposed. Non-parametric models present estimation problems due to the curse of dimensionality, while semi parametric models combine both the advantages of a parametric and non-parametric models, see linton (2008). Hefner and Rombouts (2007) developed a semi parametric models where the conditional covariance structure is specified using a parametric multivariate GARCH model and estimate non-parametrically the error structure. In this model if the errors are not normal distributed the semi parametric estimator is more efficient than the maximum likelihood estimator. A similar approach was suggested by Long and Ullah (2005), here the estimated standardized residuals are taken using a parametric model, and using the Nadaraya-Watson estimator the positive definite conditional covariance matrix is estimated. Long and Ullah (2005) estimated the positive definite conditional covariance matrix using a full nonparametric model, i.e. using a parameter-free

multivariate volatility model. In the Semi-Parametric conditional Correlation GARCH model suggested by Hefner van Dijk and Frances (2005), the conditional variances are estimated parametrically using an univariate GARCH model, and the Nardaraya-Watson estimator is use for the conditional correlations.

5. An other model which can have a dynamic correlation in a regime and constant correlation in an other is the Regime switching for Dynamic Correlations (RSDC) of Pelletier(2006). This model can be seen as a special case of both the CCC-GARCH model of Bollerslev(1990) and the DCC-GARCH model of Engle (2002). Here as in the DCC and CCC-GARCH models the conditional covariance matrix is also decomposed in conditional standard deviations and correlations, and the transitions among the regimes is ruled by Markov chain. This model presents a number of interesting advantages. The estimation of the model can be made in one or two steps depending on the number of time series, (using the maximum likelihood estimation or bayesian inferences.) and this remove the problem of dimensionality, The positive semi-definetness of the variance matrix is easy to set. Smooth patterns for the correlation matrix can be produced. It is possible to have analytically a multi-step ahead conditional expectations of the variance and correlation matrix.

In this thesis, the focus will be on the conditional variances and correlation processes, especially the DCC-GARCH model, flexible as an univariate GARCH models coupled with parsimonious parametric models for the correlations, they can be estimated with univariate or two step methods depending on the likelihood function. They perform well in a wide range of situations and gives good results.

As mentioned earlier in the conditional variances and correlations class of models, the conditional covariance matrix $\boldsymbol{\Sigma_t}$ is decomposed into conditional standard deviations and correlations. The simplest model in this class assumes the correlation matrix $\boldsymbol{\Gamma}$ is constant constant, it is the CCC-GARCH proposed by Bollerslev (1990), thus:

$$\boldsymbol{\Sigma}_t = \mathbf{D}_t \boldsymbol{\Gamma} \mathbf{D}_t$$

The CCC-GARCH model has an attractive parametrization, large models can be estimated thanks to the assumption of constant correlation matrix, empirical works have demonstrated that this assumption is too restrictive.

Tsui and Yu (1999) have shown that it can be rejected for certain assets. This model can be generalized assuming the conditional correlation matrix Γ_t is time varying. Thus:

$$\mathbf{\Sigma}_t = \mathbf{D}_t \mathbf{\Gamma}_t \mathbf{D}_t$$

Where D_t is a $n \times n$ diagonal matrix of conditional standard deviations of the return, and Γ_t is a $n \times n$ conditional correlation matrix.

This model is called DCC-GARCH model and has been proposed by Engle (2002). It is very popular in the study of contagion because it is more suitable for higher-dimension applications than other multivariate GARCH models. The DCC-GARCH model uses the standardized residuals to estimate the dynamic correlation coefficients, so it takes into account for heteroschedasticity directly (Chiang et al. 2007). Given that the volatility is adjusted by the procedure, the dynamic conditional correlation has not any bias from volatility. The DCC-GARCH model always regulates the correlation for the time-varying volatility, providing a better measure of the correlation (Cho and Parhizgari 2008). As suggested by Engle(2002) the DCC-GARCH model can be estimated in two steps:

- In the first step, all the conditional standard deviations of residuals, contained in the $n \times n$ positive definite diagonal matrix D_t are estimated one by one using univariate GARCH(P,Q) model or others appropriate univariate conditional heteroschedastic methods with normally distributed errors that satisfy the necessary conditions of non-negativity and stationarity. D_t can be defined as follow:

$$\mathbf{D}_t = \begin{pmatrix} \sqrt{\mathbf{h_{1t}}} & 0 & \dots & 0 \\ 0 & \sqrt{\mathbf{h_{2t}}} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \sqrt{\mathbf{h_{nt}}} \end{pmatrix}$$

  The conditional variance of each asset is given by:

$$\mathbf{h}_{it} = \boldsymbol{\omega}_i + \sum_{p=1}^{P_i} \boldsymbol{\alpha}_{ip} \boldsymbol{\epsilon}_{it-p}^2 + \sum_{q=1}^{Q_i} \boldsymbol{\beta}_{iq} \mathbf{h}_{it-q}$$

  for $i = 1, 2....., k$ P and Q represent the order of the GARCH model which has to satisfy the non-negativity $\boldsymbol{\omega}_i > 0$, $0 \leq \boldsymbol{\alpha}_{ip} < 1$, $0 \leq \boldsymbol{\beta}_{iq} < 1$ and stationarity $\sum_{p=1}^{P_i} \boldsymbol{\alpha}_{ip} + \sum_{q=1}^{Q_i} \boldsymbol{\beta}_{iq} < 1$. In this thesis a GARCH(1,1) is used.

- In the second step, the residuals derived from the first step are standardized $\mathbf{z}_t = \mathbf{D}_t^{-1}\boldsymbol{\epsilon}_t$ and the estimations of the conditional correlation matrix of the standardized residuals are obtained using an auxiliary variable $\mathbf{Q}_t$.

  Engle(2002) suggests two different specifications for the auxiliary variable; a GARCH(1,1) or an exponential smoothing. In this thesis GARCH(1,1) is used , and the dynamic correlation structure is given by:

$$\boldsymbol{\Gamma}_t = (diag(\mathbf{Q}_t))^{-}\frac{1}{2}\mathbf{Q}_t(diag(\mathbf{Q}_t))^{-}\frac{1}{2}$$

  Where $\mathbf{Q}_t$ is a $n \times n$ symmetric positive definite matrix such that:

$$\mathbf{Q_t} = (\mathbf{1} - \mathbf{a} - \mathbf{b})\bar{\mathbf{Q}} + \mathbf{a}(\mathbf{z_{t-1}}\mathbf{z'_{t-1}}) + \mathbf{b}\mathbf{Q_{t-1}}$$

  aandb are non-negative scalar parameters such that $\mathbf{a} + \mathbf{b} < 1$ to avoid explosive pattern, $\bar{\mathbf{Q}} = \mathbf{E}(\mathbf{z_{t-1}}\mathbf{z'_{t-1}})$ is the unconditional covariance matrix of the standardized residuals derived from the univariate GARCH equation. $(diag(\mathbf{Q}_t))^{-\frac{1}{2}}$ which rescales the elements of $\mathbf{Q_t}$ is a diagonal matrix composed of the square root of the diagonal elements of $\mathbf{Q_t}$, and is given by:

$$(\mathbf{diag}(\mathbf{Q_t}))^{-}\frac{\mathbf{1}}{\mathbf{2}} = \mathbf{diag}(\frac{\mathbf{1}}{\sqrt{\mathbf{q_{ii,t}}}}.....\frac{\mathbf{1}}{\sqrt{\mathbf{q_{nn,t}}}})$$

  The conditional correlation coefficient $\boldsymbol{\rho}_{ij}$ between the two assets i and j is expressed as follow:

$$\boldsymbol{\rho}_{ij} = \frac{\mathbf{q}_{ij}}{\sqrt{\mathbf{q}_{ii}}\sqrt{\mathbf{q}_{jj}}}$$

  so

$$\boldsymbol{\Gamma_t} = \begin{pmatrix} 1 & \boldsymbol{\rho_{12,t}} & \cdots & \boldsymbol{\rho_{1n,t}} \\ \boldsymbol{\rho_{12,t}} & 1 & \cdots & \boldsymbol{\rho_{2n,t}} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\rho_{1n,t}} & \cdots & \boldsymbol{\rho_{n-1n,t}} & 1 \end{pmatrix}$$

  is the conditional correlation matrix of the standardized residuals, by definition their elements in the diagonal are equal to one, while the others are less than one in absolute value. These condition are ensured by rescaling Q_t, which has to be positive definite.

4.2.1 Estimation

As mentioned above DCC-GARCH models are estimated in two steps, a QMLE is used by construction. In the first step, univariate GARCH models are used to estimate the variances -volatilities- of each residual series, these variances and precisely standard deviations are used in the second step to obtain the standardized residuals -to filter out the residuals from the GARCH effect- and then to obtain the dynamics correlation. Let $\boldsymbol{\theta}$ the parameters of the model be decomposed in two groups $(\boldsymbol{\xi}, \boldsymbol{\psi}) = (\boldsymbol{\xi_1}, ..\boldsymbol{\xi_n}, \boldsymbol{\psi})$, where ξ denotes the parameters obtained in the first stage -the volatility component- using univariate GARCH model for each asset series, $\boldsymbol{\xi} = (\boldsymbol{\omega}, \boldsymbol{\alpha_{1i}}, ..., \boldsymbol{\alpha_{pi}}, \boldsymbol{\beta_{1i}}, ..., \boldsymbol{\alpha_{qi}})$ and $\boldsymbol{\psi}$ denotes the parameters in the dynamics correlation obtained in the second stage. The assumption $\boldsymbol{\epsilon_t} \mid \boldsymbol{\Im_{t-1}} \sim \boldsymbol{N(0, \Sigma_t)}$ that the conditional returns follow a multivariate Gaussian distribution with zero mean and a covariance matrix $\boldsymbol{\Sigma_t}$ imply the following likelihood function for $\boldsymbol{\epsilon_t} = \boldsymbol{\Sigma_t^{1/2} z_t}$ is:

$$\boldsymbol{\ell(\theta) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{n/2}\Sigma_t^{1/2}} exp[-\frac{1}{2}\epsilon_t' \Sigma_t^{-1} \epsilon_t]}$$

taking the logarithm of the above, we get the following log-likelihood function:

$$\boldsymbol{log(\ell(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + log(\mid \Sigma_t \mid) + \epsilon_t' \Sigma_t^{-1} \epsilon_t\Big)}$$

Since $\boldsymbol{\Sigma_t = D_t \Gamma_t D_t}$ it becames:

$$\boldsymbol{log(\ell(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + log(\mid D_t \Gamma_t D_t \mid) + \epsilon_t' \ (D_t \Gamma_t D_t)^{-1} \epsilon_t\Big)}$$

so

$$\boldsymbol{log(\ell(\theta)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + 2log(\mid D_t \mid) + log(\mid \Gamma_t \mid) + \epsilon_t' \ (D_t \Gamma_t D_t)^{-1} \epsilon_t\Big)}$$

To easily estimate the parameters of the model, Engle suggested to divide the log-likelihood function in two components, the volatility component -first stage- and the dynamics correlation component -second stage-.

