UNIVERSITY OF IOANNINA

FACULTY OF ECONOMIC AND ADMINISTRATIVE SCIENCES

DEPARTMENT OF ECONOMIC SCIENCES

Topics in Applied Financial Economics

By **Konstantinos N. Tsiaras**

A dissertation submitted to

DEPARTMENT OF ECONOMIC SCIENCES

FACULTY OF ECONOMIC AND ADMINISTRATIVE SCIENCES

UNIVERSITY OF IOANNINA

for the degree of

Doctor of Philosophy

in

Economics

IOANNINA 2019

Ημερομηνία αίτησης του κ. Κωνσταντίνου Τσιάρα: Γ.Σ.: 477/16-6-2015

Ημερομηνία ορισμού Τριμελούς Συμβουλευτικής Επιτροπής: Γ.Σ.: 16/30-9-2015

Μέλη Τριμελούς Συμβουλευτικής Επιτροπής:

Επιβλέπων:
Σίμος Θεόδωρος, Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Ιωαννίνων

Μέλη:
Συμεωνίδης Σπυρίδων, Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Ιωαννίνων
Λιαργκόβας Παναγιώτης, Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Τρίπολης

Ημερομηνία ορισμού Θέματος: Γ.Σ.: 19/9-3-2016
«Topics in Applied Financial Economics»

ΔΙΟΡΙΣΜΟΣ ΕΠΤΑΜΕΛΟΥΣ ΕΞΕΤΑΣΤΙΚΗΣ ΣΥΜΒΟΥΛΕΥΤΙΚΗΣ ΕΠΙΤΡΟΠΗΣ:

Γ.Σ.: 46/18-9-2019

Σίμος Θεόδωρος	Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Ιωαννίνων
Συμεωνίδης Σπυρίδων	Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Ιωαννίνων
Λιαργκόβας Παναγιώτης	Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Τρίπολης
Μυλωνίδης Νικόλαος	Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Ιωαννίνων
Γκωλέτσης Γεώργιος	Επίκουρος Καθηγητής του Τμήματος Οικονομικών Επιστημών του Πανεπιστήμιου Ιωαννίνων
Καινούργιος Δημήτριος	Αναπληρωτής Καθηγητής του Τμήματος Οικονομικών Επιστημών του ΕΚΠΑ
Δότσης Γεώργιος	Επίκουρος Καθηγητής του Τμήματος Οικονομικών Επιστημών του ΕΚΠΑ

Έγκριση Διδακτορικής Διατριβής με βαθμό «**ΑΡΙΣΤΑ**» στις 13-11-2019.

ΠΡΟΕΔΡΟΣ ΤΟΥ ΤΜ. ΟΙΚΟΝΟΜΙΚΩΝ ΕΠΙΣΤΗΜΩΝ

Μυλωνίδης Νικόλαος
Καθηγητής

Ο Γραμματέας του Τμήματος

Αλέξανδρος Κανδρέλης

Dedicated To My Family

Acknowledgements

I am very grateful to my dissertation supervisor, Professor Theodore Simos whose comments and help have always been helpful and appreciated. During my studies in Ioannina, I had the opportunity to be advised on several topics by the other two members of the advisor committee: Professor Spyridon Symeonidis and Professor Panagiotis Liargkovas. Many thanks to them. I would like to also acknowledge the help of my parents who helped me psychologically and financially all these years.

Konstantinos N. Tsiaras

Ioannina, 2019

Declaration

The research work presented in this thesis entitled «**Topics in Applied Financial Economics**» was carried out by me independently in this university under the supervision of Mr. T. Simos, Professor in department of Economic Sciences, Faculty of Economic and Administrative Sciences, University of Ioannina. This work is original and has not been submitted in part or full, for any degree or diploma of this or any other university.

Konstantinos Tsiaras

Ioannina, 2019

Table of Contents

Dissertation Summary and Contribution

This dissertation consists of four self-contained chapters in the form of papers. The first chapter investigates the volatility spillover effects and the contagion to sovereign CDS spread returns for Germany, France, China and Japan against USA. To the best of our knowledge, this is the first empirical research in the literature, which investigates potential spillovers and contagion effects among sovereign CDS markets. We use daily data from October 2011 to February 2018. Employing a fourvariate cDCC-AR-FIGARCH model, we find evidence of spillover effects for all the pairs of markets. Furthermore, we find empirical evidence of contagion for the pairs of markets: Germany – France, Germany – Japan and France – Japan. Regarding China's CDS market we obtain little empirical support for contagion with the rest of the countries. The results are of interest to policymakers, who provide regulations for the CDS markets, as well as to market-makers.

The second chapter investigates the spillover effects and the contagion to major equity and FOREX markets of G20. The financial markets under scrutiny are those of USA, Brazil, Italy, Germany and Canada. The frequency of the data is daily. We set the sample period from April 2010 to April 2018, namely after the GFC. Other related empirical work include Kanas (2000), who investigated the existence of spillovers between national equity and FOREX markets, by employing a trivariate AR-diagonal BEKK model for S&P 500, national equity markets and the respective FOREX markets. Our empirical results find evidence of spillovers and contagion effects for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. Moreover, the pairs of markets S&P 500-CAD/USD, S&P 5000BRL/USD and BOVESPA-BRL/USD present no contagion. The results are of interest to individual investors, who want to diversify their portfolios through international financial market investments.

The third chapter investigates the spillovers and the financial contagion of four major FOREX markets. The FOREX markets are those of EUR/USD, JPY/USD, CHW/USD and GBP/USD. Lee (2010) investigates ten FOREX markets in Asia and Latin America to USD, among others and finds evidence of spillover effects from JPY/USD on Asian currency markets. A fourvariate dynamic Conditional Correlation Generalized ARCH (DCC-GARCH) model is employed for the period April 2011 to February 2018. The empirical results suggest contagion for all the pairs of markets. Additionally, we find that EUR/USD and GBP/USD present the strongest contagion effects, while CHW/USD show the lowest contagion levels with the rest of the markets.

The fourth chapter analyses the spillover and the contagion effects of MSCI (global index), NIKKEI 400 (Japan), CSI 300 (China) and S&P 500 (USA). We consider a portofolio analysis in order to produce the standardized residuals using in a trivariate cDCC-GARCH framework. Other research work include Miyakoshi (2003), who suggests the existence of spillover effects between USA and Asian national equity markets. We extend the above analysis by taking into consideration the individual effects of MSCI on three of the most important national equity markets. We use daily data for the period 2008-2018. The main empirical results are the following: (1) portfolio analysis results suggest that MSCI has a significant positive influence on all equity market returns, (2) we find empirical evidence of spillovers on all pairs and (2) we find contagion for the pairs of markets: NIKKEI 400-CSI 300, NIKKEI 400-S&P 500 and S&P 500-CSI 300 that indicate risky positive correlations from an investor's perspective.

.

Chapter 1

Contagion in major CDS markets for the post Global Financial Crisis: A multivariate AR-FIGARCH-cDCC approach

Abstract

We explore the time-varying conditional correlations of the Sovereing CDS spread returns for Germany, France, China and Japan against USA. We employ a cDCC-AR-FIGARCH model in order to capture potential contagion effects between the markets during the 2011-2018 post global financial crisis. Empirical results do not reject contagion for the country pairs: Germany – France, Germany – Japan and France – Japan while there is little support for contagion among China and the rest of the countries. From an investor's point of view, all markets provide evidence of high volatility suggesting a less reliable stability of the correlations that makes portfolio strategies difficult to implement.

1. Introduction

This paper investigates the volatility transmission among major CDS markets, considering the credit risk entailed and how easy can be transferred (Hull 2008). Although the study of integration between derivative markets and financial markets is ubiquitous, there is little work on CDS market integration (Caporale, Pittis and Spagnolo 2006). According to extant research, there are two mechanisms on volatility transmission (Stevens 2008). The first mechanism refers to the common shocks, whilst the second mechanism deals with the spillover effects (Didier, Mauro and Schmuckler 2008). For our study, we use the phenomenon of spillover effects to explain financial contagion. Today, there is still large divergence among economics about what contagion is exactly and how it should be measured and tested empirically. In this paper, we adopt the definition of contagion suggested by Forbes and Rigobon (2002). They defined contagion as a significant increase in cross-market linkages after a shock.

The main body of the current literature explores the linkages between CDS markets or between CDS markets with other financial markets, including: Meng, Gwilym and Varas (2009), Lake and Apergis (2009), Schreiber, Muller, Kluppelberg and Wagner (2009), Belke and Gokus (2011), Calice, Chen and Williams (2011), Fonseca and Gottschalk (2012), Koseoglu (2013) and Tokat (2013), among others. Meng, Gwilym and Varas (2009) examine the volatility transmission among the daily 5-year maturity bond, CDS and equity markets for ten large US companies. While they use a multivariate GARCH-BEKK model during 2003-2005, they provide evidence on spillovers. Lake and Apergis (2009) investigate the spillovers among the US and European (German, UK and Greek) 5-year maturity CDS spreads and equity returns in the period 2004-2008. By making use of daily observations, they employ and MVGARCH-M model, finding evidence of spillover effects. Schreiber, Muller, Kluppelberg and Wagner (2009) explore the volatility effects between aggregate CDS premiums, equity returns and implied equity volatility during 2004-2009. They use daily observations of the 5-year maturity CDS iTraxx Europe, Dow Jones Euro Stoxx 50 and Dow Jones VStoxx indexes. By fitting VAR-GARCH models, they show strong evidence of spillovers. Belke and Gokus (2011) examine the volatility transmission among the daily equity prices, CDS premiums and bond yields returns for four large US banks for the period 2006-2009. By employing a BEKK-

GARCH model, they capture spillover effects. Calice, Chen & Williams (2011) investigate the dynamic interactions in the Eurozone[1] between 5- and 10-year maturity sovereign CDS premiums and bonds from 2000 to 2010. Using intraday data, they employ a VAR model, pointing out spillovers. Fonseca and Gottschalk (2012) examine the volatility spillovers among CDS premium and equity returns for Australia, Japan, Korea and Hong Kong at firm and index level. To compute the realized volatility they use the TSRV estimator. They use weekly data during 2007-2010 and they show empirical evidence of spillover effects. Koseoglu (2013) investigates the way that ISE100 stock index spills over with 5-year maturity sovereign CDS premiums of Turkey during the period from 2005 to 2012. The data frequency is daily. He uses a VAR-diagonal BEKK model and he finds evidence of spillovers. Tokat (2013) empirically[2] investigates the spillover effects between daily 5-year maturity sovereign CDS values for Brazil and Turkey denominated in USD, iTraxx XO index and CDX index during the period from 2005 to 2011. He employs a full BEKK-GARCH model and he proves empirically the existence of spillovers.

In this paper, we extend the correlation analysis of Forbes and Rigobon (2002) by considering the corrected Dynamic Conditional Correlation Auto Regressive Fractionally Integrated GARCH[3] (cDCC-AR-FIGARCH) of Aielli (2008) that improves the Dynamic Conditional Correlation (DCC-GARCH) model of Engle (2002). Compared to extant empirical research, we take a different perspective by consolidating important elements of financial analysis: long memory, speed of market information and a reformulated driving process of standardized residuals. The main objective is to model financial contagion[4] phenomenon (Anderson 2010) among four major sovereign CDS spread returns (Wei 2008), namely the Germany, France, Japan and China against the USA from 5th October 2011 to 5th

[1] The countries under investigation European are: Austria, Belgium, France, Greece, Ireland, Italy, Netherlands, Portugal and Spain.

[2] Financial researchers and academics are interested to 5-year maturity CDSs, investigating the underlying contagion mechanisms in the short-term period.

[3] Worthington and Higgs (2003) highlight the importance of multivariate GARCH models.

[4] Missio and Watzka (2011) summarize all the existing different contagion definitions in the literature and draw up a report of the five most important.

February 2018[5]. We consider three dominant world economies (USA, China, Japan) and the two most important European economies (Germany, France) due to the ongoing European crisis. The data set entails 20-years maturity CDS premium mid prices[6] (Blanco, Brennan and Marsh 2005; Zhu and Yang 2004). We make the hypothesis that the sovereign CDS markets reflect the macroeconomic environment of the countries. The above countries are connected in a macroeconomic level and we expect that the respective sovereign CDS markets will be also connected.

Based on our empirical research, several questions arise: (i) does the dynamic conditional correlation between the CDS markets increase after the recent Global Financial Crisis (GFC) and the beginning of the European Sovereign Dept Crisis (ESDC) [7]? (ii) is the dynamic conditional correlation volatile? (iii) are there evidence of contagion effects?

The paper is organized at follows: Section 2 describes the CDS market framework, followed by an overview of the markets in Section 3. Section 4 describes the model and the data. Section 5 considers the empirical results, while Section 6 concludes.

2. The CDS market framework

We start this section by providing the CDS definition, the way that CDS market operates and relevant historical data. We define credit default swap (CDS) as a financial swap agreement between two parties: the protection buyer (long position) and the protection seller (short position). The protection buyer pays a periodic fee (CDS premium) to the protection seller. Normally, credit default swap protects the buyer from any future default. However, even a speculator for investment can buy a credit default swap.

Credit default swaps exist since 1994 when J.P. Morgan used them for the first time in the history. In 2007 CDS market developed rapidly. During the period 2007-2010 CDS market became a very large derivative market of a total $62.2 trillion. The main reason for this huge

[5] Firstly, we defined two periods: one crisis period (2008-2011) and one after-crisis period (2011-2018). However, we used only the after-crisis period due to autocorrelation and diagnostic tests problems of the crisis period.

[6] CDS premiums are normally affected by liquidity as many researchers have mentioned, i.e. Sarig and Warga (1989) and Chen, Lesmond and Wei (2007), among others. The most commonly used are the 5- and 10-year maturity sovereign CDS premiums.

[7] The Eurozone Sovereign Debt Crisis of 2009 is also as Aegean Contagion known by many researchers and academics, i.e. Calice, Chen, and Williams (2011), among others.

growth was the lack of regulation. Interestingly, by 2012 CDS market fell to $25.6 trillion. In 14th March 2012, European Union published a new regulation (No 236/2012) on short selling and certain aspects of CDS in the official journal of the European Union. The regulation set up some new restrictions about the short selling of sovereign debt instruments and the taking of sovereign credit default swaps positions. Credit default swaps played an important role in the recent global financial crisis of 2007. They became a leading indicator, reflecting the default risk of the banking sector and the macroeconomic environment of a country.