Lets start with the first stage where the conditional covariance matrix $\boldsymbol{\Sigma}$ is replaced with an identity matrix I_n of size n, so the volatility component quasi-likelihood function is:

$$log(\ell_1(\xi)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + 2log(\mid D_t \mid) + log(\mid I_t \mid) + \epsilon_t' \ (D_t I_t D_t)^{-1}\epsilon_t\Big)$$

$$log(\ell_1(\xi)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + 2log(\mid D_t \mid) + log(\mid I_t \mid) + \epsilon_t' \ (D_t)^{-2}\epsilon_t\Big)$$

$$log(\ell_1(\xi)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + \sum_{n=1}^{k}\Big(log(h_{it}) + \frac{\epsilon_{it}^2}{h_{it}}\Big)\Big)$$

$$log(\ell_1(\xi)) = -\frac{1}{2}\sum_{n=1}^{k}\Big(Tlog(2\pi) + \sum_{t=1}^{T}\Big(log(h_{it}) + \frac{\epsilon_{it}^2}{h_{it}}\Big)\Big)$$

Resulting in the sum of log-likelihoods of the univariate GARCH models for each assets. Given the estimates of the variance component -the volatility parameters-, the second stage-correlation component- is estimated using correctly specified likelihood function:

$$log(\ell_2(\psi)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + 2log(\mid D_t \mid) + log(\mid \Gamma_t \mid) + \epsilon_t' \ (D_t \Gamma_t D_t)^{-1}\epsilon_t\Big)$$

Since $z_t = D_t^1 \epsilon_t$ so:

$$log(\ell_2(\psi)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(klog(2\pi) + 2log(\mid D_t \mid) + log(\mid \Gamma_t \mid) + Z_t' \ \Gamma_t^{-1} Z_t\Big)$$

What really matters for the maximization problem in this step is the correlation component, consequently it is sufficient to maximize:

$$log(\ell_2(\psi)) = -\frac{1}{2}\sum_{t=1}^{T}\Big(log(\mid \Gamma_t \mid) + Z_t' \ \Gamma_t^{-1} Z_t\Big)$$

It is shown that under a sufficient set of assumptions the two stage DCC estimator provides consistent and asymptotically normal parameters estimate, see also White (1994). Various estimators can be used providing consistent but inefficient estimates of the parameters of the model.

5 Correlation test

A widely used approach to test for the presence of financial contagion is the analysis of the cross-market correlations using the simple Pearson correlation coefficient (see King and Wadhwani (1990)). Therefore, this approach analyzes if the variation in the correlation coefficients between a crisis and non-crisis periods are statistically significant or not. A statistically significant increase in the correlation coefficients may indicate the presence of contagion phenomena. While a statistically insignificant increase in the correlation coefficients indicate the presence of only interdependence and not financial contagion.

Correlation coefficients tend to increase during periods of high volatility, i.e. they are upward biased, given thought particular attention should be paid to the interpretation of the test because the results would indicate a spurious contagion. Forbes and Rigobon (2002) developed an adjusted correlation coefficient which accounts for the increase in volatility in crisis periods. The adjusted (unconditional) correlation coefficient is given by:

$$\dot{\rho} = \frac{\rho}{\sqrt{1 + \gamma[1 - \rho^2]}}$$

Where

- $\dot{\rho}$ represent the adjusted correlation coefficient;
- ρ represent the unadjusted correlation coefficient;
- γ represent the relative increase in the conditional variance of the source country, and is given by $\gamma = \frac{\sigma_c^2 - \sigma_{pc}^2}{\sigma_{pc}^2}$.

To test the presence of financial contagion between a pre-crisis (low volatile) period and a crisis (high volatile) period the following hypothesis system is used:

$$H_0 : \dot{\rho}_c = \dot{\rho}_{pc}$$
$$H_1 : \dot{\rho}_c > \dot{\rho}_{pc}$$

Where

- $\dot{\rho}_c$ represent the adjusted correlation coefficient in crisis period;
- $\dot{\rho}_{pc}$ represent the adjusted correlation coefficient in pre-crisis period;

To test the hypothesis above after the estimation of the VAR model a Fisher Z transformations[12] (Morrison (1983)) is used:

$$\boldsymbol{Z} = \frac{\frac{1}{2}\boldsymbol{ln}(\frac{1+\dot{\rho_c}}{1-\dot{\rho_c}}) - \frac{1}{2}\boldsymbol{ln}(\frac{1+\dot{\rho_{pc}}}{1-\dot{\rho_{pc}}})}{\sqrt{\frac{1}{N_c-3} + \frac{1}{N_{pc}-3}}}$$

where $\mathbf{N_c}$ and $\mathbf{N_{pc}}$ represent the relative sample sizes of the crisis and pre-crisis periods.

The Fisher Z transformation improve the finite sample properties of the t-statistic. Critical values of the Z-test statistic greater than the Fisher Z critical values of 1.28, 1.65, and 2.33 indicate the presence of contagion at 10%, 5%, and 1% critical values, while smaller values of the Z-test statistic indicate the presence of only interdependence.

However, to test the hypothesis above after the estimation of the DCC model the following student test is used:

$$\boldsymbol{T} = \frac{\dot{\rho_c} - \dot{\rho_{pc}}}{\sqrt{\frac{VAR(\dot{\rho_c})}{N_c} + \frac{VAR(\dot{\rho_{pc}})}{N_{pc}}}}$$

Where T follows a Student with $(\mathbf{N_c} + \mathbf{N_{pc}} - \mathbf{4})$ degrees of freedom

[12]For further details refers to Kendall and Stuart (1969, Vol.1, p.391)

6 Empirical results

Before estimating the DCC-GARCH model, a Vector Autoregressive (VAR) model for the return indexes was estimated (Lee(2006) and Crespo-Cuaresma and Wójcik (2006)). The first important element to determine in a VAR model is the optimal lag length using model selection criteria. The standard approach is to estimate VAR(P) models starting with a long lag length, for example 12, and choose the lag which minimize the selection criteria. The most commonly used information criteria are the Akaike (AIC), Schwarz-Bayesian (BIC) and Hannan-Quinn Criteria (HQC). Based on the sample size the performance of the model selection criteria differ. The AIC tends to overestimate the optimal lag length, but it works well in small sample. The BIC and HQC information criteria work well in large sample size giving consistent estimate of the optimal lag length (see Latkepohl (1991) chapter four, and Liew (2004)). In this thesis, the BIC is used to determine the optimal lag length of the VAR model. Figure(3) present the result of the BIC criteria, which select 1 lag.

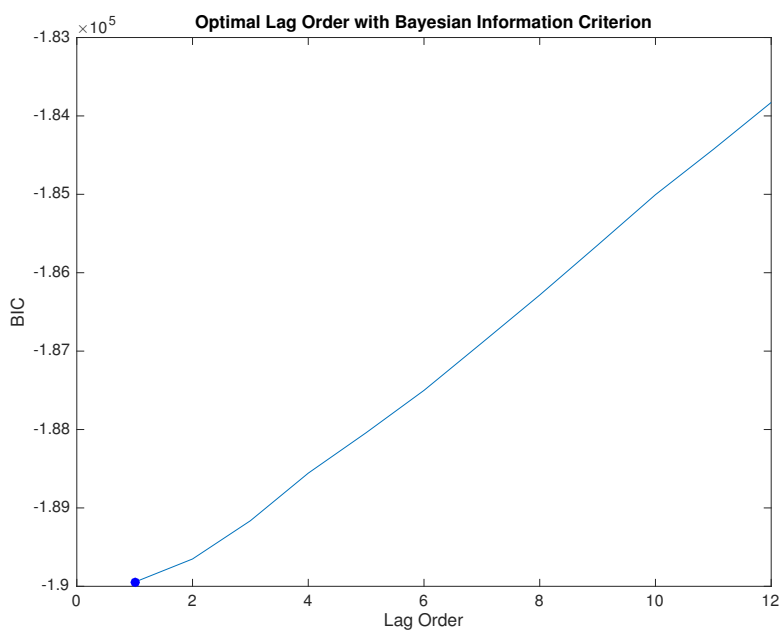

Figure 3: Optimal Lag Length using BIC

The output of the VAR model shows that, each equation can be explained by 11 parameters (a constant plus 10 autoregressive coefficients of each return index). The output also indicates that in each equation the Dow Jones return

index relative to each country is significantly explained by past values of others return indexes. This indicates that the feedback mechanism among these return indexes are bidirectional [13].

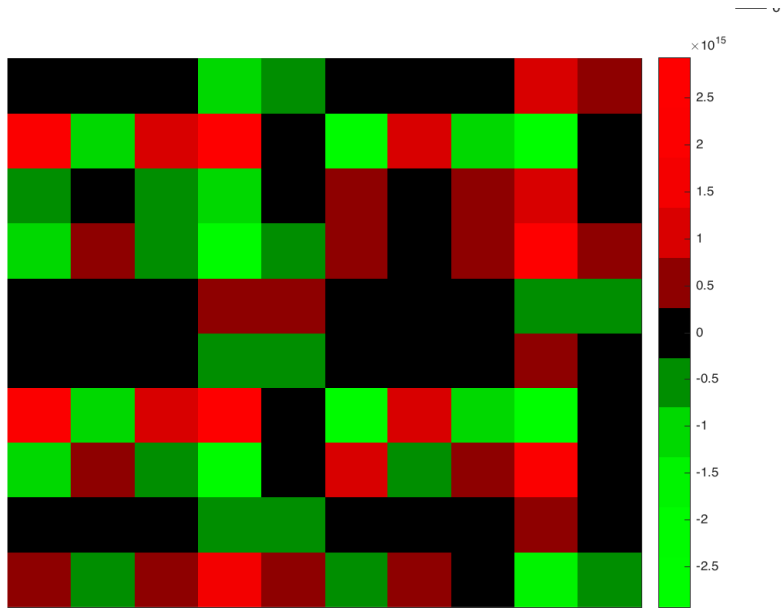

Figure 4: shows the t-statics of the estimated coefficients for the VAR model

A test for the stability of the VAR part of the model, and the invertibility of the VMA part is performed, The Boolean value of 1 indicates that the model is stable and invertible. This means that all eigenvalues have modulus less than 1 and so fall inside the unit circle. Stability and invertibility are very important for the credibility of the results.

Finally after estimating a VAR model, the residuals are used as inputs for the DCC-GARCH model.

Table (10) shows the results of the DCC-GARCH model, indicating their flexibility in capturing the evolution of the dynamic conditional covariance matrix. If 5% represent the critical value, all the estimated coefficients of the variance equations are statistically significant [14], allowing for both autoregres-

[13]Figure(4) is a Heatmap which reports the t-statistics of the estimated coefficients for the VAR model. A t-statistic greater than 1.96 or less than -1.96 indicates that the coefficient is insignificant in explaining the dependent variable

[14] The results are presented in the appendix where ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

sive and moving average components to influence the time varying conditional variances. All the variance equations satisfy both the positivity condition of the variances $\boldsymbol{\omega_i > 0, 0 \leq \alpha_i < 1, 0 \leq \beta_i < 1}$ and the stationarity condition $\boldsymbol{\alpha_i + \beta_i < 1}$, the latest condition also indicate that the unconditional variance of the GARCH(1,1) model is finite. The values assumed by lagged return innovation coefficients $\boldsymbol{\alpha_i}$ indicate the effect of an immediate shock in the conditional variances, if $\boldsymbol{\alpha}$ is above 0.1 means that the conditional variance is very sensitive to market shocks (carol Alexander 2008). While the sum of the values assumed by lagged variance coefficients and lagged return innovation coefficients $(\alpha + \beta)$ are near to unity indicating high persistence in the conditional variances, and meaning that the conditional volatility die out after a long time hereinafter a crisis in the market. Also the parameters of the DCC, i.e. $\boldsymbol{\alpha_{DCC}, \beta_{DCC}}$ model are statistically significant, the large value assumed by $\boldsymbol{\beta_{DCC}}$ indicates a high persistence in the correlation.

Figure(14) shows the Dynamic conditional correlations between all the considered Dow Jones return indexes Islamic and non-Islamic. All the conditional correlations have time varying patterns. It is possible to observe 3 different levels of correlations. The first, very high correlations range approximately from 0.85 to 0.97, and they are between the pairwise of return indexes Islamic and conventional relative to the same country. The second, still high correlations range approximately from 0.4 to 0.8, and are between the cross pairs United Kingdom, Canada, United State Islamic and conventional return indices. While the last level correlations range from -0.2 to 0.4, and are between United Kingdom, Canada, United State Islamic-conventional return indices with Japan, and Malaysia Islamic-Conventional return indexes. Also the cross pairs of Japan and Malaysia Islamic-Conventional return indices are parts of the last level correlations.

Figure (15) shows the plot of the Dynamic conditional correlations between the U.S DJ index considered as the contagion source and the other non-Islamic indexes. It is possible to observe that during the U.S subprime crises, the conditional correlations increase in proximity to the start of the turmoil period. However, during the turmoil period the correlations decrease significantly in the beginning of the period, after that they increase reaching their peak during the 2008. While the conditional correlations decrease and are stable after the peak, they exhibit a higher average level of correlations respect to the conditional correlations before the sharp increase. From these result it is possible to conclude that the first pattern where the correlations increase is and indicator of contagion, while the second pattern where the correlations develop on a higher level indicates a transition to herding behavior (Chian et al., 2007; Turgutlu et al., 2010). Some exception can be seen in the

case of the DJ Islamic and conventional Japan indexes. Even in the case of the dynamic conditional correlation between the U.S DJ Islamic index and the rest of the Islamic indices, figure(16), it is obsessed the same scenery as above [15][16]

Figure(5) presents the average dynamic conditional correlation between the U.S considered as the source of crisis and the rest of the conventional indices. It also presents the average dynamic conditional correlation between the U.S Islamic DJ index considered also in this case as the source of crisis and the rest of the Islamic indices .

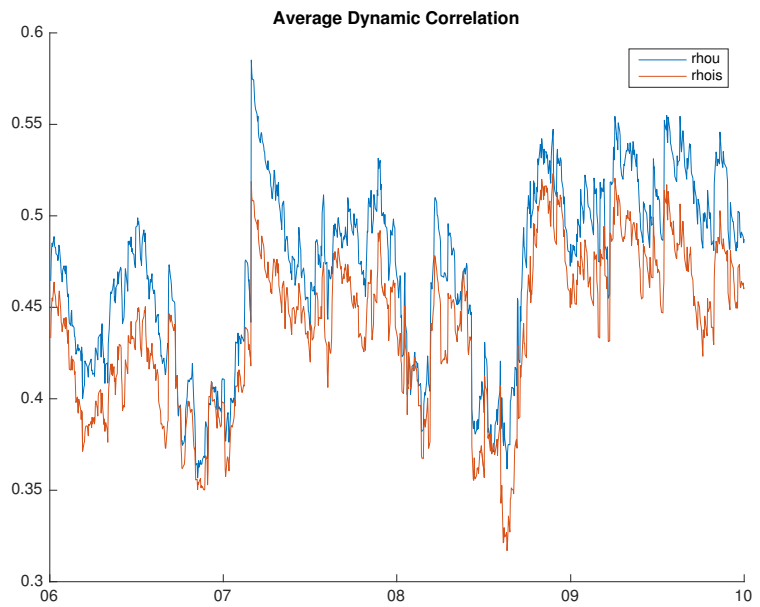

Figure 5: Average Dynamic Conditional Correlations Islamic-Conventional

In both cases, i.e. Islamic and conventional, it is possible to observe both surges and sharp decreases characterize the average conditional correlations. Even in this case the conditional correlations increase in proximity to the start of the turmoil period. However, during the turmoil period the correlations decrease significantly in the beginning of the period, after that they start increasing reaching their peak during the 2008. Even if the conditional correlations decrease for a short period and are stable after the peak, they exhibit

[15] As already explained Islamic indices are obtained filtering the non Islamic indices from the companies which doest not satisfy the Islamic guidelines.

[16] **?**

a higher average level of correlations respect to the conditional correlations before the sharp increase. Figure(6) shows the difference between the average dynamic conditional correlation conventional indices and the average dynamic conditional correlation Islamic indices. It is possible to observe that this difference is small, it ranges between -0.01 and 0.07, using a t-test Figure(6) it results to be highly significant.

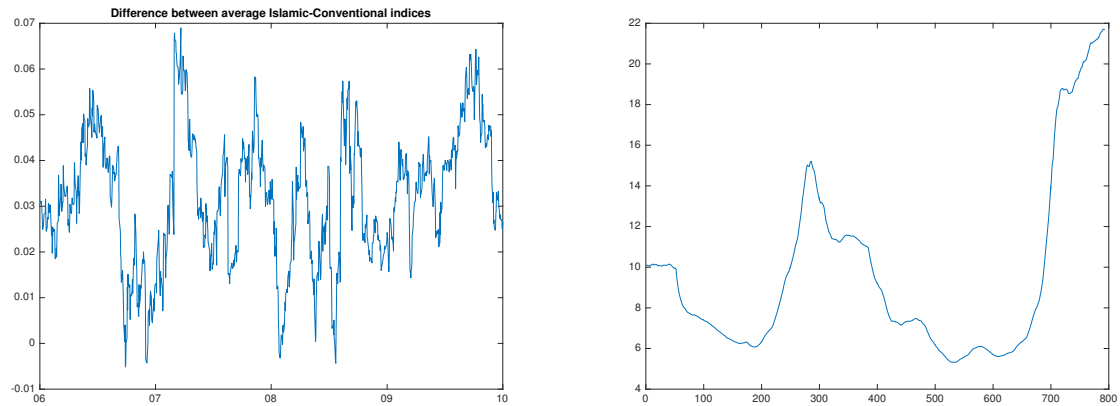

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Figure 6: Average Dynamic Conditional Correlations Islamic-Conventional and T-test of the difference

To determine the existence of contagion, i.e., to test if there is or not a significant increase in the correlation coefficients, the z-test is used after the estimation of the VAR model, while the DCC means difference test is used after the estimation of the dynamic conditional correlations.

Following Forbes and Rigobon (2002), the adjusted correlation coefficient are calculated after the estimation of the VAR model. As a result, the evidence of contagion is present for most of the indices Islamic-Conventional, except DJ Islamic-Conventional Japan index and DJ Conventional Malaysia index[17].

Therefore, to refine the analysis taking into account the dynamic nature of the correlation coefficients and contagion, which is very quick and short lived, the DCC-GARCH model is estimated. Table(25-30)[18]. show that for all indices the mean of the DCC coefficients increase significantly in the crisis period respect to the pre-crisis period except for the DJ Japan Islamic-conventional indices which decrease. However, the evidence of contagion during the U.S.

[17] 15-17 show the results of the test for the conventional indices, while table 22-24 show the results of the test for the Islamic indices

[18] 25-27 show the results of the test for the conventional indices, while table 28-30 show the results of the test for the Islamic indices

subprime crisis is find between most of the DJ Islamic-Conventional indices. Relatively to the increase in the DCC mean in percentage terms the country most affected by the contagion is UK.