CDS market has been developed as unregulated market. Large banks and financial institutions play the role of credit default swaps dealer. Today, the International Swaps and Derivatives Association (ISDA) set up the regulation framework including the rules how CDS market operates and the recovery rates. Interestingly, there are 14 dealers entailing 97% of Credit Default Swap contracts (Chen, Fleming, Jackson and Sarkar 2011), namely the Citigroup, Credit Suisse, Deutsche Bank AG, BHP Paribas, Barclays Capital, J.P. Morgan, The Royal Bank of Scotland Group, HSBC Group, Bank of America-Merrill Lynch, UBS AG, Societe Générale, Wells Fargo, Morgan Stanley and Goldman Sachs & Co.

Figure 1 provides the 20-year maturity sovereign CDS premium mid values for Japan, China, Germany, France and USA, during a period from 5th October 2011 until 5th February 2018. We extract some important drawbacks. Interestingly, all CDS markets[8] are bouncing above and beyond over the time period, following a common downward trend.

3. Overview of the Markets

In table 1, we state the main annual macroeconomics market figures for Germany, France, China, Japan and USA, from 2011 to 2017, namely: GDP per capita growth, unemployment rate, net acquisition of government financial assets, exports of goods and services, imports of goods and services and stocks traded. We use the above macroeconomic figures in order to explain the volatility transmission. The dataset is downloaded from the World Bank. Next, we present the selected macroeconomic figures for each country.

[8] Japan and UK markets couldn't recover from the recent GFC even after 2011 due to their huge exposure to USA's financial market and the huge loses that are not still fully regained.

Germany (Panel A of table 1) exhibits the highest imports and the highest exports in 2011, 2015, 2016 and 2017 among the five markets. It is widely held that the rest of the European countries cannot follow up with the trade surplus of Germany, especially Portugal, Greece and Spain.

France (Panel B of table 1) presents the highest unemployment rate suffering from the recent GFC (2007) and its consequences. A second reason, at least in the short run, for the high unemployment rate is that France has heavily invested in technological innovations, which modernized the production methods and increased automation. Based on the above, we expect France to present higher volatility levels in comparison with the rest four markets.

Japan (Panel C of table 1) states the highest levels of exports in 2014 and the highest net acquisition of government financial assets in 2014. After 2008, Japan's economy never shrunk, reflecting its steady economic conditions. The main reason is the technological innovations, defining Japan as a developed and market-oriented economy. It is worth mentioning that Japan has the third-largest economy in the world based on nominal GDP.

Regarding China (Panel D of table 1), we distinguish GDP growth among macroeconomic figures. China is the only country with a positive GDP growth over time, reflecting the immunity of Chinese economy. Additionally, in 2015 China exhibits the highest levels of stocks traded.

USA (Panel E of table 1) exhibits the highest unemployment rate in 2011, reflecting the USA economic conditions, the persistent trade balance deficit, among others. In addition, USA exports are the highest in 2012 and 2013. However, USA presents the highest levels of net acquisition of financial assets in 2013, 2015 and 2016.

All the above economies are major trading partners in financial markets, so it is rational to assume that the above markets are also interconnected[9] in a macroeconomic level. Moreover, sovereign CDS market is an indicator of economic performance and volatility transmission among CDS markets becomes of major importance.

[9] The interconnections among global major markets have increased after the Global Financial Crisis of 2007 for various major reasons, i.e. the hedge funds' growth, the Exhange-Traded Funds' growth, the liquidity by the central banks, the information' speed, among others.

4. Model and data description

4.1 Model description

In this section, we describe the models employed. First we define the univariate AR (1)-FIGARCH model. Then, we use the estimates of standardized residuals in a fourvariate cDCC framework, producing the fourvariate conditional variance matrix. Finally, we present the estimated log-likelihood.

We use an autoregressive *AR(*1*)* process and a constant (μ) in mean equation in order to generate the daily CDS spread returns (y_t):

$$(1 - VL)y_t = \mu + \varepsilon_t, \text{ with } t = 1,\ldots,T. \tag{1}$$

and

$$\varepsilon_t = \sqrt{h_t}u_t, \text{ where } \varepsilon_t \sim N(0, H_t) \text{ and } u_t \text{ are i.i.d.} \tag{2}$$

where $|V|<1$ is a parameter, ε_t is standardized residuals, h_t is the univariate conditional variance matrix, u_t is stardardized errors and H_t is multivariate conditional variance matrix. In addition, L is back shift operator.

Next, we use the univariate FIGARCH(*p,d,q*) model (Baillie, Bollerslev and Mikkelsen 1996) in order to generate the conditional variance (h_t):

$$h_t = \omega[1 - b(L)]^{-1} + \{1 - [1 - b(L)]^{-1}\Phi(L)(1 - L)^d\}\varepsilon_t^2 \tag{3}$$

where ω is mean of the logarithmic conditional variance, $\Phi(L) = [1 - a(L) - b(L)](1 - L)^{-1}$ is lag polynomial of order p and $(1 - L)^d$ is fractional difference operator. Furthermore, $b(L)$ and $a(L)$ are autoregressive polynomials of order p and q generated by: $b(L) = 1 - \sum_{k=1}^{p} b_k L^k$ and $a(L) = 1 + \sum_{l=1}^{q} a_l L^l$.

Finally, with the selected lag order equal to 1, we estimate the FIGARCH(1*, d,* 1) model.

Next, we specify cDCC model of Aielli (2009) as an extension of DCC model of Engle (2002). We define the fourvariate conditional variance matrix as:

$$H_t = D_t R_t D_t \tag{4}$$

where H_t is $N \times N$ matrix and

$$D_t = diag\left(h_{11t}^{\frac{1}{2}} \ldots h_{NNt}^{\frac{1}{2}}\right), \text{ where } N \text{ is the number of markets } (i = 1,\ldots,N) \tag{5}$$

h_t is conditional variance of univariate FIGARCH(1, d, 1) model and

$$R_t = diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) Q_t diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) \quad (6)$$

where R_t conditional correlation.

Let $P_t = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}\right)$ and $u_t^* = P_t u_t$. The cDCC model of Aielli (2009) is defined as in the DCC model of Engle (2002) but the $N \times N$ symmetric positive definite matrix $Q_t = (q_{ij,t})$ is now given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}^* u_{t-1}^{*\prime} + \beta Q_{t-1} \quad (7)$$

where $\bar{Q}$ is the $N \times N$ unconditional variance matrix of u_t^* (since $\mathrm{E}[u_t^* u_t^{*\prime} | \Omega_{t-1}] = Q_t$)[10], α and β are nonnegative scalar parameters satisfying $\alpha + \beta < 1$.

For the cDCC model, the estimation of the matrix $\bar{Q}$ and the parameters α and β are intertwined, since $\bar{Q}$ is estimated sequentially by the correlation matrix of the u_t^*. To obtain u_t^* we need however a first step estimator of the diagonal elements of Q_t. Thanks to the fact that the diagonal elements of Q_t do not depend on $\bar{Q}$ (because $\overline{Q_{ii}} = 1$ for $i = 1,\dots,N$), Aielli (2009) proposed to obtain these values $q_{11,t},..,q_{NN,t}$ as follows:

$$q_{ii,t} = (1 - \alpha - \beta) + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1} \quad (8)$$

for $i = 1,\dots,N$. In short, given α and β, we can compute $q_{11,t},..,q_{NN,t}$ and thus u_t^*, then we can estimate $\bar{Q}$ as the empirical covariance of u_t^*.

Next, we estimate the model using Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors. We maximize the log-likelihood as follows:

$$\sum_{t=1}^{T}\left[log \frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{N}{2}}} - \frac{1}{2}\log\left(|H_t|\right) - \left(\frac{N+\nu}{2}\right) log\left[1 + \frac{\varepsilon_t{}' H_t{}^{-1} \varepsilon_t}{\nu-2}\right]\right] \quad (9)$$

where N is the number of markets, $\Gamma(.)$ is the Gamma function and ν is the degrees of freedom.

4.2 Data description

In this study, we use daily data for 20-year maturity sovereign CDS premium mid values[11]. The sample consists of five countries (Germany, France, Japan, China and USA). The period

[10] Aielli (2009) has recently shown that the estimation of $\bar{Q}$ as the empirical correlation matrix of u_t is inconsistent because: $\mathrm{E}[u_t\ u_t\ ] = \mathrm{E}[\mathrm{E}[u_t' u_t\ |\Omega_{t-1}] = \mathrm{E}[R_t\ ] \neq \mathrm{E}[Q_t\ ]$.

[11] We define the mid-price as the average of the current bid and ask prices being quoted.

of observation starts at 5th October 2011, one month after Standard & Poor's downgraded America's credit rating from AAA to AA+ (6 August 2011) for the first time since 1941 and one day after the S&P 500 faced a decline of 21.58% for last time after GFC and ends at 5th February 2018. All prices have been extracted from *Datastream® Database.* For each market we use 1656 observations. CDS spreads are evaluated from USA and CDS spread logarithmic returns generated by $r_t = ln(p_t) - ln(p_{t-1})$, where p_t is the price of CDS spread on day *t*.

Table 2 displays the summary statistics for CDS spread returns. While all CDS market returns are skewed to the left, Japan market returns are skewed to the right. Interestingly, China returns exhibit larger fluctuations compared to the rest market returns, according to the higher standard deviation, the highest maximum and the lowest minimum return prices, foreshadowing the results of contagion effects. Additionally, all market returns present excess kurtosis, suggesting leptokurtic behavior (fat tails). Based on the Jarque-Bera statistic, we reject the null hypothesis of normality for all market returns, suggesting the use of student-*t* distribution as the most appropriate for the empirical analysis (Dimitriou, Kenourgios and Simos 2013; Forbes and Rigobon 2002). All of the market returns were subjected to unit-root testing using Augmented Dickey Fuller test (ADF) (Dickey and Fuller 1979), showing the rejection of the null hypotheses of unit root at 1% level and indicating the daily market returns appropriate for further testing. Furthermore, GSP and GPH tests reject the null hypothesis of no long memory at 1% level for the returns of France and China, whilst the returns of Germany and Japan exhibit long memory effects. (R/S) test results reject the null hypothesis of no long term dependence at 1% level for the returns of China and at 5% level for the returns of France.

In figure 2, we plot the actual series of CDS spreads and their respective logarithmic returns for China (Graph A), France (Graph B), Germany (Graph C) and Japan (Graph D). The visual inspection of CDS spread logarithmic returns provides a clear view of the trend for all markets. The above graphs indicate the presence of heteroskedasticity rationalizing the use of the dynamic conditional correlations in the multivariate AR(1)-FIGARCH(1,d,1) framework.

5. Empirical results

This section is divided into five subsections. First, in section 5.1., the results from the cDCC-AR(1)-FIGARCH(1,d,1) model are described. Second, section 5.2. presents the estimates of simple correlation analysis. Third, in section 5.3., the estimates of conditional variance and covariance statistics are stated. Fourth, section 5.4. provides an explicit economic analysis based on dynamic conditional correlations (DCCs), whilst in section 5.5., we present the diagnostic tests.

5.1 Results of the cDCC-AR(1)-FIGARCH(1,d,1) model

Table 3 reports estimated values for mean equation (Equation 1) and univariate AR(1)-FIGARCH(1,d,1) model[12] (Equation 3). Mean equation exhibits significant μ value only for Japan. The $AR(1)$ is positive for Germany, France, and Japan due to partial adjustment, indicating that relevant market information is rapidly reflected in CDS market prices, whilst the negative $AR(1)$ of China suggests the existence of positive feedback, see for instance Antoniou, Koutmos and Pecli (2005). Based on FIGARCH, our findings show the existence of long memory for Germany, France and China ($0<d<1$) and that Japan has no long memory ($d>1$). In addition, all the ARCH (a) and GARCH (b) terms are highly significant except for the ARCH (a) term of Japan.

Table 4 reports the results of the fourvariate cDCC model estimations (Equation 7 and Equation 9). The cDCC model results show significant α and β parameters, indicating strong ARCH and GARCH effects. This suggests empirical evidence that the CDS markets are integrated (Belke and Gokus 2011). In addition, we provide the estimates of the degrees of freedom (v) and of the log-likelihood.

5.2 Simple Correlation Analysis

In order to measure the financial contagion phenomenon, we implement the Spearman rank correlation approach. If the correlations are statistically significant, we may conclude the existence of transmission mechanisms of shocks between two markets. For a sample size of T

[12] The selected lag order (p, d, q) = (1, d, 1) is sufficient for the estimation of conditional variance as many researchers have mentioned, i.e. Bolleslev, Chou and Kroner (1992), among others.

observations, the T raw scores i_t, j_t ($i \neq j = 1,\ldots,N$ markets and $t = 1,\ldots,T$ observations) are converted to ranks rg_i, rg_j. Spearman proposes to compute the correlation coefficients (ρ_{rg_i,rg_j}) in the following way:

$$\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}} \quad (10)$$

where $cov(rg_i, rg_j)$ is the covariance of the rank variables. Additionally, σ_{rg_i} and σ_{rg_j} are the standard deviations of the rank variables.

The empirical results are summarized in Table 5. Our evidence show the highest rank correlation for the pairs of markets Germany-France (ρ_{rg_1,rg_2}), Japan-France (ρ_{rg_2,rg_3}) and Germany-Japan (ρ_{rg_1,rg_3}), suggesting a level of integration among Germany, France and Japan. The above results are explained by two main reasons: (1) the membership of Germany and France in the common currency union, and (2) the high exposure of Japan into the European financial market: According to Foreign direct investments (FDIs), Japan has increased the inward investment stock, going from €122 billion in 2008 to more than €200 billion in 2016 (European Commission's Directorate-General for Trade, 2018). Of particular interest is our finding that the pairs of markets Germany-China(ρ_{rg_1,rg_4}), France-China (ρ_{rg_2,rg_4}) and Japan-China (ρ_{rg_3,rg_4}) are not significant, suggesting the immunity of Chinese CDS market.

5.3 Estimates of conditional variance and covariance statistics

Table 6 reports the estimated average values ($\overline{h_{ij}}$) of conditional variances and conditional covariances, with i, j = 1,…, N. First we calculate and store the conditional variances and conditional covariances generated by the fourvariate cDCC model. Then, we estimate a regression equation for the conditional variances and conditional covariances on a constant and a trend, generating the conditional variance and covariance statistics. We assume that the average values reflect the own volatility and the cross-volatility spillovers.