Finally, to understand the dynamic nature of contagion during the U.S subprime crisis, a rolling DCC means difference test of length m is adopted (the considered windows length 250 observations before the crisis and 250 observations after the crisis). Since the DCC means difference test has a t-student distribution, using a 5% critical value we consider as contagion windows the periods of time which have a t-statistic in absolute value higher than the critical value of 1.96. This means that the values of the test outside the blue dotted line indicate periods of contagion, while the values inside the blue dotted line indicate periods of interdependency. Approximately, from figure(7) it is possible to distinguish 3 periods. The first period characterized by financial contagion run from observation 0 till observation 100. The second period characterized by interdependency run from observation 120 till observation 450, while the last period is characterized by financial contagion too. The same scenario can be seen in the case of the Islamic indices. However, from the rolling analysis it is possible to understand in general how contagion spreads in time between two asset returns. This analysis supports the use of DCC-GARCH model as the main analysis to investigate the presence of contagion.

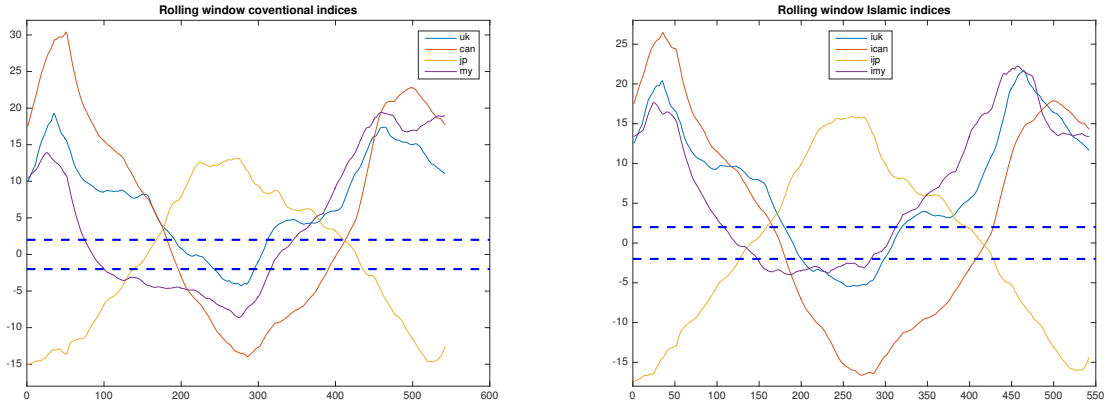

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Figure 7: Rolling DCC means difference test of 250 observations before the crisis and 250 observations after the crisis

In line with the analysis of Forbis and Rigobon (2002) which argue that an increase in correlations during the crises period is due to an increase in international stock markets volatility, which was affected by the crises. The results show that the U.S subprime crises has significantly affected the con-

ditional correlations of most considered indices. Which means that shocks in the U.S stock market is transmitted to the stock prices of the other considered countries.

7 Summary and Conclusions

This thesis investigates the existence of financial contagion between Dow Jones conventional indices of U.K, Canada, U.S, Japan, and Malaysia, and also between Dow Jones Islamic indices relative to the same countries during the U.S. subprime crisis. To determine the stable and turmoil periods we have used as references Dungy (2009), Horta, Carlos, Mendes and Vieira (2008), and starting from the above two references an analysis of the conditional variances provided by the DCC-GARCH models of the crisis-generating country, i.e. U.S., is used to determine another potential crisis date. To test for contagion the very restrictive definition is used, where contagion is defined as the propagation of shocks between two countries (or group of countries) in excess of what should be expected by fundamentals and considering the co-movements triggered by the common shocks (Billio and Pelizzon, 2003). Following Forbes and Rigobon (2002), the adjusted correlation coefficient are calculated after the estimation of the VAR model. Therefore, to test for contagion the Fisher Z transformation is adopted. As a result, the evidence of contagion is present for all the indices Islamic-Conventional, except DJ Islamic-Conventional Japan index and DJ Conventional Malaysia index which present only interdependency.

Then, to refine the analysis we take into account the dynamic nature of the correlation coefficients and contagion, known to be very quick and short lived. As Consequence, the DCC-GARCH model developed by Engle (2002) is estimated. To assess the presence of an increase in cross-market correlations both the analysis of the patterns of the dynamic correlation coefficients and the application of the DCC means difference t-test are adopted.

The results of the DCC analysis are as follow: First, using the DCC means difference test, the existence of financial contagion during the U.S. subprime crisis is present in almost all the indices Islamic-Conventional, except for DJ Islamic-conventional Japan indices. Consequently financial contagion is present in both emerging and developed countries. This result is also consistent with the pattern's analysis of the dynamic conditional correlations which show both the presence of contagion in the early stage of the crisis, as it is shown by the DCC means difference test, and also the herding behavior in the last stages of the crisis. Second, Using another insight to investigate the

presence of contagion, i.e. the average correlations, Conventional indices turn out to be even slightly more contagious than Islamic indices. The difference between the Conventional-Islamic average correlation coefficients results to be highly significant using a t-test.

Finally, to understand the dynamic nature of contagion during the U.S subprime crisis, a rolling DCC means difference test of length m is adopted (the considered windows length 250 observations before the crisis and 250 observations after the crisis). Since the DCC means difference test has a t-student distribution, using a 5% critical value we consider as contagion windows the periods of time which have a t-statistic in absolute value higher than the critical value of 1.96, while the other periods indicate only interdependency. Consequently, it is possible to distinguish approximately 3 periods. The first period and the last period of the rolling window are characterized by financial contagion, while the second period is characterized by only interdependency. The same scenario can be observed in the case of the Islamic indices.

These findings are relevant to understand the vulnerability of the financial markets. However, the results might be relevant for central banks and policy makers to promote financial stability, and contain contagion risk during periods of crisis, given their serious economic and social effects on the global economy. For international investors and portfolio manager which can increase the gain from portfolio diversification including not only conventional indices but also Islamic indices in their portfolio. The later characterized by lower leverage, small number of firms and under-diversification of the market respect to conventional indices, and consequently more resilient to a crisis.

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A Appendix

Date	Variances
11/07/2007	6.5380e-05
12/07/2007	8.2746e-05
13/07/2007	8.2461e-05
16/07/2007	7.6760e-05
17/07/2007	7.1578e-05
18/07/2007	6.6868e-05
19/07/2007	6.9136e-05
20/07/2007	7.7122e-05
23/07/2007	7.3534e-05
24/07/2007	1.1044e-04
25/07/2007	1.0271e-04
26/07/2007	1.3930e-04
27/07/2007	1.5459e-04
30/07/2007	1.4708e-04
31/07/2007	1.4944e-04
01/08/2007	1.3909e-04
02/08/2007	1.2989e-04
03/08/2007	1.6712e-04
06/08/2007	1.8092e-04
07/08/2007	1.7037e-04
08/08/2007	1.6865e-04

Table 1: shows the evolution of the Dynamic conditional correlations of the crisis-generating country U.S.

/////////	uk	can	usa	jp	my	iuk	ican	iusa	ijp	imy
p-value	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71	0.71

Table 2: shows the ADF-test on Stock Prices indices.

/////////	uk	can	usa	jp	my	iuk	ican	iusa	ijp	imy
p-value	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 3: Shows ADF-test on return indices.

Returns	Lenght	Mean	Median	Min	Max	Std	Skewness	Kurtosis
can-r	2570	2.43e-05	8.91e-04	-0.1359	0.0996	0.0153	-0.7295	12.4742
ican-r	2570	-6.04e-05	5.92e-04	-0.1377	0.1187	0.0187	-0.6819	11.8036
uk-r	2570	2.47e-05	5.51e-04	-0.1034	0.1195	0.0150	-0.1412	11.5503
iuk-r	2570	4.31e-05	2.53e-04	-0.0957	0.1168	0.0154	-0.1072	10.1389
usa-r	2570	2.11e-04	4.47e-04	-0.0963	0.1091	0.0131	-0.3773	13.2124
iusa-r	2570	2.59e-04	4.69e-04	-0.0970	0.1174	0.0124	-0.1676	13.9118
jp-r	2570	-1.94e-05	1.24e-04	-0.0914	0.1125	0.0140	-0.2143	8.4333
ijp-r	2570	4.68e-05	2.12e-04	-0.0955	0.1066	0.0137	-0.2286	8.1902
my-r	2570	2.06e-04	1.86e-04	-0.1093	0.0543	0.0102	-0.7363	11.9279
imy-r	2570	1.86e-04	4.98e-05	-0.1283	0.0849	0.0106	-1.0786	20.7908

Table 4: shows the descriptive statistics of return indices for entire period (02.01.2006-25.11.2015)

/////////	uk	can	usa	jp	my	iuk	ican	iusa	ijp	imy
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
statistics	7831	9832.1	11220	3178.4	8760.7	5458	12752.2	11789	2904.7	34365

Table 5: Jarque-Bera test on return indices

Indices	Can	Ican	Uk	Iuk	Usa	Iusa	Jp	Ijp	My	Imy
Can-r	1	95.78	68.14	67.43	73.62	74.25	16.91	16.79	27.53	24.27
Ican-r		1	62.02	63.01	66.05	68.90	16.53	16.57	25.56	22.57
Uk-r			1	97.42	56.57	57.10	22.51	22.72	39.00	35.99
Iuk-r				1	54.10	55.67	21.49	21.87	37.90	35.39
Usa-r					1	98.28	1.61	1.69	15.22	12.63
Iusa-r						1	2.77	3.03	16.00	13.54
JP-r							1	97.55	37.68	33.63
Ijp-r								1	37.11	33.35
My-r									1	94.17
Imy-r										1

Table 6: shows the correlation coefficients between return indices for entire period (02.01.2006-25.11.2015).

Returns	Lenght	Mean	Median	Min	Max	Std	Skewness	Kurtosis
Can-pc	399	9.35e-04	0.0020	-0.0359	0.0359	0.0095	-0.4693	4.0099
Ican-pc	399	5.98e-04	7.24e-04.	-0.0359	0.0250	0.0072	-0.2907	5.1000
Uk-pc	399	8.95e-04	0.0015	-0.0347	0.0287	0.0089	-0.2684	4.295
Iuk-pc	399	8.64e-04	8.73e-04	-0.0428	0.0339	0.0101	-0.2801	4.2600
US-pc	399	5.56e-04	7.75e-04	-0.0348	0.0228	0.0067	-0.3949	5.5375
Iusa-pc	399	9.66e-04	0.0024	-0.0456	0.0441	0.0138	-0.4714	3.6272
Jp-pc	399	1.41e-04	3.57e-04	-0.0433	0.0411	0.0120	-0.2930	4.2298
Ijp-pc	399	2.16e-04	2.22e-05	-0.0410	0.0434	0.0115	-0.2852	4.2749
My-pc	399	0.0014	0.0015	-0.0515	0.0290	0.0083	-1.2027	9.1245
Imy-pc	399	0.0013	0.0012	-0.0392	0.0331	0.0077	-0.5640	6.3794

Table 7: shows the descriptive statistics for pre-Crisis period (02.01.2006- 17-07-2007)

Returns	Lenght	Mean	Median	Min	Max	Std	Skewness	Kurtosis
Can-c	642	-3.13e-04	0.0015	-0.1359	0.0996	0.0240	-0.6321	7.4813
Ican-c	642	-2.72e-04	6.27e-04	-0.0970	0.1174	0.0186	0.0167	9.5802
Uk-c	642	-7.02e-04	0	-0.1034	0.1195	0.0228	0.0072	7.6737
Iuk-c	642	-3.98e-04	1.56e-04	-0.0957	0.1168	0.0224	0.0535	7.5663
Usa-c	642	-4.85e-04	1.86e-04	-0.0963	0.1091	0.0204	-0.1748	7.8685
Iusa-c	642	-2.06e-04	0.0011	-0.1377	0.1187	0.0291	-0.6247	7.4360
Jp-c	642	-6.21e-04	-1.32e-04	-0.0914	0.1125	0.0191	0.0135	6.6651
Ijp-c	631	-5.22e-04	-4.43e-06	-0.0955	0.1066	0.0190	-0.1307	6.6839
My-c	642	-1.89e-04	0	-0.1093	0.0527	0.0136	-0.9357	11.1433
Imy-c	642	-1.91e-04	0	-0.1283	0.0840	0.0154	-1.2488	16.8305

Table 8: shows the descriptive statistics for the crisis period (01.08.2007-17.12.2009)

Returns	Lenght	Mean	Median	Min	Max	Std	Skewness	Kurtosis
Can-a	1529	-7.16e-05	5.68e-04	-0.0572	0.0550	0.0113	-0.2757	5.6582
Ican-a	1529	-3.94e-04	2.93e-04	-0.0641	0.0459	0.0100	-0.3788	6.9392
Uk-a	1529	1.03e-04	4.79e-04	-0.0637	0.0703	0.0118	-0.2424	5.7516
Iuk-a	1531	1.40e-05	1.41e-04	-0.0722	0.0585	0.0126	-0.3001	5.5144
Usa-a	1531	4.13e-04	4.05e-04	-0.0720	0.0487	0.0101	-0.4692	7.7046
Iusa-a	1531	-2.67e-04	1.65e-04	-0.0605	0.0629	0.0136	-0.2564	5.0511
Jp-a	1531	1.91e-04	1.8839e-04	-0.0893	0.0722	0.0118	-0.4429	7.8500
Ijp-a	1531	2.42e-04	3.78e-04	-0.0684	0.0676	0.0114	-0.2282	6.1481
My-a	1531	5.28e-05	-3.89e-05	-0.0432	0.0543	0.0089	-0.1113	7.0170
imy-c	1531	5.39e-05	0	-0.0460	0.0495	0.0085	-0.1332	6.3661

Table 9: shows the descriptive statistics for after crisis period (01.01.2010-25.11.2015)

Indices	ω	α	β	α_{DCC}	β_{DCC}
///	///	///	///	0.0161	0.9552
UK	2.22e-06	0.1299	0.8694	///	///
Can	3.40e-06	0.1080	0.8831	///	///
US	1.23e-06	0.0796	0.9157	///	///
Jp	5.72e-06	0.1002	0.8689	///	///
My	2.21e-06	0.1763	0.8236	///	///
Iuk	3.81e-06	0.1322	0.8597	///	///
Ican	8.29e-06	0.1098	0.8751	///	///
Ius	2.13e-06	0.0895	0.8988	///	///
Ijp	4.37e-06	0.1069	0.8709	///	///
Imy	1.71e-06	0.1367	0.8632	///	///

Table 10: Estimation parameters of the variances and correlations model

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.4996	0.6487	3.5076	C
Can	0.7548	0.5979	0.7683	5.1024	C
Jp	0.0674	0.1152	0.0627	-0.8277	N
My	0.2163	0.1829	0.2226	0.6469	N

Table 11: shows unadjusted correlation coefficient conventional Indices. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.1931	0.2794	1.4291	C
Can	0.7548	0.2467	0.3791	2.3001	C
Jp	0.0674	0.0396	0.0214	-0.2835	N
My	0.2163	0.0634	0.0777	0.2249	N

Table 12: pre-crisis period is 02.01.2006-17.07.2007. Crisis period is 18.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using only the stable period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.1940	0.2787	1.4076	C
Can	0.7548	0.2440	0.3788	2.3453	C
Jp	0.0674	0.0383	0.0216	-0.2622	N
My	0.2163	0.0614	0.0778	0.2588	N

Table 13: pre-crisis period is 02.01.2006-23.07.2007. Crisis period is 24.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using only the stable period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.2070	0.2882	1.3614	C
Can	0.7548	0.2650	0.3896	2.1986	C
Jp	0.0674	0.0379	0.0224	-0.2435	N
My	0.2163	0.0608	0.0812	0.3221	N

Table 14: pre-crisis period is 02.01.2006-31.07.2007. Crisis period is 01.08.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using only the stable period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.4247	0.5699	3.0303	C
Can	0.7548	0.5188	0.6986	4.5346	C
Jp	0.0674	0.0940	0.0511	-0.6743	N
My	0.2163	0.1497	0.1826	0.5300	N

Table 15: pre-crisis period is 02.01.2006-17.07.2007. Crisis period is 18.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using the entire period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.4260	0.5685	2.9826	C
Can	0.7548	0.5139	0.6980	4.6273	C
Jp	0.0674	0.0908	0.0513	-0.6230	N
My	0.2163	0.1448	0.1827	0.6092	N

Table 16: pre-crisis period is 02.01.2006-23.07.2007. Crisis period is 24.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using the entire period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Uk	0.6369	0.4366	0.5682	2.7792	C
Can	0.7548	0.5333	0.6965	4.1747	C
Jp	0.0674	0.0866	0.0513	-0.5576	N
My	0.2163	0.1383	0.1838	0.7334	N

Table 17: pre-crisis period is 02.01.2006-31.07.2007. Crisis period is 01.08.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using the entire period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.4762	0.6458	3.9087	C
Ican	0.7174	0.6393	0.7275	2.6031	C
Ijp	0.0920	0.1138	0.0904	-0.3708	N
Imy	0.1816	0.0672	0.1946	2.0292	C

Table 18: shows unadjusted correlation coefficient conventional Indices. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.2130	0.3223	1.8439	C
Ican	0.7174	0.3174	0.3926	1.3472	C
Ijp	0.0920	0.0461	0.0365	-0.1499	N
Imy	0.1816	0.0271	0.0796	0.8234	N

Table 19: pre-crisis period is 02.01.2006-17.07.2007. Crisis period is 18.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using only the stable period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.2131	0.3213	1.8287	C
ican	0.7174	0.3142	0.3919	1.3922	C
ijp	0.0920	0.0449	0.0365	-0.1309	N
imy	0.1816	0.0271	0.0794	0.8222	N

Table 20: pre-crisis period is 02.01.2006-23.07.2007. Crisis period is 24.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using only the stable period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.2262	0.3295	1.7601	C
ican	0.7174	0.3297	0.4003	1.2822	C
Ijp	0.0920	0.0461	0.0374	-0.1373	N
Imy	0.1816	0.0246	0.0825	0.9127	N

Table 21: pre-crisis period is 02.01.2006-31.07.2007. Crisis period is 01.08.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using only the stable period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.4075	0.5718	3.4020	C
Can	0.7174	0.5652	0.6580	2.3281	C
Ijp	0.0920	0.0940	0.0746	-0.3061	N
Imy	0.1816	0.0554	0.1614	1.6773	C

Table 22: pre-crisis period is 02.01.2006-17.07.2007. Crisis period is 18.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using the entire period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.4079	0.5706	3.3757	C
Ican	0.7174	0.5610	0.6573	2.4100	C
Ijp	0.0920	0.0916	0.0747	-0.2673	N
Imy	0.1816	0.0553	0.1609	1.6754	C

Table 23: pre-crisis period is 02.01.2006-23.07.2007. Crisis period is 24.07.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using the entire period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	Z-statistics	Contagion
Iuk	0.6278	0.4195	0.5703	3.1569	C
Ican	0.7174	0.5705	0.6560	2.1599	C
Ijp	0.0920	0.0914	0.0742	-0.2724	N
Imy	0.1816	0.0489	0.1626	1.8075	C

Table 24: pre-crisis period is 02.01.2006-31.07.2007. Crisis period is 01.08.2007-31.12.2009. The relative increase in the conditional variance of U.S is calculated using the entire period. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Mean entire sample	Mean stable period	Mean crisis period	T-statistics	p-values	Contagion
Uk	0.6278	0.5386	0.5818	18.0351	0.0000	C
Can	0.7174	0.6389	0.6875	14.0311	0.0000	C
Jp	0.0920	0.0478	0.0182	-8.4198	0.0000	N
My	0.1816	0.1651	0.1889	5.0330	0.0000	C

Table 25: pre-crisis period is 02.01.2006-17.07.2007. Crisis period is 18.07.2007-31.12.2009. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Mean entire Sample	Mean stable period	Mean crisis period	T-statistics	p-values	Contagion
Uk	0.6278	0.5386	0.5819	17.9927	0.0000	C
Can	0.7174	0.6397	0.6874	13.7639	0.0000	C
Jp	0.0920	0.0468	0.0186	-7.9938	0.0000	N
My	0.1816	0.1654	0.1889	4.9890	0.0000	C

Table 26: pre-crisis period is 02.01.2006-23.07.2007. Crisis period is 24.07.2007-31.12.2009. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Mean entire Sample	Mean stable period	Mean crisis period	T-statistics	p-values	Contagion
Uk	0.6278	0.5400	0.5816	17.1960	0.0000	C
Can	0.7174	0.6409	0.6871	13.2655	0.0000	C
Jp	0.0920	0.0453	0.0194	-7.3221	0.0000	N
My	0.1816	0.1650	0.1894	5.2148	0.0000	C