Results state strongest own volatility effects for China ($\overline{h_{44}}$), Germany ($\overline{h_{11}}$), France ($\overline{h_{22}}$) and Japan ($\overline{h_{33}}$). Economic conditions of China may explain the higher own volatility. Global managers invest into Chinese CDS market[13], creating turmoil in the CDS market due to the increased concerns about: (1) an economic slowdown, (2) a property bubble, and (3) the shadow banking system. In addition, Japan[14] exhibits the lowest own volatility. This is interpretable regarding that Japanese CDS market is less exposed compared to other CDS markets globally, considering that companies in Japan prefer more to borrow from banks than to borrow from capital markets.

According to the cross-volatility spillovers, we note that $\overline{h_{12}} > \overline{h_{13}} > \overline{h_{23}} > \overline{h_{34}} > \overline{h_{14}} > \overline{h_{24}}$. The above results suggest that spillover effects for the pairs of countries Germany-Japan ($\overline{h_{13}}$), France-Japan ($\overline{h_{23}}$) and Germany-France ($\overline{h_{12}}$) are relatively stronger, indicating that Germany, France and Japan are integrated. Two are the major reasons for the higher integration for Germany, Japan and France: (1) the membership of Germany and France in the common currency union and (2) the high exposure of Japan into the European financial market. (European Commission's Directorate-General for Trade 2018). Furthermore, our evidence suggest the lowest cross-volatility spillovers for the pairs of markets Japan-China ($\overline{h_{34}}$), Germany -China ($\overline{h_{14}}$) and France-China ($\overline{h_{24}}$), implying low or no contagion.

Figure 3 plots the behavior of conditional variances for China (Graph A), France (Graph B), Germany (Graph C) and Japan (Graph D). By contacting a visual exploration, we observe that all markets exhibit strong ups and downs over time. France and Germany experience large spikes in the start of the sample period revealing the effects of Eurozone debt crises.

In figure 4 we graph the conditional covariances. Results suggest positive values for the conditional covariances between Germany and France (Graph A), whilst the rest pairs of markets exhibit positive and negative values. Specifically, for the market pairs Germany-Japan (Graph B), France-Japan (Graph C) and Japan-China (Graph F) conditional covariances stay positive for a longer period, while for the market pairs, Germany-China (Graph D) and France-China (Graph E) conditional covariances stay negative for a longer period.

[13] Estimates put the total size of the market at over $500bn. China's government promoted small and medium-sized enterprises by providing them with credit guarantee, defining China's CDS market as one of the most popular worldwide.

[14] Japan CDS market has traditionally experienced tighter spreads than their USA and their European counterparts have been trading wider.

5.4 Economic analysis of dynamic conditional correlation coefficients

We proceed with the fourvariate AR(1)-FIGARCH(1,d,1)-cDCC's estimation, using sovereign CDS spread returns of Germany, France, China and Japan against USA, illustrated graphically in Figure 5. The dynamic conditional correlation coefficient (DCC coefficient) estimates aim to give us a much clearer view of contagion effects.

As depicted in graph A of figure 5, the DCC coefficient between Germany and France are positive and persistently high in two periods (30/09/2013 to 28/02/2017 and 28/07/2017 to 5/02/2018), foreshadowing interdependence phenomenon, see for instance, Forbes and Rigobon (2002). The membership of Germany and France in Eurozone rationalizes the strong economic interdependence between the two countries. Moreover, DCC coefficient is positive and highly volatile in the two periods (6/08/2011 to 29/09/2013 and 01/03/2017 to 27/07/2017), implying contagion effects and generating two important ramifications from the investor's perspective. First, a highly volatile DCC coefficient implies that the stability of the correlation is less reliable in guiding portfolio decision. Second, a DCC coefficient with positive values suggests that the benefit from market-portfolio diversification becomes less, since holding a portfolio with diverse sovereign CDS premiums for Germany and France is subject to systematic risk. Furthermore, DCC coefficient exhibits two main jumps over time (28/11/2012, 23/04/2017) considering the European Commission's approval of Spanish government's plan to shrink and restructure three major Spanish banks and sell a fourth (28/11/2012) and the French Presidential elections[15] (23/04/2017).

Next, the DCC coefficients for the pairs of countries Germany-Japan (Graph B of figure 5) and France-Japan (Graph C of figure 5) exhibit strong co-movements, since Germany and France are Eurozone members and they are economically interdependent. Although DCC coefficients are positive and extremely volatile over time, they present some signs of negative values, providing evidence of contagion effects that imply increasing riskiness from an investor's point of view. In addition, DCC coefficients demonstrate three common extreme jumps (07/01/2015, 20/09/2015, 23/06/2016) that can be attributed to: (a) Charlie Hebdo attack in Paris (07/01/2015), (b) Greek domestic conditions e.g. legislative elections

[15] In 23rd April 2017 took place the first round of the French Presidential Elections of 2017. Emmanuel Macron, who received 24 % of the first round vote, and Marine Le Pen, who received 21.3 %, received the highest vote shares.

(20/09/2015), and (c) the United Kingdom European Union membership referendum (23/06/2016). The above economic events may have caused short-term global markets drop.

Moreover, the DCC coefficients for the pairs of countries Germany-China (Graph D of figure 5) and France-China (Graph E of figure 5) demonstrate strong co-movements justified by the membership of Germany and France in Eurozone. However, DCC coefficients stay negative for a long period and they are extremely volatile. Additionally, DCC coefficients present some common jumps over time with some of the most important generated by short-term global market drops of the following economic facts: (a) the 19bn euros worth bailout of Spain's fourth largest bank, Bankia (25/05/2012), (b) the day The President of the Catalonia, Artur Mas i Gavarró dropped plans for a referendum on independence on 9/11/2014 from Spain (14/10/2014), and (c) the European Central Bank announcement of an aggressive money-creation program, printing more than one trillion new euros (22/01/2015).

Graph F of figure 5 show that the DCC coefficient between Japan and China are mainly positive, however are extremely volatile over time, indicating a low stability of the correlation. Interestingly, we observe some extreme jumps over time (30/03/2015, 02/04/2016) including jumps generated by major economic events, i.e. (a) on 30/03/2015, the BOJ decided to keep in place its massive easing program of purchasing 80 trillion yen ($670 billion) worth of assets annually, and (b) foreign investors bought a net of ¥ 415.2 billion worth of Japanese stocks in the week that ended 02/04/2016 bringing an end to 12 weeks of net selling, among others.

5.5 Diagnostic tests, hypothesis testing & information criteria

Hypothesis testing results and information criteria are exhibited in table 3, $x^2(8)$ statistic results suggest that the null hypothesis of no spillovers is rejected at 1% significance level. In addition, Ljuing-Box test results (Hosking 1980; Li-McLeod 1983) provide evidence of no serial autocorrelation, suggesting the absence of misspecification errors of the estimated MGARCH model. Furthermore, AIC and SIC information criteria are provided for our model.

6. Conclusions

In this article, we study the volatility transmission among 20-year maturity sovereign CDS markets using data for USA, Germany, France, Japan and China for the period 2011 – 2018.

We apply a fourvariate cDCC-AR(1)-FIGARCH(1,d,1) framework suggested by Aielli (2009). To the best of our knowledge no empirical study has attempted to analyze the volatility effects among the under investigation sovereign CDS markets in order to quantify and measure potential contagion effects.

We first measure contagion by using the Spearman's rank correlation coefficient. The main empirical findings of our analysis reveal evidence of financial contagion in the country pairs: Germany-France, Germany-Japan and France-Japan, whilst the pairwise correlations between China with the rest countries indicate low or no contagion. Next, we contacted a similar analysis for contagion by using conditional variance and covariance statistics. Results indicate contagion effects in the pairs: Germany-France, Germany-Japan and France-Japan, confirming the results of Spearman's rank correlation. China proved to be extremely volatile, supporting the results from the basic statistics. Then, we have extended our analysis by considering the DCC coefficients between CDS markets. Graph results confirm the former analysis and find evidence of stronger contagion for the pairs of markets Germany-France, Germany-Japan and France-Japan.

Our empirical findings are important for investors and policy makers. Investors can use the information about the contagion effects among the above markets, quantify the risk, and gain the flexibility to top-up their investments in CDS market at any time. They should be cautious about simultaneously investing into markets that exhibit contagion effects. Furthermore, the policy makers should examine possible strategies that take into account the spillovers of the above markets during future crises.

References

Aielli, G. P.: Dynamic conditional correlations: on properties and estimation. Technical report, Department of Statistics, University of Florence (2009)

Anderson, M.: Contagion and Excess Correlation in Credit Default Swaps. Working Paper, Department of Finance, Fisher College of Business, Ohio State University (2010)

Antoniou, A, Koutsmos, G., Percli, A.: Index futures and positive feedback trading: evidence from major stock exchanges. Journal of Empirical Finance. Vol. 12. No. 2, 219-238 (2005)

Baillie, R. T., Bollerslev, T. Mikkelsen, H. O.: Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics. Vol. 74. No. 1, 3-30 (1996)

Belke A., Gokus, C.: Volatility Patterns of CDS, Bond and Stock Markets before and during the Financial Crisis Evidence from Major Financial Institutions. Working Papers, Deutsches Institut fur Wirtschaftsforschung (2011)

Blanco, R., Brennan, S., Marsh, I. W.: An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps. The Journal of Finance. Vol. 60. No. 5, 2255-2281 (2005)

Bollerslev, T., Chou, R., Kroner, K. F.: ARCH modeling in finance: A review of the theory and empirical evidence. Journal of Econometrics. Vol. 52. No. 1-2, 5-59 (1992)

Calice, G., Chen, J., Williams, J.: Liquidity Spillovers in Sovereign Bond and CDS Markets. Paolo Baffi Centre Research Paper (2011)

Caporale, G. M., Pittis, N., Spagnolo, N.: Volatility Transmission and Financial Crises. Journal of Economics and Finance. Vol. 30. No. 3, 376-390 (2006)

Chen, K, Fleming, M., Jackson, J., Li, A., Sarkar, A.: An Analysis of CDS Transactions: Implications for Public Reporting. Federal Reserve Bank of New York, Staff Reports. No. 517 (2011)

Chen, L., Lesmond, D. A., Wei, J.: Corporate Yield Spreads and Bond Liquidity. Journal of Finance. Vol. 62. No. 1, 119-149 (2007)

Dickey, D. A., Fuller, W. A.: Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association. Vol. 74, 427-431 (1979)

Didier, T., Mauro, P., Schmuckler, S.: Vanishing financial contagion?. Journal of policy modeling. Vol. 30, 775-791 (2008)

Dimitriou, D, Kenourgios, D., Simos, T.: Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH-DCC approach. International Review of Financial Analysis. Vol. 30, 46-56 (2013)

Engle, R. F.: Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics. Vol. 20, 339-350 (2002)

European Commission’s Directorate-General for Trade: The economic impact of the EU-Japan economic partnership agreement (EPA). European Commision (2018)

Fonseca, J. D., Gottschalk, K.: The Co-movement of Credit Default Swap Spreads, Stock Market Returns and Volatilities: Evidence from Asia-Pacific Markets. Tech. rep., Working Paper, May 31 (2012)

Forbes, K. J., Rigobon, R.: No Contagion, Only Interdependence: Measuring Stock Market Comovements. The Journal of Finance. Vol. 57. No. 5, 2223-2261 (2002)

Hull, J.C.: Options, Futures and Other Derivatives. 6th edition, Prentice Hall (2008)

Koseoglu, S. D.: The Transmission of Volatility between the CDS Spreads and Equity Returns Before, During and After the Global Financial Crisis: Evidence from Turkey. Proceedings of 8th Asian Business Research Conference 1 - 2 April 2013, Bangkok, Thailand (2013)

Lake, A., Apergis, N.: Credit default swaps and stock prices: Further evidence within and across markets from mean and volatility transmission with a MVGARCH-M model and newer data. University of Pireaeus (2009)

Meng, L., Gwilym, O., Varas, J.: Volatility Transmission among the CDS, Equity, and Bond Markets. Journal of Fixed Income. Vol. 18. No. 3, 33-46 (2009)

Sarig, O., Warga, A.: Some empirical estimates of the risk structure of interest rates. Journal of Finance. Vol. 44. No. 4, 1351-1360 (1989)

Schreiber, I., Müller, G., Klüppelberg, C., Wagner, N.: Equities, Credits and Volatilities: A Multivariate Analysis of the European Market During the Sub-prime Crisis. in: Working Paper, TUM, University of Passau, Germany, in: http://ssrn.com/abstract=1493925, accessed on: January 02, 2013 (2009)

Stevens, G.: Economic prospects in 2008: An antipodean view. Address by the Governor of the Reserve Bank of Australia to Australian Business, January 18, London, UK (2008)

Tokat, H. A.: Understanding volatility transmission mechanism among the cds markets: Europe & North America versus Brazil & Turkey. Economia Aplicada. Vol. 17, No. 1 (2013)

Watzka, S., Missio, S.: Financial Contagion and the European Debt Crisis. CESIFO working paper. No. 3554 (2011)

Wei, C. C.: Multivariate GARCH Modeling Analysis of Unexpected USD, Yen and Euro-Dollar to Reminibi Volatility Spillover to Stock Markets. Economics Bulletin. Vol. 3. No. 64, 1-15 (2008)

Worthington, A.C., Higgs, H.: A Multivariate GARCH Analysis of the Domestic Transmission of Energy Commodity Prices and Volatility: A Comparison of the Peak and Off-Peak Periods in the Australian Electricity Spot Market. Queensland University of Technology, School of Economics and Finance, Discussion Paper No: 140 (2003)

Zhu, L., Yang, J.: The Role of Psychic Distance in Contagion: A Gravity Model for Contagious Financial Crises. Working Paper, The George Washington University (2004)

Appendix

Table 1

Major annual macroeconomic figures of Germany, France, Japan, China and USA.