Table 27: pre-crisis period is 02.01.2006-31.07.2007. Crisis period is 01.08.2007-31.12.2009. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Mean entire Sample	Mean stable period	Mean crisis period	T-statistics	p-values	Contagion
Iuk	0.6278	0.5212	0.5653	16.9535	0.0000	C
Ican	0.7174	0.6443	0.6620	5.5383	0.0000	C
Ijp	0.0920	0.0544	0.0320	-5.9143	0.0000	N
Imy	0.1816	0.1103	0.1563	11.5865	0.0000	C

Table 28: pre-crisis period is 02.01.2006-17.07.2007. Crisis period is 18.07.2007-31.12.2009. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Mean entire Sample	Mean stable period	Mean crisis period	T-statistics	p-values	Contagion
Iuk	0.6278	0.5215	0.5655	16.9326	0.0000	C
Ican	0.7174	0.6448	0.6618	5.3070	0.0000	C
Ijp	0.0920	0.0534	0.0324	-5.5322	0.0000	N
Imy	0.1816	0.1111	0.1561	11.3463	0.0000	C

Table 29: pre-crisis period is 02.01.2006-23.07.2007. Crisis period is 24.07.2007-31.12.2009. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

Indices	Entire Sample	Stable period	Crisis period	T-statistics	p-values	Contagion
Iuk	0.6278	0.5226	0.5652	16.2475	0.0000	C
Ican	0.7174	0.6456	0.6614	4.9220	0.0000	C
Ijp	0.0920	0.0522	0.0331	-5.0188	0.0000	N
Imy	0.1816	0.1114	0.1563	11.3701	0.0000	C

Table 30: pre-crisis period is 02.01.2006-31.07.2007. Crisis period is 01.08.2007-31.12.2009. ***, ** and * indicate the significance level at 1%, 5%, 10% respectively

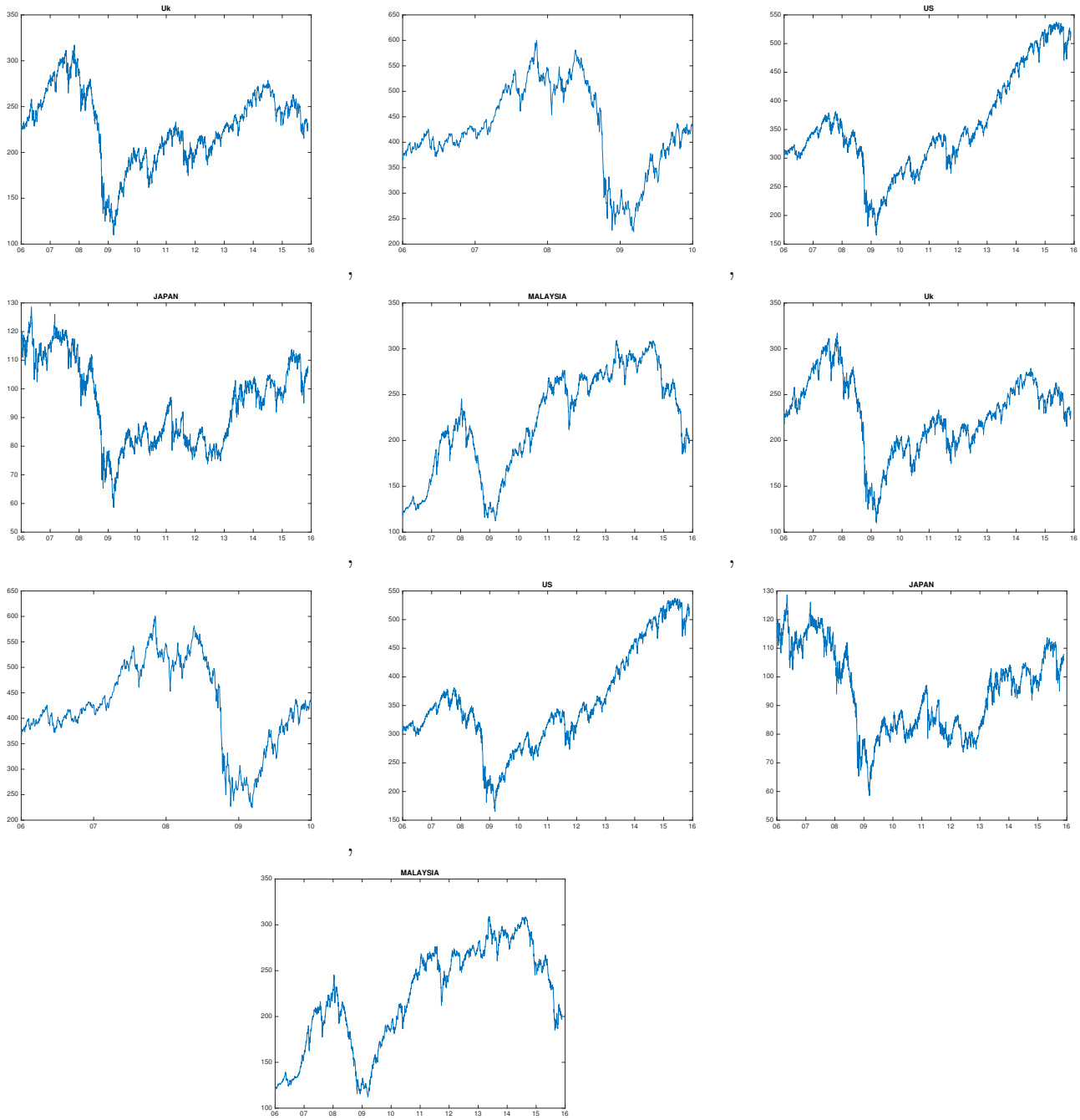

Figure 8: Plot Stock Prices Indices

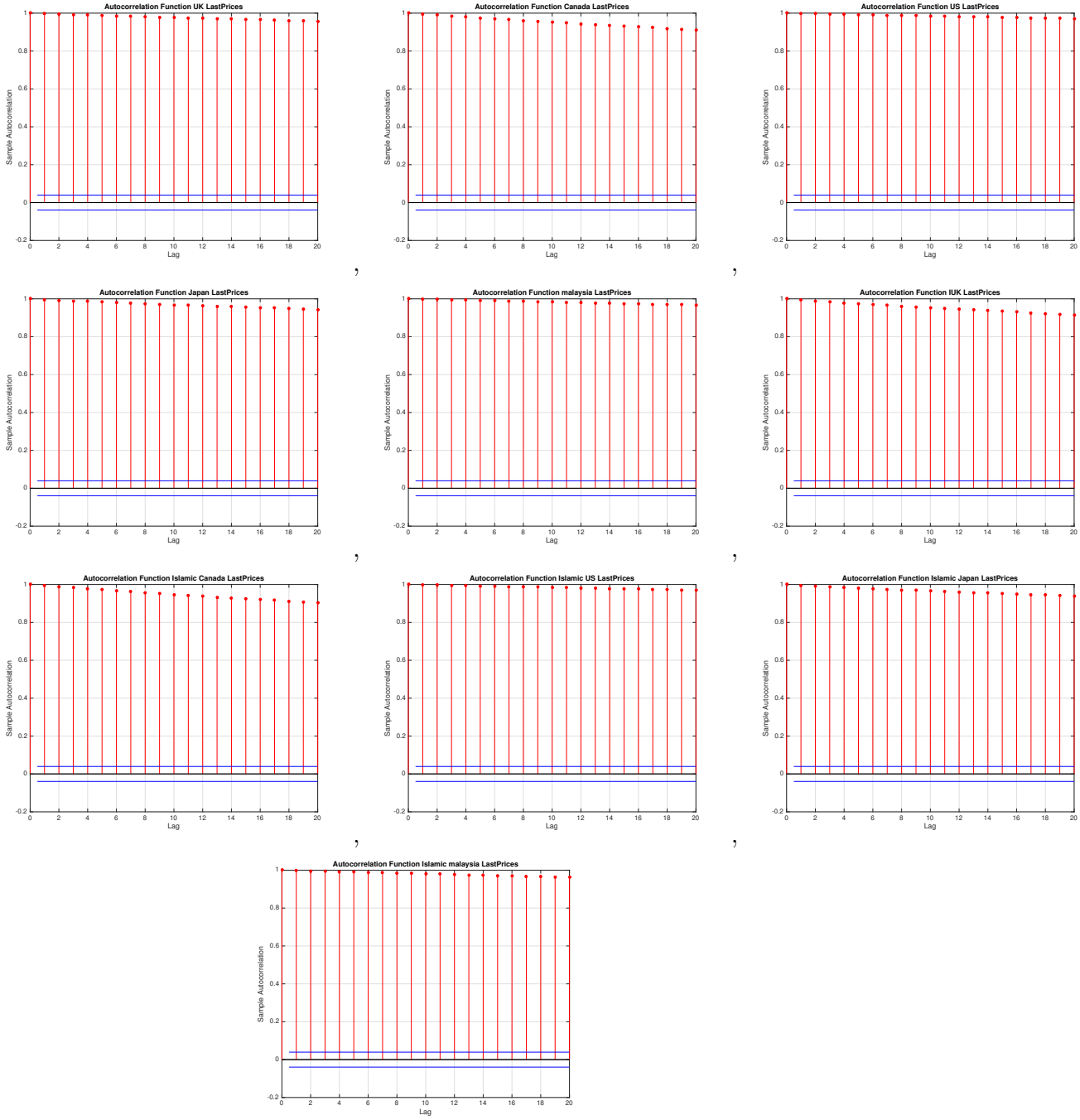

Figure 9: Autocorrelation Functions Stock Price Indices

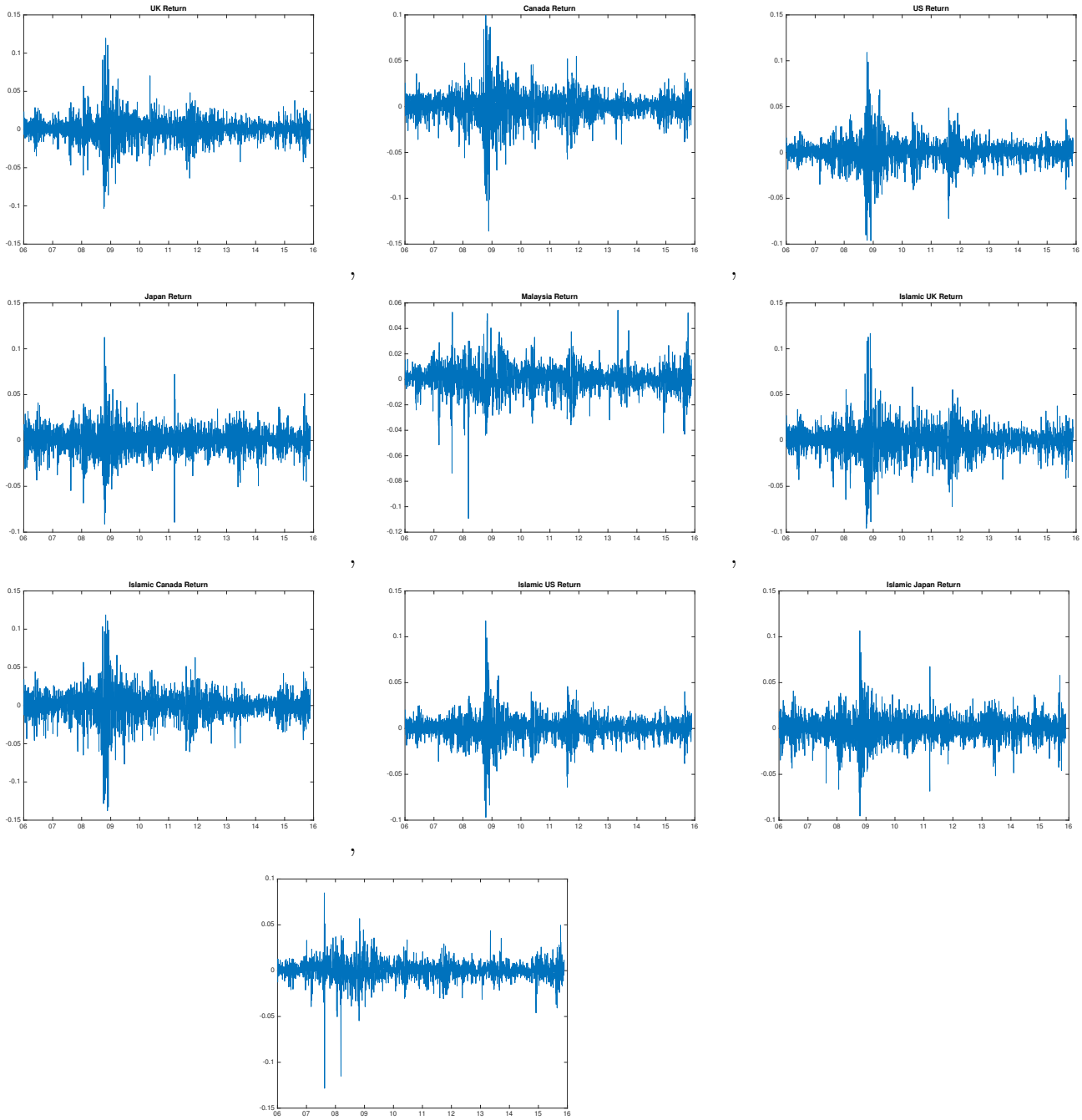

Figure 10: Plot Stock Return Indices

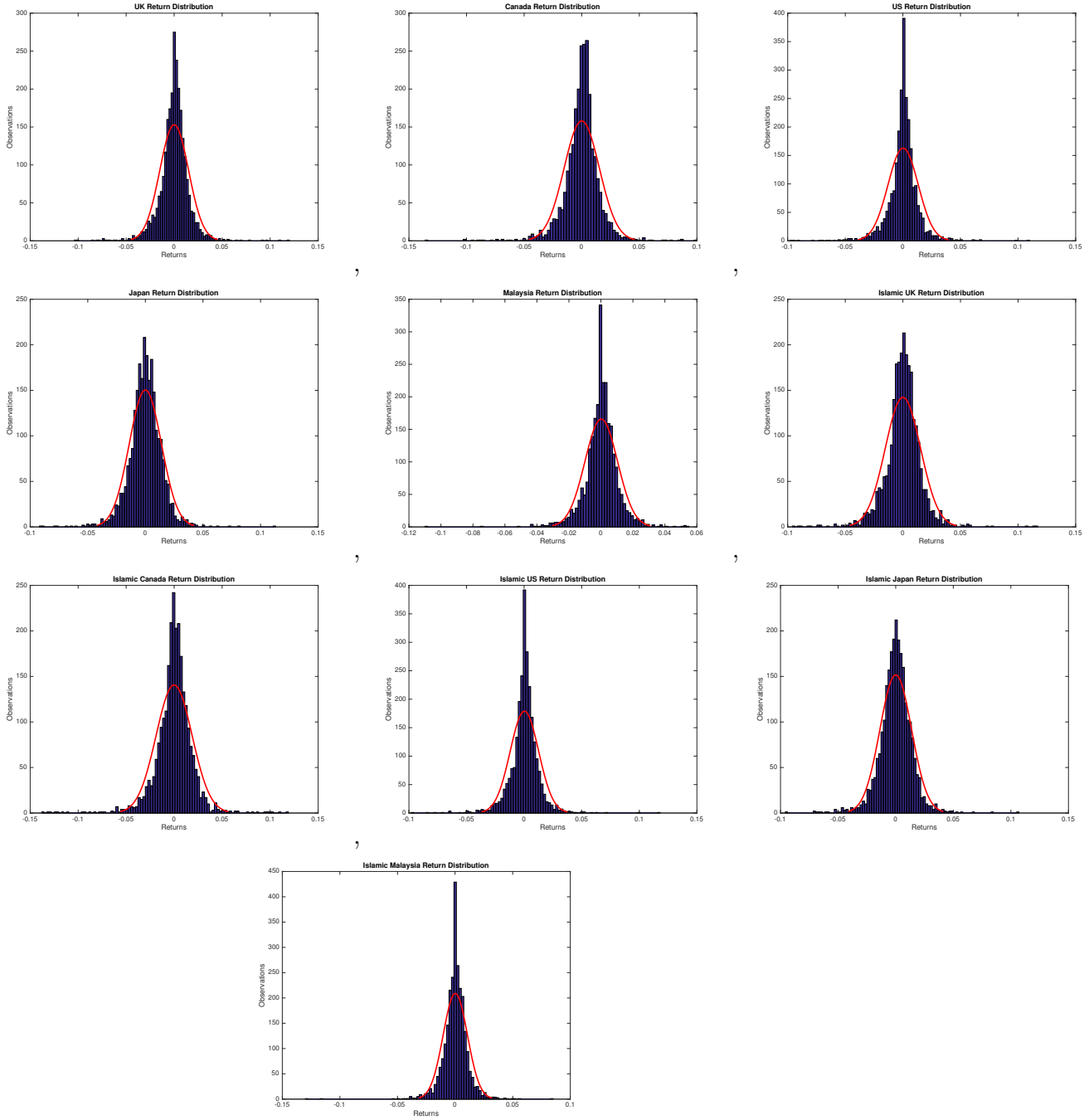

Figure 11: Histigrams Return Indices

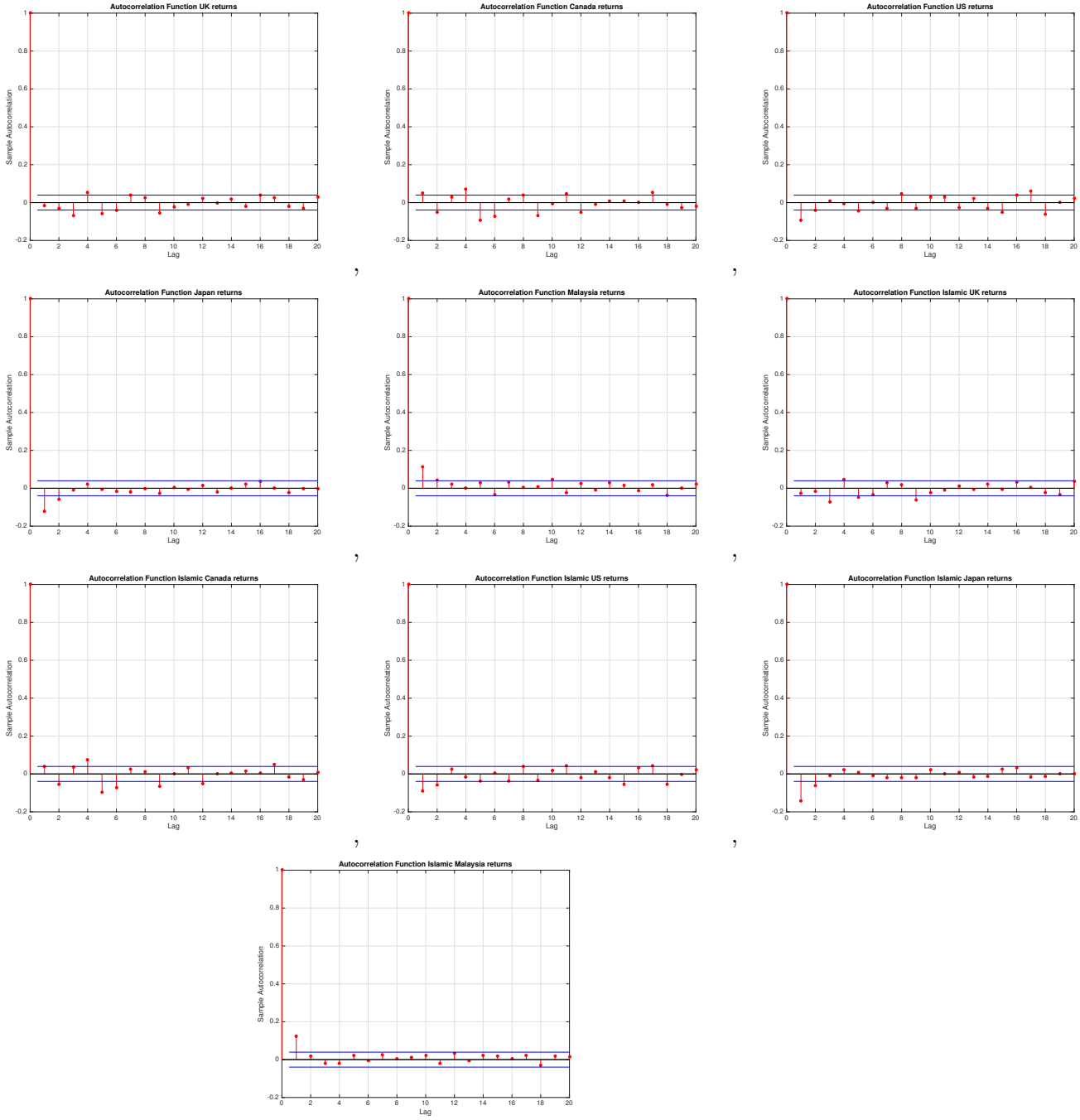

Figure 12: Autocorrelation Functions Stock Return Indices