	2011	2012	2013	2014	2015	2016	2017
Panel A: Germany							
GDP per capita growth (annual %)	5,599	0,303	0,215	1,505	0,866	1,124	1,794
Unemployment, total (% of total labor force)	5,82	5,38	5,23	4,98	4,619	4,119	3,736
Net acquisition of financial assets (% of GDP)	-0,79	1,126	-0,07	0,388	-0,44	0,031	NA
Exports of goods and services (annual % growth)	8,28	2,826	1,715	4,635	5,232	2,63	4,617
Imports of goods and services (% of GDP)	39,92	39,89	39,43	38,78	38,88	38,14	39,66
Stocks traded, total value (% of GDP)	41,87	35,26	34,97	32,61	42,79	32,32	42,38
Panel B: France							
GDP per capita growth (annual %)	1,586	-0,3	0,059	0,464	0,646	0,784	1,426
Unemployment, total (% of total labor force)	8,81	9,399	9,92	10,3	10,35	10,06	9,68
Net acquisition of financial assets (% of GDP)	0,666	2,335	0,352	0,344	0,486	-0,39	NA
Exports of goods and services (annual % growth)	6,879	2,539	1,909	3,312	4,265	1,847	3,12
Imports of goods and services (% of GDP)	30,36	30,49	30,39	30,81	31,15	30,97	31,98
Stocks traded, total value (% of GDP)	46,47	40,03	39,32	40,97	NA	NA	NA
Panel C: Japan							
GDP per capita growth (annual %)	0,069	1,657	2,147	0,507	1,461	1,054	1,88
Unemployment, total (% of total labor force)	4,55	4,349	4,03	3,579	3,329	3,13	2,831
Net acquisition of financial assets (% of GDP)	2,376	-0,95	0,384	1,581	-1,43	-0,03	NA
Exports of goods and services (annual % growth)	-0,24	-0,08	0,761	9,29	2,941	1,338	NA
Imports of goods and services (% of GDP)	15,46	16,09	18,23	20	18	15,14	NA
Stocks traded, total value (% of GDP)	70	53,94	117,9	99,88	126,7	105,6	118,6
Panel D: China							
GDP per capita growth (annual %)	9,012	7,332	7,226	6,755	6,358	6,123	6,303
Unemployment, total (% of total labor force)	4,34	4,469	4,539	4,592	4,605	4,649	4,675
Net acquisition of financial assets (% of GDP)	NA	NA	NA	NA	NA	NA	NA
Exports of goods and services (annual % growth)	NA	NA	NA	NA	NA	NA	NA
Imports of goods and services (% of GDP)	24,10	22,69	22,06	21,38	18,10	17,37	18,04
Stocks traded, total value (% of GDP)	88,13	58,72	80,10	114	355,4	163,4	140,7
Panel E: USA							
GDP per capita growth (annual %)	0,849	1,459	0,956	1,8	2,087	0,742	1,546
Unemployment, total (% of total labor force)	8,949	8,069	7,38	6,17	5,28	4,849	4,438
Net acquisition of financial assets (% of GDP)	-1,16	0,705	1,303	0,996	1,293	1,133	NA
Exports of goods and services (annual % growth)	6,851	3,417	3,481	4,274	0,409	-0,32	NA
Imports of goods and services (% of GDP)	17,31	17,10	16,58	16,54	15,39	14,68	NA
Stocks traded, total value (% of GDP)	264,5	200,2	199,1	223,6	228,4	225,8	205,1

Notes: This table presents the major annual macroeconomics figures of Germany, France, Japan, China and USA for the period 2008 to 2017. Per capita GDP growth the GDP growth of a country divided by the number of people in every country. Unemployment rate is generated by the number of unemployed persons as a percentage of the labor force. Net acquisition of government financial assets includes domestic and foreign financial claims, SDRs, and gold bullion held by monetary authorities as a reserve asset as a percentage of GDP. Exports and imports are generated as a percentage of GDP. Stocks traded refer to the total value of shares traded during the period as a percentage of GDP.

Table 2
Summary statistics of daily CDS spread returns, sample period: 5 October, 2011 – 5 February, 2018.

	Germany	France	Japan	China
Panel A: descriptive statistics				
Mean	4,8354e-005	0,00014198	0,00014917	1,4653e-005
Minimum	-0,060419	-0,031304	-0,030351	-0,064374
Maximum	0,035634	0,026861	0,0416	0,0445
Std. Deviation	0,00062582	0,0060526	0,0035332	0,0083296
Panel B: Normality Test				
Skewness	-0,75460***	-0,32524***	0,45489***	-0,60806***
t-Statistic	12,544	5,4066	7,5617	10,108
p-Value	4,2955e-036	6,4230e-008	3,9784e-0,14	5,0964e-024
Excess Kyrtosis	7,0450***	2,4768***	19,639***	7,4978***
t-Statistic	58,590	20,599	163,33	62,356
p-Value	0,0000	2,8021e-094	0,0000	0,0000
Jarque-Bera	3579,6***	452,22***	26654***	3978,6***
p-Value	0,0000	6,3323e-099	0,0000	0,0000
Panel C: Unit Root Test				
ADF	-23,4825***	-23,0794***	-249286***	-30,0984***
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663
Panel D: Long memory tests GPH (1983) test and GSP Robinson (1998) test- d estimates				
GPH	0,0286919	0,0756086***	0,0299162	-0,264283***
p-Value	0,2358	0,0018	0,2165	0,0000
Badwidth	827	826	825	823
GSP	0,0167657	0,060499***	0,0211289	-0,211763***
p-Value	0,3349	0,0005	0,2243	0,0000
Badwidth	827	827	827	827
Panel E: Rescaled variance test-absolute returns				
Number of autocorrelations=5, RV stat.	1,07767	1,17736**	1,01701	0,42751***
ZN stat.	1,21807	2,65094	0,17515	-6,10866
p-Value	0,22320	0,00803	0,86096	0,0000
Number of autocorrelations=10, RV stat.	1,07182	1,20385**	0,95419	0,34330***
ZN stat.	0,74996	2,00223	-0,32245	-4,94988
p-Value	0,45328	0,04526	0,74711	0,0000

Notes: Panel A presents the descriptive statistics of the daily CDS spread returns, Panel B shows the normality test, Panel C demonstrates the unit root tests. We used intercept and a time trend to generate the ADF statistic. Panel D reveals the Geweke and Porter-Hudak's (1983) (GPH) test and the Gaussian semi parametric (GSP) test of Robinson (1995). We used the above tests in order to examine the existence of long memory for the absolute daily CDS spread returns. In Panel E we observe the (R/S) tests' results. We used the (R/S) tests in order to examine the long term dependence.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3

Estimates of AR(1)-FIGARCH(1,d,1) model, sample period: 5 October, 2011 – 5 February, 2018.

	Germany	**France**	**Japan**	**China**
constant *(μ)*	0,000160	0,000170	0,0001426**	0,000075
t-Statistic	1,056	1,198	2,111	0,7000
p-Value	0,2913	0,2312	0,0349	0,4840
$AR(1)$	0,051693	0,085445***	0,054843	-0,264252***
t-Statistic	1,745	3,112	1,566	-9,037
p-Value	0,0812	0,0019	0,1177	0,0000
constant *(ω)*	1,392983	0,661540	0,050242	0,417351**
t-Statistic	1,505	1,532	1,474	2,086
p-Value	0,1325	0,1258	0,1408	0,0371
d-Figarch	0,254917***	0,437523***	1,202851***	0,903731***
t-Statistic	3,700	3,554	9,330	4,783
p-Value	0,0002	0,0004	0,0000	0,0000
ARCH *(a)*	0,745088***	0,473286***	-0,006364	0,296672**
t-Statistic	4,651	5,310	-0,04924	2,082
p-Value	0,0000	0,0000	0,9607	0,0375
GARCH *(b)*	0,843556***	0,786766***	0,955730***	0,900421***
t-Statistic	6,844	11,93	37,13	19,59
p-Value	0,0000	0,0000	0,0000	0,0000

Notes: Table 3 presents the results of univariate AR(1)-FIGARCH(1,d,1) model.
** and *** denote statistical significance at the 5% and 1% levels, respectively
Mean equation: $(1 - VL)y_t = \mu + \varepsilon_t$, with t = 1,…,T.
Variance equation: $h_t = \omega[1 - b(L)]^{-1} + \{1 - [1 - b(L)]^{-1}\Phi(L)(1 - L)^d\}\varepsilon_t^2$.

Table 4

Estimates of the fourvariate cDCC model, degrees of freedom, log-likelihood, diagnostic tests and information criteria, sample period: 5 October, 2011 – 5 February, 2018.

Panel A: estimates of cDCC model	
alpha *(α)*	0,021472***
t-Statistic	5,900
p-Value	0,0000
beta *(β)*	0,965965***
t-Statistic	185,5
p-Value	0,0000
degrees of freedom *(v)*	5,615230***
t-Statistic	13,24
p-Value	0,0000
log-likelihood	26982,488
Panel B: diagnostic tests	
$x^2(8)$	4791,3**
p-Value	0,0000
$Hosking^2$ (50)	680,102
p-Value	0,9990111
$Li\text{-}McLeod^2$ (50)	682,579
p-Value	0,9987552
Panel C: Information Criteria	
Akaike	0,020177
Schwarz	0,128081

Notes: Panel A shows the results of the conditional correlation driving process Q_t, the degrees of freedom and the log-likelihood whilst Panel B demonstrates the diagnostic tests of Hosking (1980) and McLeod and Li (1983). In Panel C we see the information criteria of AR(1)-FIGARCH(1,d,1)-cDCC model. The symmetric positive definite matrix Q_t is generated using one lag of Q and of u^*. P-values have been corrected by 2 degrees of freedom for $Hosking^2$ (50) and $Li\text{-}McLeod^2$ (50) statistics.

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

Conditional correlation driving process equation of standardized residuals (u_t): $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u^*_{t-1} u^{*\prime}_{t-1} + \beta Q_{t-1}$.

Log-likelihood equation: $\sum_{t=1}^{T} \left[log \frac{\Gamma\left(\frac{v+N}{2}\right)}{[v\pi]^{\frac{N}{2}} \Gamma\left(\frac{v}{2}\right) v - 2^{\frac{N}{2}}} - \frac{1}{2} log\left(|H_t|\right) - \left(\frac{N+v}{2}\right) log\left[1 + \frac{\varepsilon_t{}' H_t{}^{-1} \varepsilon_t}{v-2}\right]\right]$.

Table 5

Estimates of Spearman's rank correlation coefficient (ρ_{rg_i,rg_j}), sample period: 5 October, 2011 – 5 February, 2018.

Market i	**Germany (i=1)**	**France (i=2)**	**Japan (i=3)**	**China (i=4)**
ρ_{rg_i,rg_1}	**1**			
t-Statistic	-			
p-Value	-			
ρ_{rg_i,rg_2}	0,864735***	**1**		
t-Statistic	47,91	-		
p-Value	0,0000	-		
ρ_{rg_i,rg_3}	0,118823**	0,125056**	**1**	
t-Statistic	2,006	2,274	-	
p-Value	0,0450	0,0231	-	
ρ_{rg_i,rg_4}	-0,002745	-0,007022	0,053556	**1**
t-Statistic	-0,05070	-0,1303	0,9892	-
p-Value	0,9596	0,8963	0,3227	-

Notes: Table 5 exhibits the estimates of elements (ρ_{rg_i,rg_j}) of rank correlation.

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

Spearman's rank correlation equation: $\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}}$.

Table 6

Average values of conditional variances and covariances ($\overline{h_{ij}}$), sample period: 5 October, 2011 – 5 February, 2018.

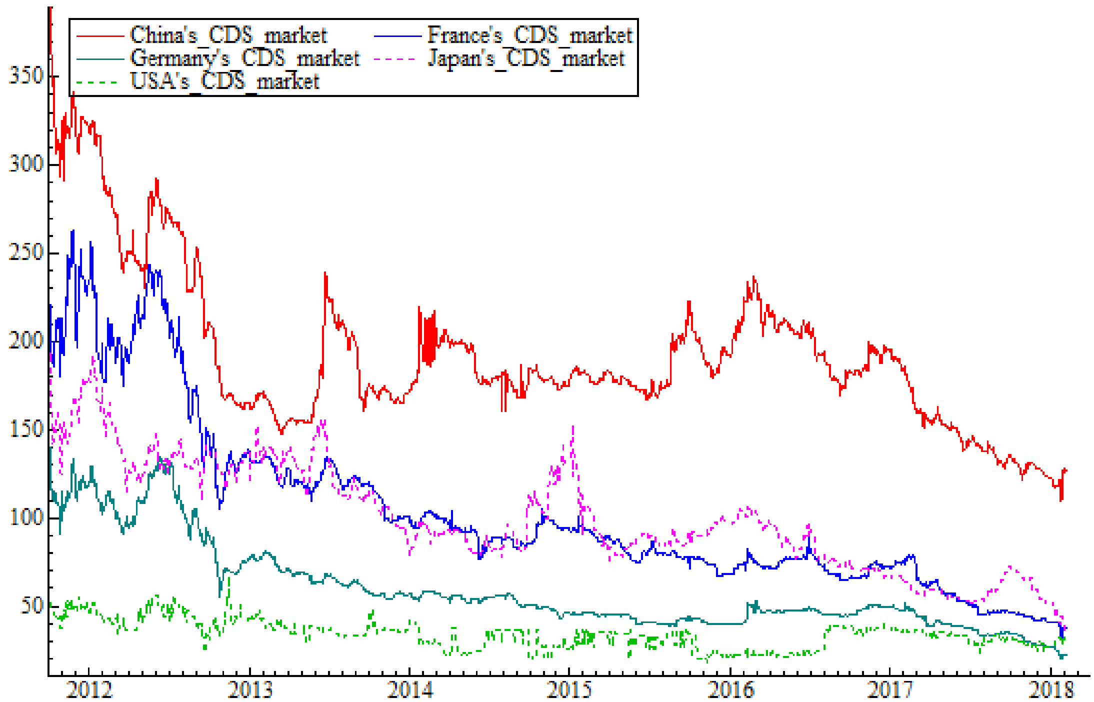
	Average	**St. Deviation**	**Trend (*1000)**	**t-statistic**	**P-value**
Panel A: Conditional variance statistics					
Germany ($\overline{h_{11}}$)	3,96754e-005	2,19406e-005	-4,75369e-009***	-4,23	0,0000
France ($\overline{h_{22}}$)	3,86536e-005	2,20288e-005	-3,35696e-009***	-2,97	0,0030
Japan ($\overline{h_{33}}$)	1,39287e-005	2,33194e-005	7,55481e-010	0,630	0,5291
China ($\overline{h_{44}}$)	6,76721e-005	8,88338e-005	-6,58625e-008***	-15,4	0,0000
Panel B: Conditional covariance statistics					
Germany-France ($\overline{h_{12}}$)	3,07734e-005	1,63941e-005	5,92074e-009***	7,12	0,0000
Germany-Japan ($\overline{h_{13}}$)	3,69396e-006	3,86692e-006	1,70267e-009***	8,75	0,0000
Germany-China ($\overline{h_{14}}$)	-2,51417e-007	4,09229e-006	3,91582e-010	1,86	0,0631
France-Japan ($\overline{h_{23}}$)	3,50061e-006	3,76781e-006	1,35679e-009***	7,10	0,0000
France-China ($\overline{h_{24}}$)	-5,47391e-007	3,50787e-006	8,51301e-010***	4,75	0,0000
Japan-China ($\overline{h_{34}}$)	1,07559e-006	2,0075e-006	-5,51186e-010***	5,38	0,0000

Notes: $\overline{h_{ij}}$, with i, j = 1,…,N, denotes the average values of conditional variances and conditional covariances. We calculate and store the conditional variances and conditional covariances generated by the cDCC model. Then, we estimate a regression equation for the conditional variances and conditional covariances on a constant and a trend, generating the conditional variance and covariance statistics.

*** denote statistical significance at 1% level.

Multivariate conditional variance equation: $H_t = D_t R_t D_t$.

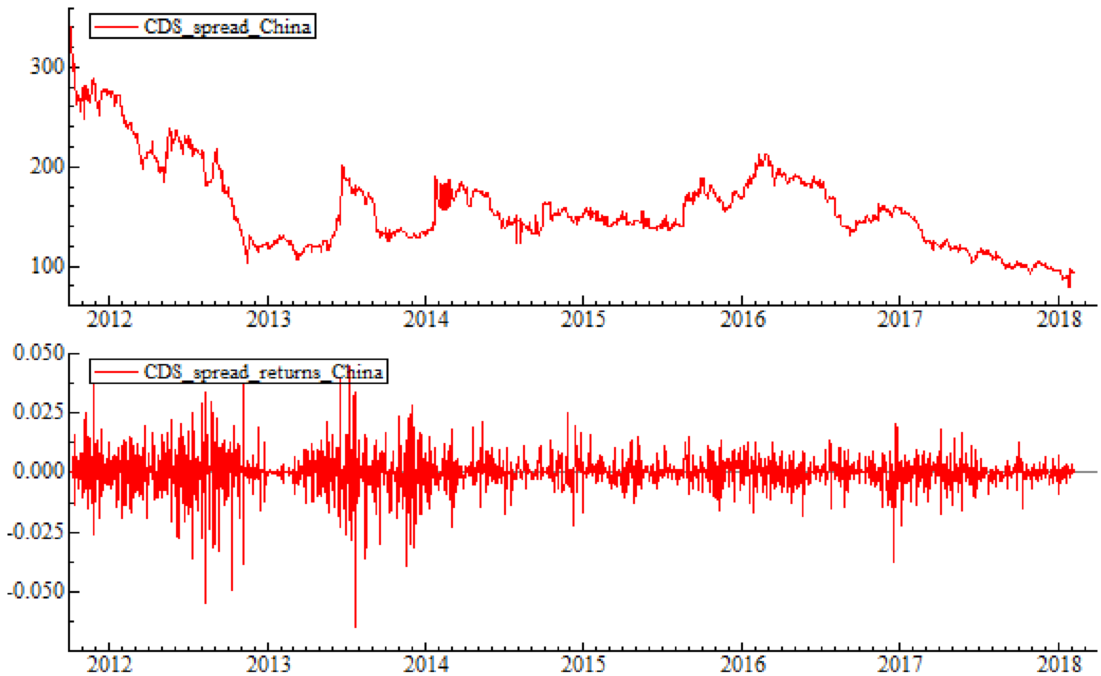
Figure 1. Actual series of 20-year maturity CDS premium mid prices for all markets.



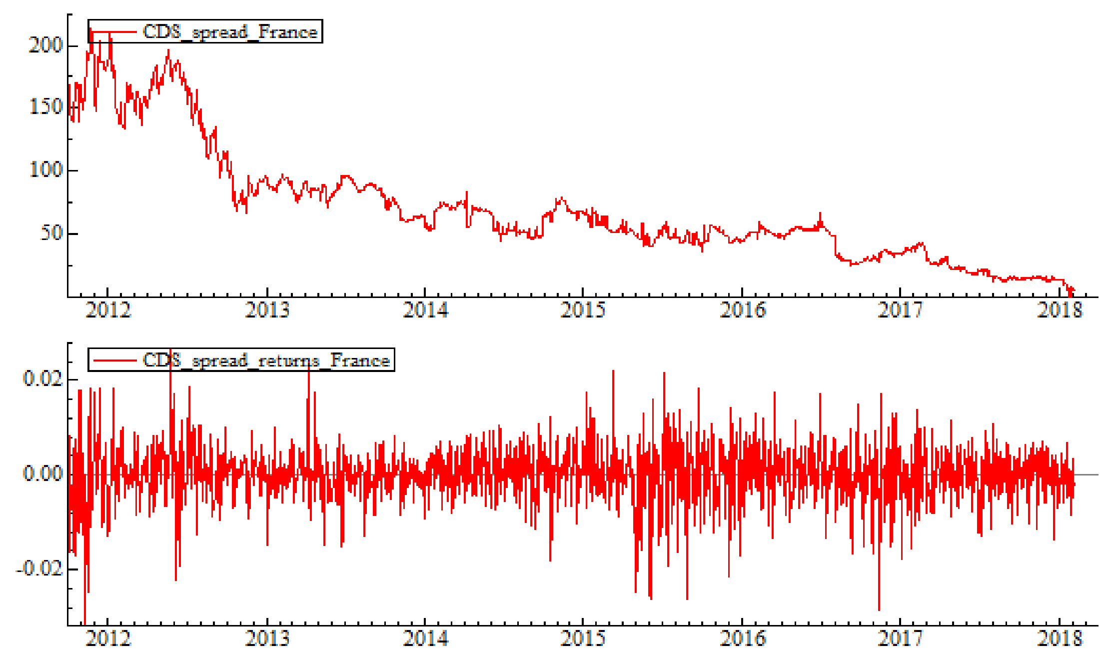
Notes: The lines represent the sovereign CDS premium mid prices for China, Germany, USA, France and Japan.

Figure 2. Actual series of 20-year maturity sovereign CDS spreads and their respective logarithmic returns.

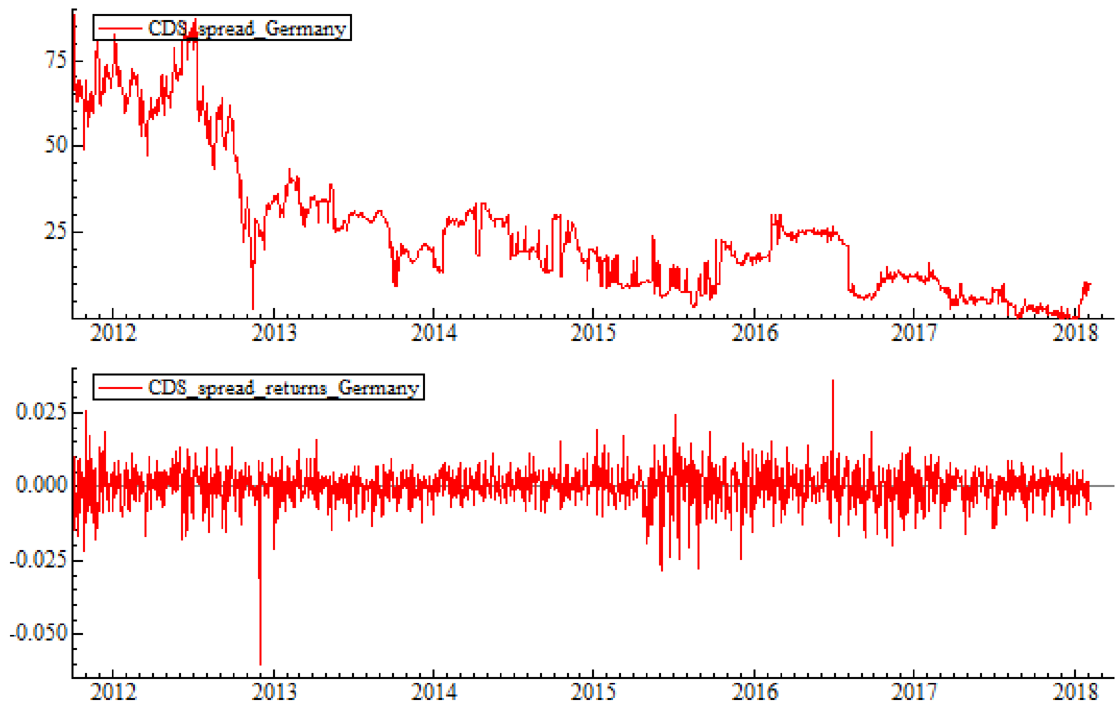
Graph A. China



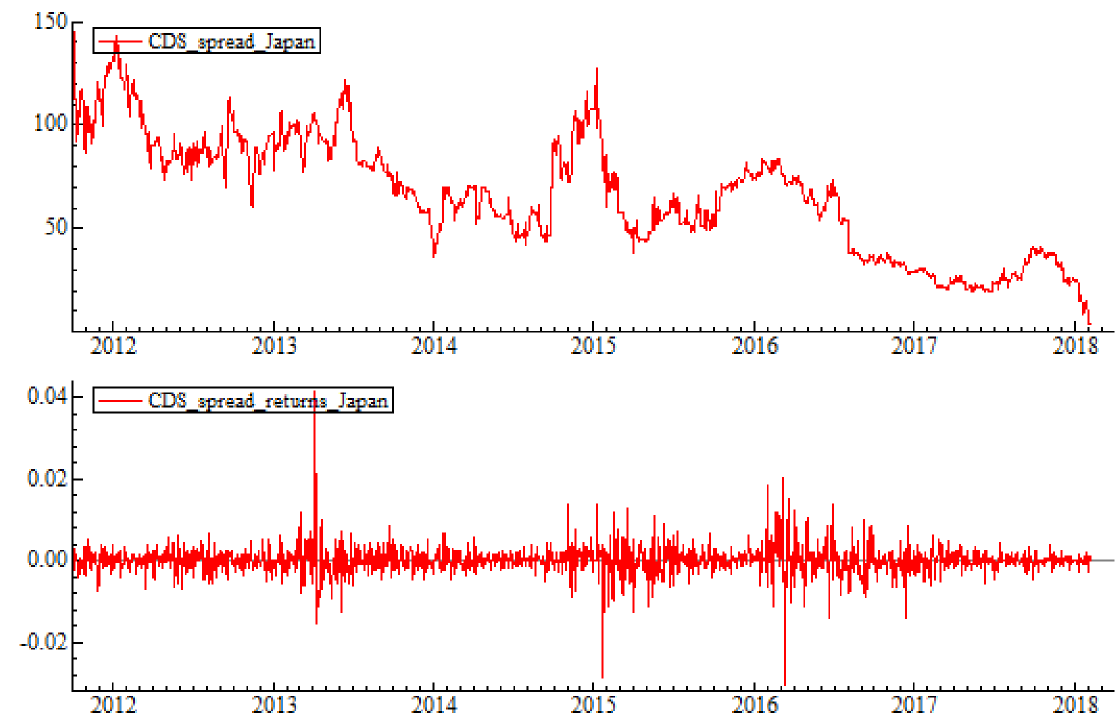
Graph B. France



Graph C. Germany



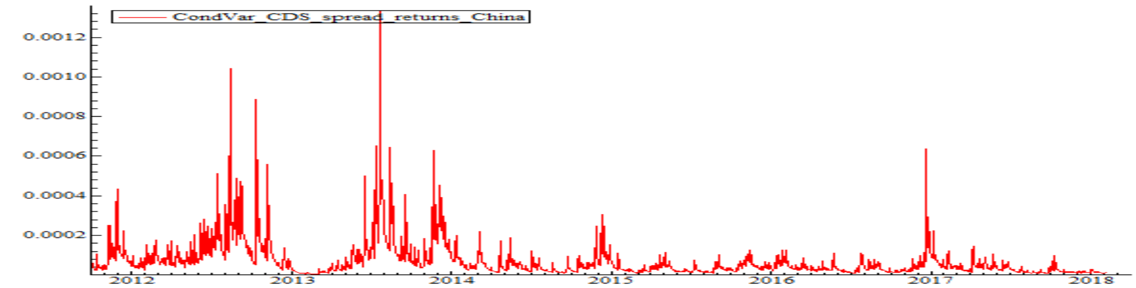
Graph D. Japan



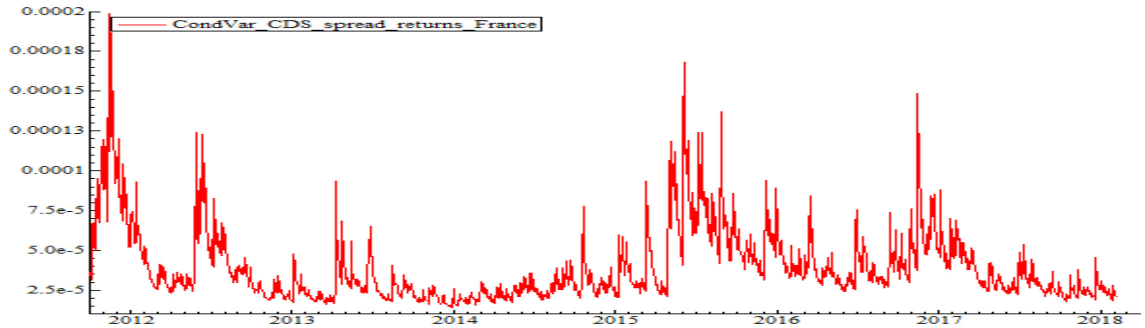
Notes: Based on USA, we calculate CDS spread logarithmic returns using the equation: $r_t = ln(p_t) - ln(p_{t-1})$.

Figure 3. Conditional variances of the univariate AR(1)-FIGARCH(1,d,1) model.