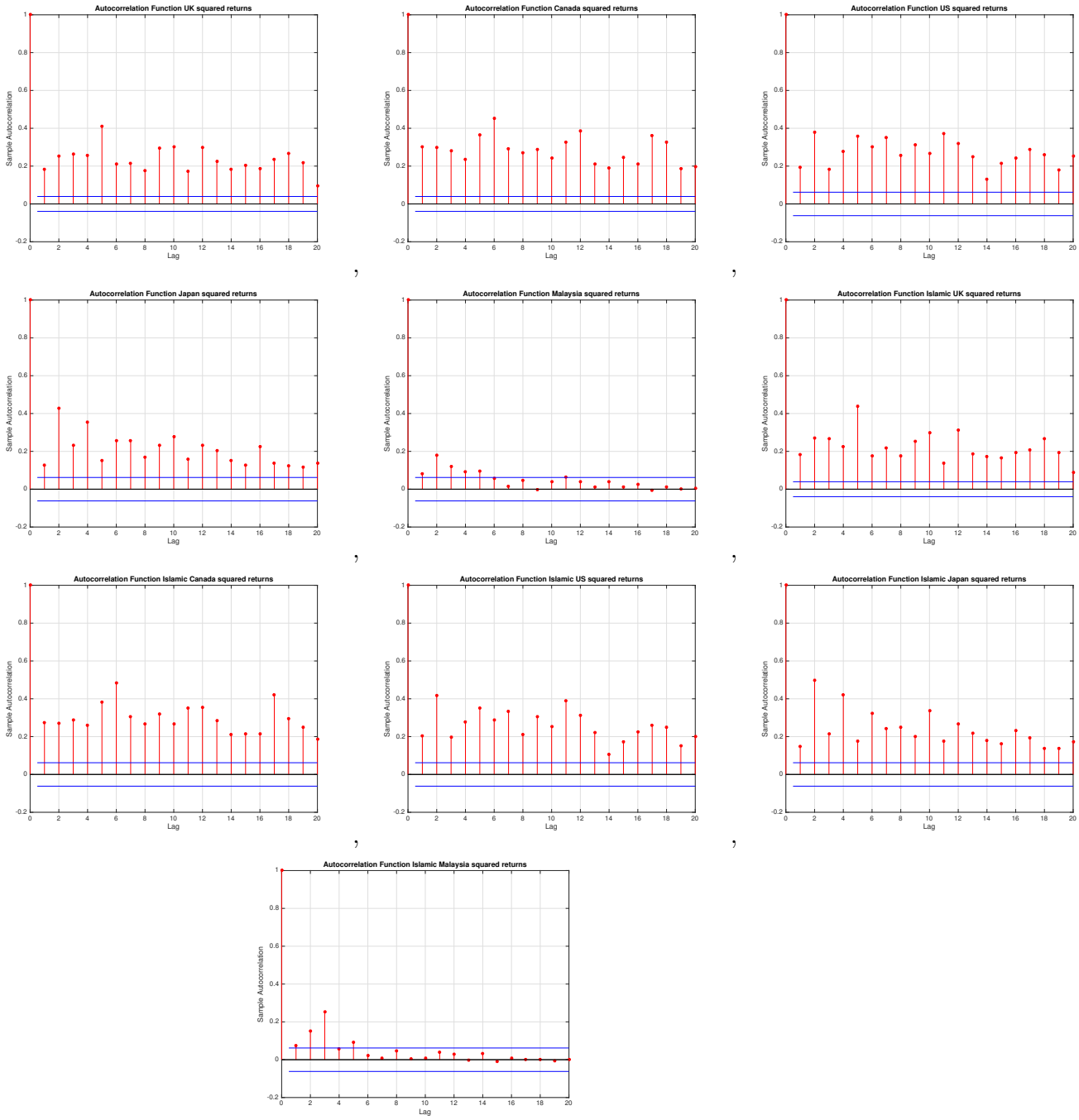

Figure 13: Autocorrelation Functions Squared Return Indices

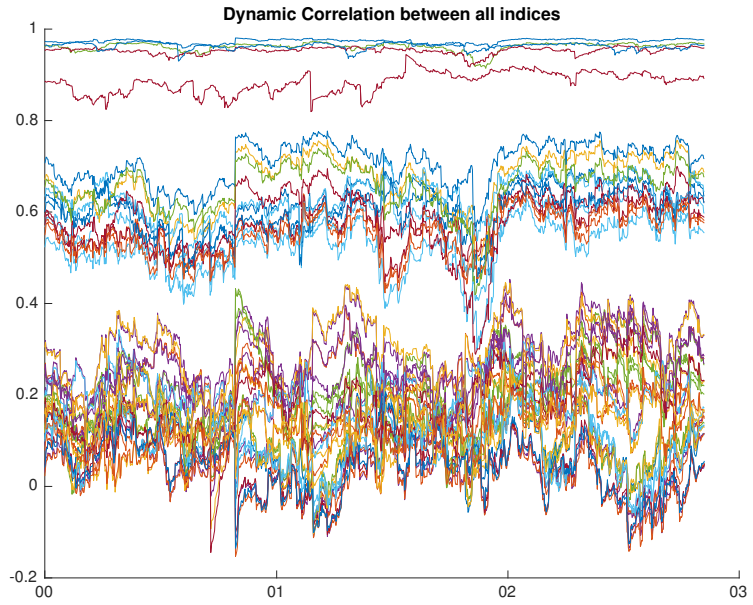

Figure 14: Dynamic Conditional Correlation between All the Indices

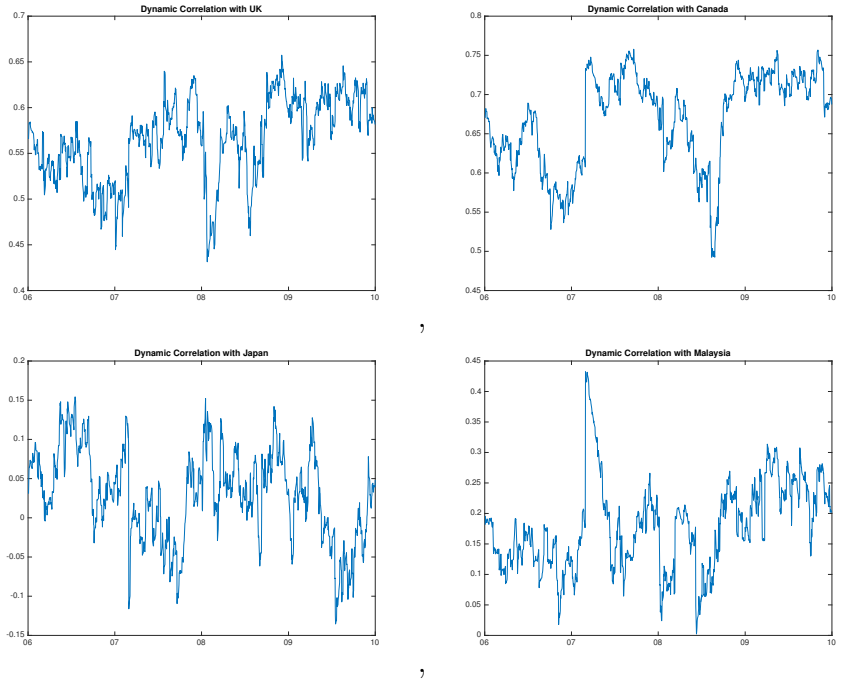

Figure 15: Dynamic Conditional Correlation between Conventional Indices

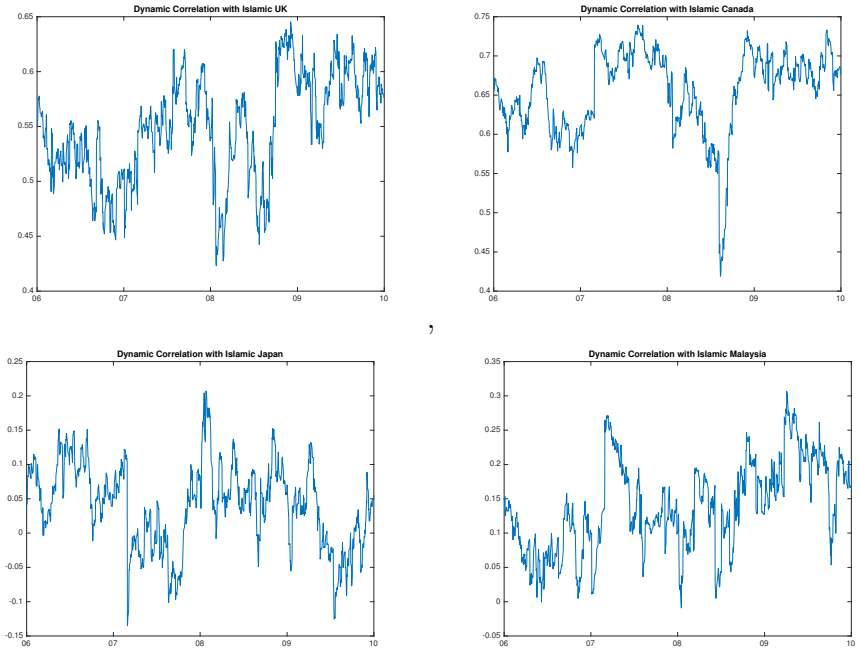

Figure 16: Dynamic Conditional Correlation between Islamic Indices