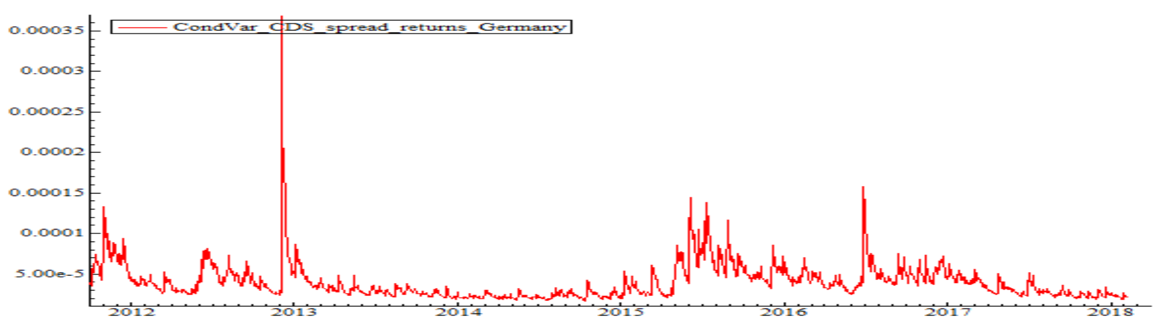
Graph A. China



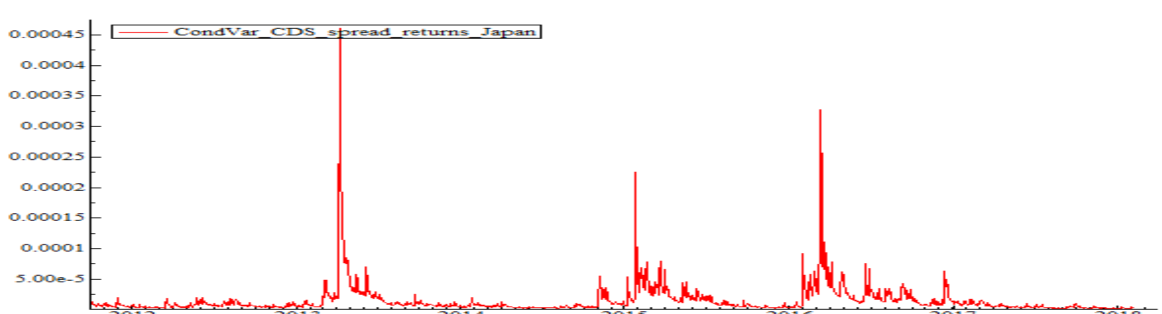
Graph B. France



Graph C. Germany



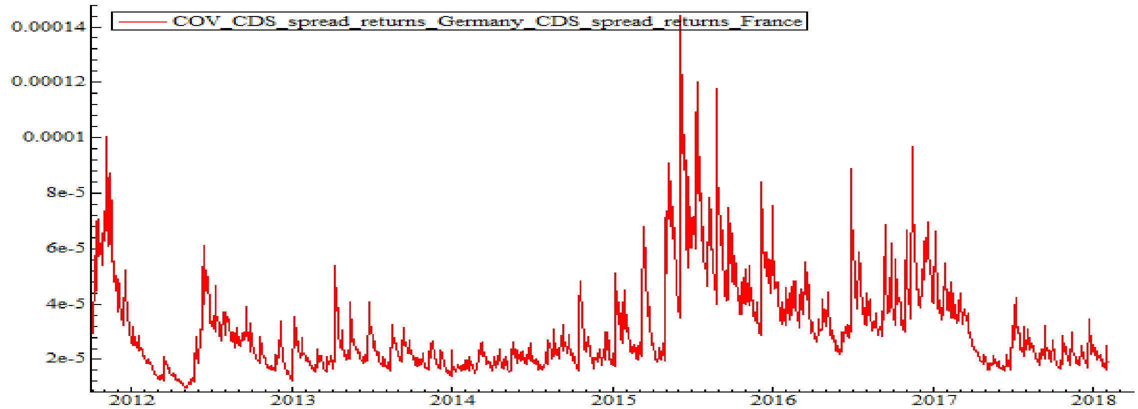
Graph D. Japan



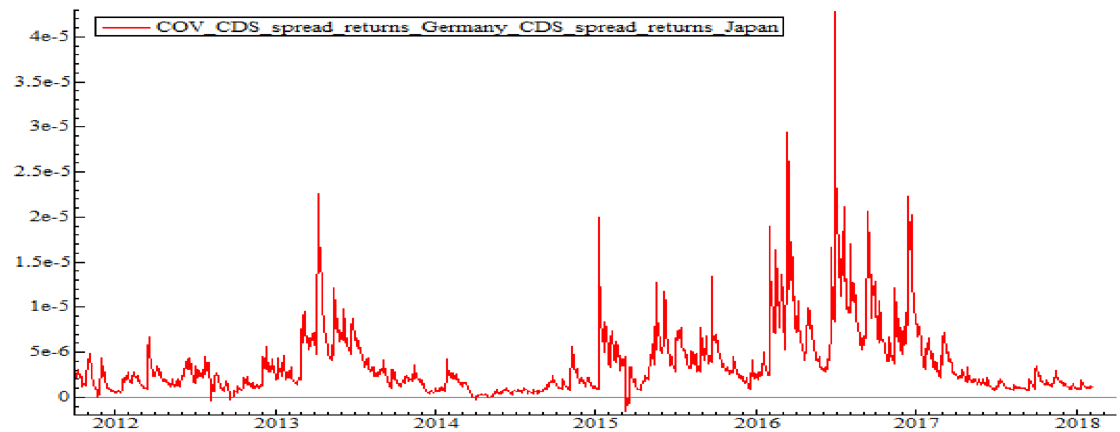
Notes: The red lines represent the conditional variance (h_t) for all markets, generated by Equation 3.

Figure 4. Conditional covariances of the fourvariate AR(1)-FIGARCH(1,d,1)-cDCC model.

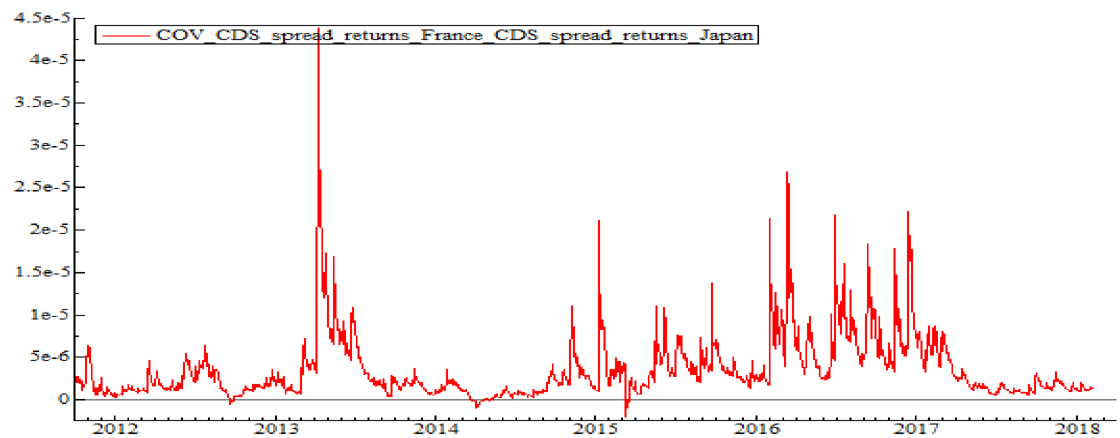
Graph A. Germany-France



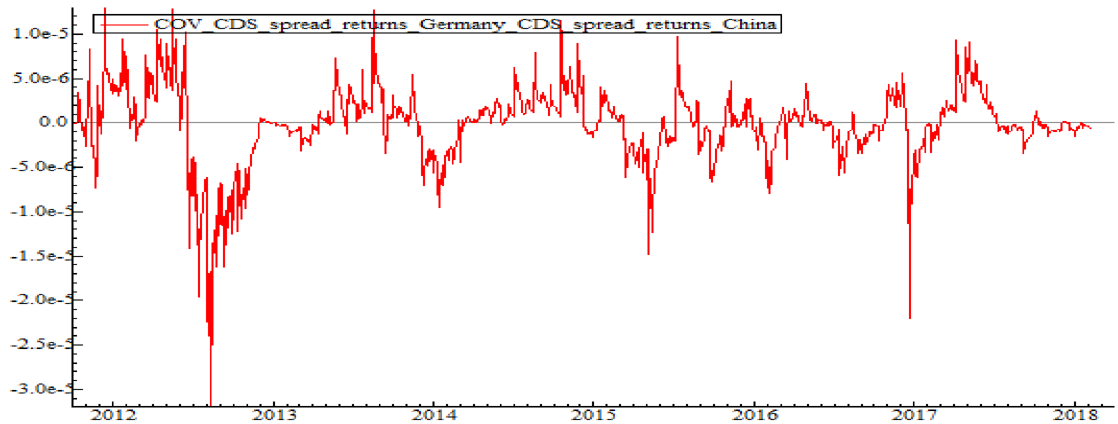
Graph B. Germany-Japan



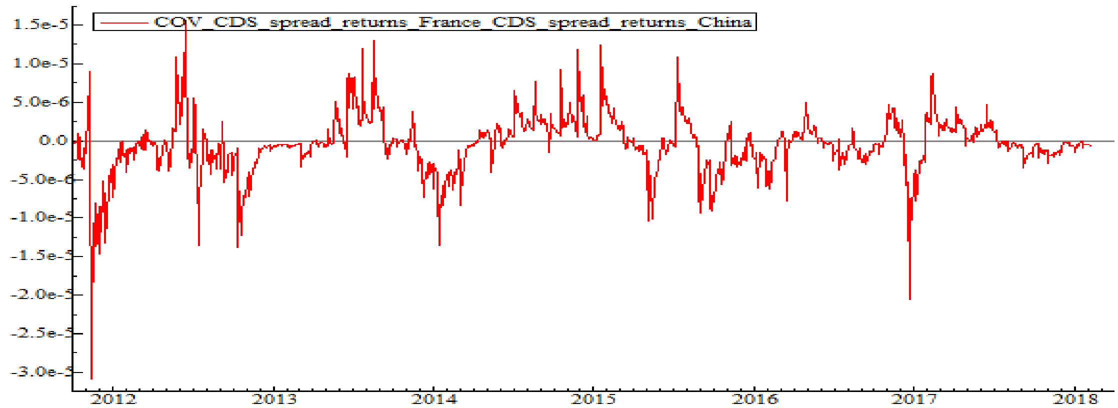
Graph C. France-Japan



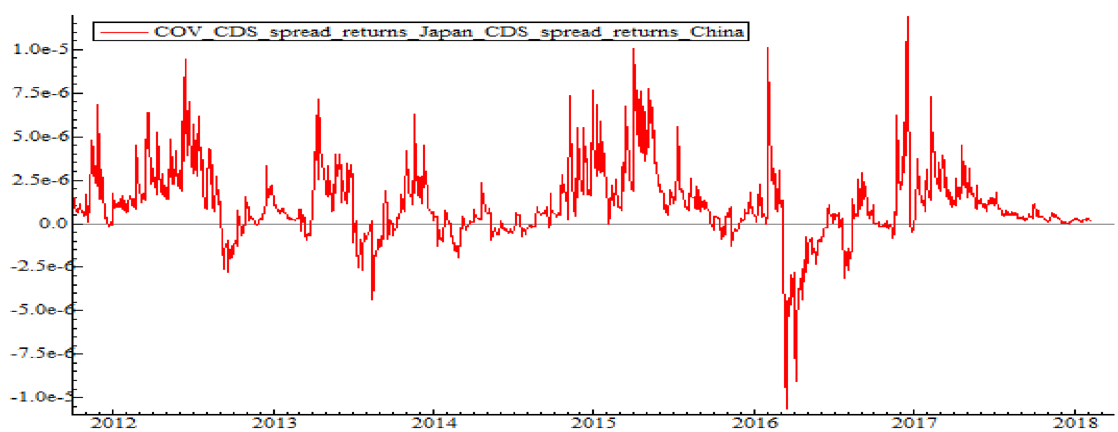
Graph D. Germany-China



Graph E. France-China



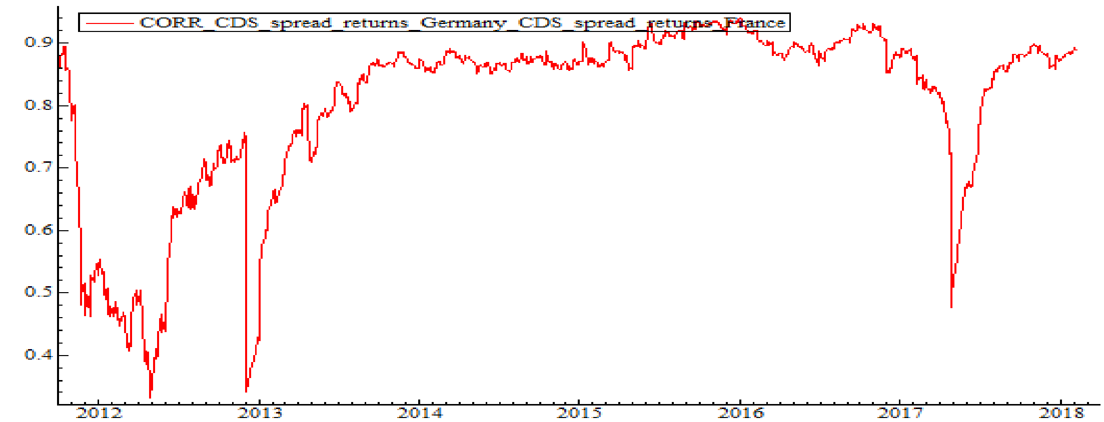
Graph F. Japan-China



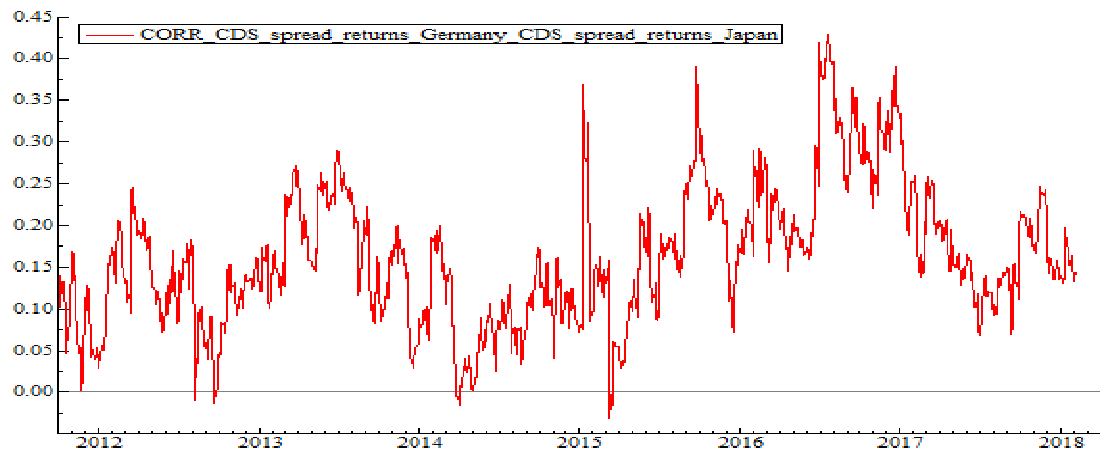
Notes: The red lines represent the conditional covariances of the fourvariate conditional variance matrix (H_t) for all the pairs of markets, generated by Equation 4.

Figure 5. Dynamic conditional correlations of the fourvariate AR(1)-FIGARCH(1,d,1)-cDCC model.

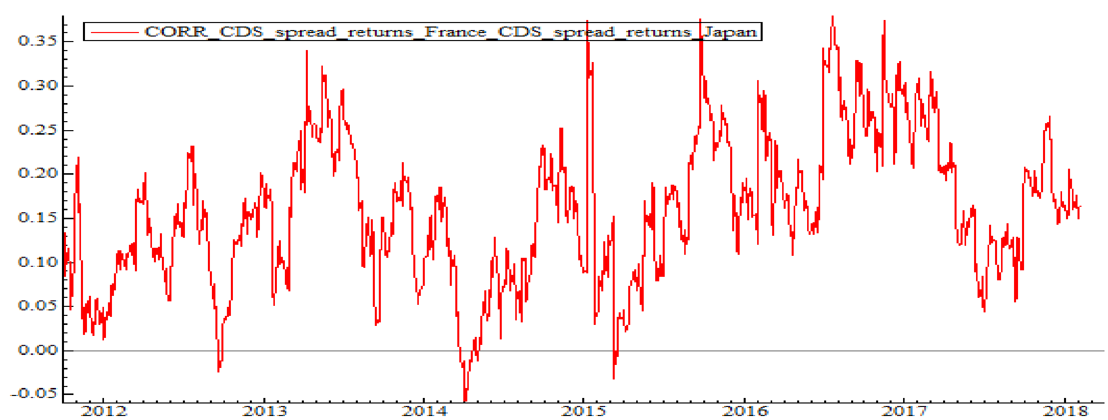
Graph A. Germany-France



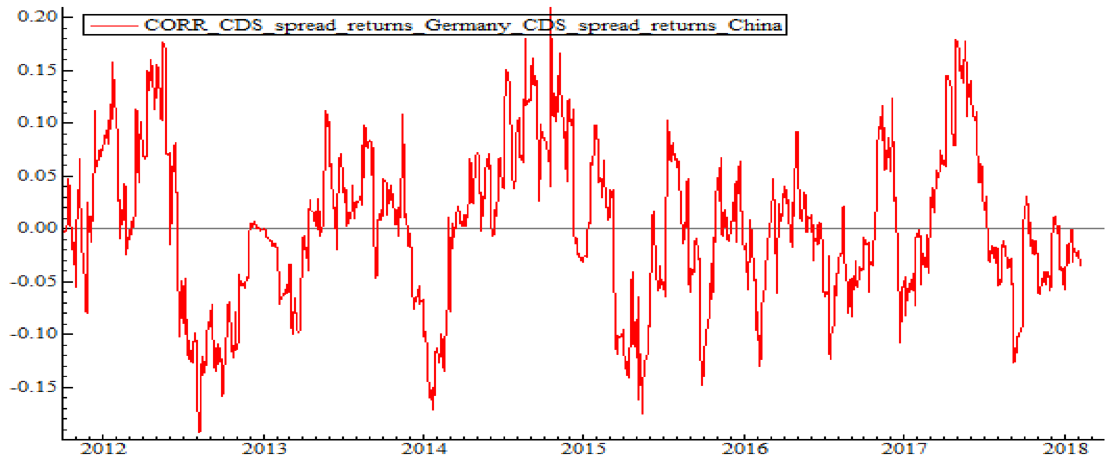
Graph B. Germany-Japan



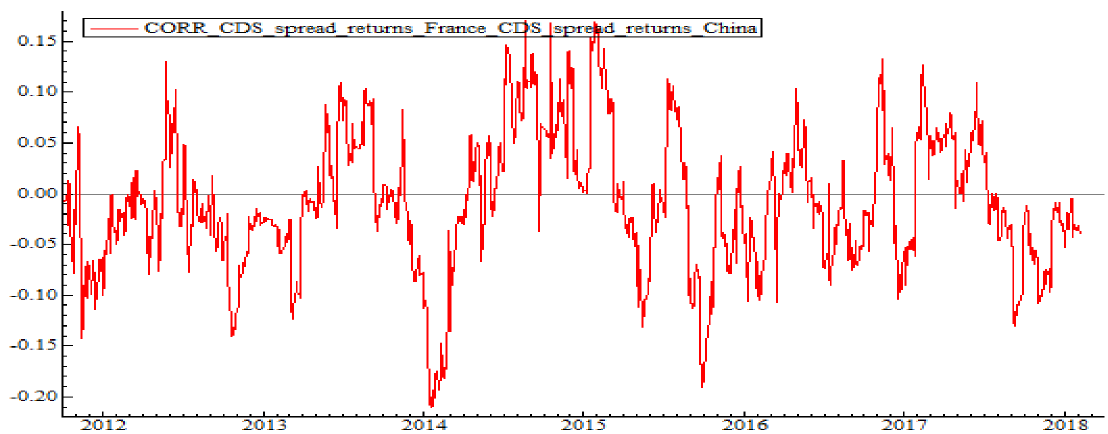
Graph C. France-Japan



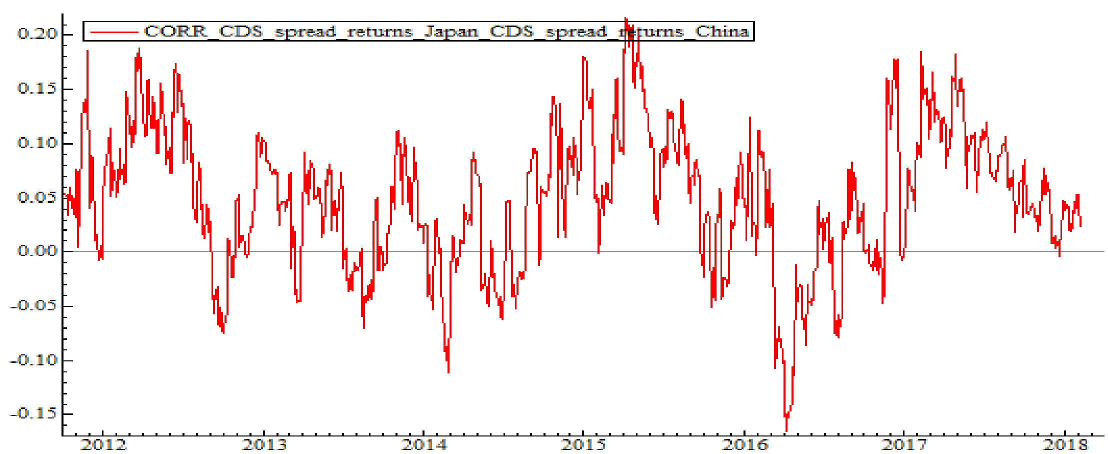
Graph D. Germany-China



Graph E. France-China



Graph F. Japan-China



Notes: The red lines illustrate the dynamic conditional correlations (R_t), generated by Equation 6 for all the pairs of markets.

Chapter 2

FOREX and equity markets spillover effects among USA, Brazil, Italy, Germany and Canada in the aftermath of the Global Financial Crisis

Abstract

In this paper we investigate the spillover effects of FOREX and equity markets for USA, Brazil, Italy, Germany and Canada on the basis of daily data. We test for contagion co-movements for the period 2010-2018 post global financial crisis, using the trivariate AR-diagonal BEKK model. The estimated dynamic conditional correlations show the strongest contagion effects for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. For institutions, multinational corporations and active investors, a portfolio consisting of financial assets from the above markets is extremely risky.

1. Introduction

The purpose of this paper is to investigate the intedependence of equity and FOREX market returns between USA and four other countries[16] of G20 namely the Germany, Italy, Brazil and Canada in the aftermath[17] of the recent GFC (2007). Based on the conditional second moments of the distribution of equity and FOREX market returns, we quantify the volatility spillover effects by using four trivariate BEKK models[18]: (1) S&P500, BOVESPA, BRL/USD, (2) S&P500, FTSEMIB, EUR/USD, (3) S&P500, DAX30, EUR/USD, and (4) S&P500, DAX30, EUR/USD.

The contagion among financial markets is now at the center of financial analysis (Ku and Wang 2008; Yilmaz 2010; Jiang and Xing 2010; Akar 2011; Sehgal 2015). The recent global financial crisis (GFC) (2007-2009) has brought significant attention to the financial contagion phenomenon (Billio and Caporin 2010; Dimitriou and Kenourgios 2015; Li and Giles 2015). Initially, the financial crisis was triggered by the subprime mortgage market crisis in the USA (2007) and developed into a full-blown international banking crisis with the collapse of Lehman Brothers (2008), generating financial distress in the global financial markets. The growing globalisation of financial markets played an important role for the increased spread of the crisis. Serious financial crises (Mexican crisis of 1994, Asian financial crisis of 1997, Russian dept crisis of 1998, Brazilian currency crisis of 1999, Greek debt crisis of 2010) forced investors to rekindle their perspective about the way that financial markets operate and interact (Burzała 2014; Burzała 2015). Thus, the way that shocks are transmitted from one financial market to another financial market after major crises has been studied by many researchers, i.e. Forbes and Rigobon (2002) and Pericoli and Sbracia (2003), among others. Forbes and Rigobon (2002) defined contagion phenomenon as a significant increase in cross-market linkages after a shock. Focusing on the above narrow definition of contagion, we

[16] Initially, we wanted to apply the model for all the countries of G20. However, the optimization algorithm failed to converge for the rest countries of G20 except the under investigation countries.

[17] At first, we applied the trivariate models for the crisis period and the after crisis period. Unfortunately we faced two major problems in the crisis period and we used only the after crisis period: (1) the optimization algorithm failed to converge for the most countries, and (2) we didn't find consistent diagnostic tests for all the countries of G20.

[18] We tried different multivariate models without success. The diagonal BEKK model was the only model that we succeeded to employ by finding consistent diagnostic tests.

empirically investigate the linkages among major FOREX and equity markets in light of the financial crisis of 2007.

Earlier authors have suggested that during a financial crisis, FOREX markets are under significant pressure, resulting to a risk transfer from FOREX markets to equity markets (Corsetti, Pericoli and Sbracia 2005). Several researchers note that exchange rates have an impact on daily equity markets (Joseph 2002; Kim 2003; Kurihara 2006). Today, empirical tests of the volatility spillover effects between equity market returns and exchange rate returns have been limited to the use of either simple regression of cointegration methods.

Smith (1992) contacts a regression analysis between stock markets and exchange rate markets for Germany, USA and Japan. He uses quarterly data from 1974 to 1988 obtained from OEDC. He finds that both USA and German stock prices have a significant effect on the German mark - US dollar exchange rate, and that Japanese and USA stock prices affect the Japanese yen - US dollar exchange rate.

Ajayi and Mougoue (1996) examine the sensitivity of stock prices to exchange rate changes. They use daily closing stock market indices and exchange rates for Canada, France, Germany, Italy, Japan, The Netherlands, United Kingdom, and United States sourced from Citibase Data Services and Data Resource International. They examine the period from April 1985 to July 1991. By employing an error correction model, they find that an increase in aggregate domestic stock price has a negative short-run effect on domestic currency value.

Kanas (2000) investigates the volatility spillovers of stock returns and exchange rate changes within the same economy for the US, the UK, Japan, Germany, France and Canada. He uses daily closing stock prices denominated in local currency for all the equity markets for the period from 1 January, 1986 to 28 February, 1998 (3173 obs.). additionally, he employs a bivariate EGARCH model. He finds evidence of spillover effects from stock returns to exchange rate changes for five of the six countries except the case of Germany.

Grambovas (2003) uses cointegration methods to quantify the sensitivity of equity prices to exchange rate changes for Greece, Czech Republic and Hungary. He uses weekly data for the time period 1994-2000. The data is obtained from datastream. He finds that there is relationship between Hungarian exchange rates and stock prices, as well in the case of Greece.

He concludes that these results illustrate that changes in the stock markets may affect exchange rates.

Vugodina (2006) investigates the causality relation between USA stock prices and USA dollar exchange rate controlling for the size and international exposure of the sample firms. He uses daily data for the time period 1987-2005. Additionally, he employs the Granger (1969) causality test. He finds evidence of Granger causality form large-cap stock prices to exchange rate, but no such relation between small-cap stock prices and the exchange rate is observable.

Yau and Nieh (2006) examine the interrelationships among stock prices of Taiwan and Japan and NTD/Yen exchange rate. They use monthly observations for the period 1991-2005. They employ unit root, cointegration and Granger's causality tests. First, they find that the stock prices of Taiwan and Japan impact each other for short durations. Second, they prove that the portfolio approach is supported for the short-term and the traditional approach is more plausible for the long-term in the Taiwanese financial market, whereas the portfolio approach is not suitable for the Japanese stock market. Third, they find no long-term relation between NTD/Yen exchange rate and the stock prices of Taiwan and Japan.

This paper contributes to the literature on equity and FOREX markets volatility modeling in several ways. S&P 500 appears to have the strongest own volatility spillovers, meaning that the equity markets of USA has not been mainly affected by the GFC (2007) in contrast to the rest equity and FOREX markets. Dynamic conditional correlations reveal evidence of contagion for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. Recapping, these results are of interest to institutions, to multinational corporations, which can use risk management strategies in order to mix equity and FOREX market investments within their portfolios.

The structure of the present paper has the following form: Chapt. 2 presents the methodology, while in Chapt. 3 we discuss the data and the empirical results. The conclusions are stated in Chapt. 4.

2. Econometric methodology

In a first step, we calculate the daily returns (y_t), using an autoregressive $AR(1)$ process and a constant (μ) in the mean equation as follows:

$$(1 - fL)y_t = \mu + \varepsilon_t, \text{ with } t = 1,\ldots,T. \quad (1)$$

$AR(1)$ term captures the speed that market information is reflected in market values. Additionally, $|f|<1$ is a parameter, L is back shift operator and $\varepsilon_t|\Omega_{t-1} \sim N(0, H_t)$, where Ω_{t-1} is the information set at time t-1.

Next, we employ the Engle and Kroner (1995)[19] representation of multivariate GARCH model. Specifically, we use the diagonal BEKK (p,q) model, in order to parameterize the multivariate conditional variance H_t as follows:

$$H_t = C'C + \sum_{k=1}^{q} A_k A_k' \varepsilon_{t-k} \varepsilon_{t-k}' + \sum_{l=1}^{p} G_l G_l' H_{t-l} \quad (2)$$

where H_t is multivariate conditional variance matrix of daily returns and positive definite for all t. C is a N x N upper triangular matrix and A_k and are G_l diagonal matrices of dimension N x 1. Coefficients of matrix C state the constant components, coefficients of matrix A_k measure the intensity of spillover effects and coefficients of matrix G_l show the persistence of conditional variance.

We finally estimate the diagonal BEKK (1,1) model, as Bollerslev (1992) has mentioned sufficient to estimate the trivariate conditional variance matrix, of the following form:

$$H_t = C'C + A_1 A_1' \varepsilon_{t-1} \varepsilon_{t-1}' + G_1 G_1' H_{t-1} \quad (3)$$

where H_t depends on H_t and ε_t for each market lagged one period. The coefficients of C ($c_{i,j}$, with $i, j = 1, \ldots, N$), A_1 ($a_{i,j}$, with $i = j = 1, \ldots, N$) and G_1 $\left(g_{i,j}, \text{with } i = j = 1, \ldots, N\right)$ matrices are estimated as follows:

$$C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{12} & c_{22} & 0 \\ c_{13} & c_{23} & c_{33} \end{bmatrix}, A_1 = \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix}, G_1 = \begin{bmatrix} g_{11} & 0 & 0 \\ 0 & g_{22} & 0 \\ 0 & 0 & g_{33} \end{bmatrix}$$

We use the diagonal BEKK (1,1) type model, which is more parsimonious and reduces the number of ARCH and GARCH parameters to $[N(N+1)/2](1+p+q) = 18$, where N is the number of markets. The diagonal BEKK model trivially satisfies the equation $G_1 = A_1 D$, where D is a diagonal matrix.

[19] BEKK model of Engle and Kroner (1995) is a special case of the VEC model of Bolleslev, Engle and Wooldridge (1988).

We estimate the model using Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors. The estimates of FIML are generated by maximizing the log-likelihood $\sum_{t=1}^{T} l_t$, where

$$l_t = log \frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{N}{2}}} - \frac{1}{2}\log(|H_t|) - \left(\frac{N+\nu}{2}\right) log\left[1 + \frac{{\varepsilon_t}' {H_t}^{-1}\varepsilon_t}{\nu-2}\right] \quad (4)$$

where ν is the degrees of freedom, *Γ(.)* is the Gamma function and *N* the number of markets.

3. Data, results and economic analysis of DCCs

This section is divided into three subsections. In sub-sect. 3.1., we present the data and descriptive statistics. In sub-sect. 3.2. we present the results from the AR(1)-diagonal BEKK(1,1) model and the diagnostic tests. In sub-sect. 3.3. we provide an economic analysis of dynamic conditional correlations (DCCs).

3.1. Data and descriptive statistics

Our sample construction begins with daily values for S&P500 (USA), BOVESPA (Brazil), S&PTSX (Canada), FTSEMIB (Italy), DAX30 (Germany), USD, CAD, BRL and EUR from 13th April 2010 until 18th April 2018. The data were sourced from *Datastream® Database.* Local currencies are denominated in USD, whilst logarithmic returns are generated by $r_t = log(p_t) - log(p_{t-1})$ for t = 1,2,…,2091, where p_t is the price of the market at the end of the day t and p_{t-1} is the price of the market at the end of the day t – 1. While daily data can reveal disruptions lasting for only a day, the use of that data may entail noisy problems. Additionally, we set the beginning of our research one month before the creation of European Financial Stability Facility (EFSF) (April 2010) due to the ongoing European Sovereign Debt Crisis (ESDC).

Tables 1 and 2 provide summary statistics for equity and FOREX markets returns. In general, we observe positive sample mean for all variables of interest. The Jarque-Bera (JB), kurtosis (>3) and skewness (negative) statistics imply the departure from normality, indicating appropriate the use of student-t distribution for the empirical analysis (Massacci 2014). Surprisingly, FTSEMIB returns exhibit the highest standard deviation, the highest maximum and the lowest minimum return prices, suggesting that FTSEMIB returns experience larger fluctuations compared to the rest market returns. Additionally, the findings of Augmented Dickey Fuller (Dickey and Fuller 1979) and SCHMIDT-PHILLIPS with the Z(tau) and Z(rho) statistics tests suggest the rejection of the null hypotheses of a unit root at the 1% level.

In figure 1 we present graphs of the actual series and their respective logarithmic returns for S&P500 (Graph A), S&PTSX (Graph B), DAX30 (Graph C), FTSEMIB (Graph D), BOVESPA (Graph E), BRL/USD (Graph F), CAD/USD (Graph G), EUR/USD (Graph H). We observe time varying levels of fluctuations. Specifically, results reveal time periods of relative calm, whilst there are time periods of positive and negative outliers. Based on the above graphs, clearly there are evidence of volatility clustering effect and heteroskedasticity[20].

3.2. Estimates of mean and variance equations and diagnostic tests

Tables 3, 4, 5 and 6 report the estimated coefficients of C ($c_{i,j}$, with $i, j = 1, \dots, N$), A_1 ($a_{i,j}$, with $i = j = 1, \dots, N$) and G_1 ($g_{i,j}$, with $i = j = 1, \dots, N$) matrices, parameter H_t (Equation 3). We extract some important drawbacks. According to the estimates, we note some statistically insignificant coefficients for the constant C matrix. The matrices governing the own volatility and the intensity of spillovers (A_1 and G_1) exhibit statistically significant coefficients ($a_{i,i}$, $g_{i,i}$) for all triplets of markets. Interestingly, the diagonal elements of matrix A_1 of own volatility suggest that the S&P500 exhibits the strongest own spillover effects. This implies that the S&P500[21] presents the strongest one way causal relationship between past volatility shocks and current volatility, showing that the effects of the shock take longer time to dissipate and indicating that the equity market of USA has not been affected extensively as a result of the recent GFC (2007).

Tables 7, 8, 9 and 10 report the estimated values for mean equation (Equation 1). While the constant term in the mean equation (μ) is significant for equity markets, FOREX markets demonstrate an insignificant constant term (μ). The negative $AR(1)$ term for S&P500, DAX30, FTSEMIB, BOVESPA, BRL/USD, CAD/USD and EUR/USD imply evidence of positive feedback, while the positive $AR(1)$ term for S&PTSX suggests partial adjustment and that

[20] A time series is defined as heteroscedastic if its variance changes over time, otherwise it is called homoscedastic.

[21] S&P500 is one of the most widely quoted USA index, representing the largest publicly traded corporations in the USA and leading the global equity market.

relevant market information is rapidly reflected in S&PTSX values. Furthermore, we report the estimates of log-likelihood parameter (l_t) (Equation 4). Estimates of degrees of freedom (v) are all around 7, indicating fat tails and the student-t distribution (v > 4) as the most appropriate distribution for the empirical analysis.

Tables 11 and 12 provide the estimated diagnostic tests and information criteria. Hosking (1980) and Li-McLeod (1983) autocorrelation test results provide evidence of no autocorrelation and therefore no evidence of statistical misspecification. $x^2(6)$ statistic results suggest the rejection of the null hypothesis of no spillover effects at 1% significance level. In addition, we state the AIC and SIC information criteria for the selected model.

Figure 2 (Graph A to D) plots the conditional variances. Results reveal a common pattern of movement for conditional variances for all markets triplets. Interestingly, we clearly recognize large ups and downs, revealing extreme volatility.

Figure 3 (Graph A to D) plots the conditional covariances. All the pair-wise conditional covariances are highly volatile with some jumps over time. This observation is in line with the stochastic properties of the multivariate AR-diagonal BEKK model reported in tables 3 to 10. Interestingly, we notice that the pair-wise conditional covariances for the pairs of markets S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX have extreme volatility and positive values. The above observation means that investors should be cautious when it comes to investing into two or more of the above equity markets.

3.3. Economic analysis of dynamic conditional correlations (DCCs)

Figure 4 presents the evolution of dynamic conditional correlations (DCCs) for the triplets of markets: (a) S&P500, BOVESPA, BRL/USD (Graph A), (b) S&P500, FTSEMIB, EUR/USD (Graph B), (c) S&P500, DAX30, EUR/USD (Graph C), and (d) S&P500, S&PTSX, CAD/USD (Graph D). Estimates of DCCs indicate the contagion effects between the markets. Contagion means that the financial market participants transmit the risk of economic events to the other markets. The main findings for the pairwise DCCs for all the triplets of markets are as follows.

First, graph A of figure 4 provides the estimated DCCs for the pairs of markets S&P500-BOVESPA, S&P500-BRL/USD and BOVESPA-BRL/USD. The estimated DCC between

S&P500 and BOVESPA has mostly positive values and it is extremely volatile over time, indicating contagion effects and implying a less reliable stability of the correlation for any investor. Moreover, the estimated DCCs for the pairs of markets S&P500-BRL/USD and BOVESPA-BRL/USD have mostly negative values and they are extremely volatile. This is not strong enough to support evidence of contagion. Interestingly, the estimated DCCs exhibit some common extreme jumps over time, some of which (27/10/2011, 28/06/2013 and 27/07/2017) are generated by the following economic facts: (a) the Eurozone debt crisis deal[22] (27/10/2011), (b) Gold fell below $1200 per ounce for the first time since 2010[23] (28/06/2013), and (c) President-elect Jair Bolsonaro's announcement of moving Brazil's embassy from Tel Aviv to Jerusalem (27/07/2017).

Next, graph B of figure 4 illustrates the estimated DCCs for the pairs of markets S&P500-FTSEMIB, S&P500-EUR/USD and FTSEMIB-EUR/USD. The estimated DCC between S&P500 and FTSEMIB has positive values and it is persistently volatile, suggesting contagion and implying that the correlation is risky from an investor's perspective. Additionally, the estimated DCCs for the pairs of markets S&P500-EUR/USD and FTSEMIB-EUR/USD are extremely volatile and have a trending behavior (upward) (from October 2012 until the end of the period) and mostly negative values, providing evidence of contagion effects and suggesting that correlations are risky from an investor's point of view. Furthermore, the estimated DCCs demonstrate two common extreme jumps (03/11/2015 and 12/09/2016) due to the following reasons: (a) the European migrant crisis and the announcement of Angela Merkel's plan[24] to register and distribute incoming refugees throughout the European Union (03/11/2015), and (b) Federal Reserve set the benchmark interest rate lower than expected (12/09/2016).

Graph C of figure 4 plots the estimated DCCs for the pairs of markets S&P500-DAX30, S&P500-EUR/USD and DAX30-EUR/USD. We observe that the estimated DCC between S&P500 and DAX30 is erratic and has positive values, indicating contagion and a risky

[22] European Union leaders announced an agreement on debt crisis measures, including a hard-fought deal with private sector investors to take a 50% loss on Greek bonds.

[23] Gold fell below $1,200 an ounce for the first time in almost two years Thursday as traders anticipated an eventual end to the Federal Reserve's economic stimulus program.

[24] Refugees would be stopped at EU borders, have their application processed, and then, if accepted, sent to one of the Union's 28 member states.

correlation for any investor. Thus, the estimated DCC between S&P500 and EUR/USD presents high volatility levels, while it has a trending behavior (upward) (from January 2012 until the end of the period) and mostly negative values, providing evidence of contagion effects and indicating for an investor a less reliable stability of the correlation. Moreover, the estimated DCC between DAX30 and EUR/USD is highly volatile, while it has a trending behavior (upward) (from January 2012 until the end of the period) and mostly positive values, suggesting evidence of contagion effects and implying that investors should be cautious about the reliability of the correlation. Additionally, the estimated DCCs show two common extreme jumps (03/11/2015 and 12/09/2016) generated by the following reasons: (a) Angela Merkel announced a new European migrant crisis plan (03/11/2015), and (b) Federal Reserve set the benchmark interest rate lower against all expectations (12/09/2016).

Last, graph D of figure 4 graphs the estimated DCCs for the pairs of markets S&P500-S&PTSX, S&P500-CAD/USD and S&PTSX-CAD/USD. The estimated DCC between S&P500 and S&PTSX show extreme volatility levels and has positive values, implying contagion and defining correlation risky for any investor. Moreover, the estimated DCC between S&P500 and CAD/USD has two different trending behaviors: (1) an upward trend from January 2012 until March 2014 and from September 2016 until the end of the period, and (2) a downward trend from March 2014 until September 2016. Additionally, it fluctuates violently and has mostly negative values. The above drawbacks are not robust enough to support evidence of contagion. Furthermore, the estimated DCC between S&PTSX and CAD/USD present two different trending behaviors as follows: (1) an upward trend from January 2012 until March 2014 and from September 2016 until the end of the period, and (2) a downward trend from March 2014 until September 2016. In addition, it demonstrates some extreme fluctuations, while it has mostly negative values, suggesting contagion effects and a risky correlation for investors. Additionally, estimated DCCs show two common extreme jumps (02/11/2015 and 12/09/2016) due to the following economic events: (a) Territorial disputes in the South China Sea between China and USA (02/11/2015), and (b) Federal Reserve set the benchmark interest rate lower than expected (12/09/2016).

4. Conclusions

In this paper, we study the spillover dynamics among returns of equity and FOREX markets for USA, Germany, Italy, Brazil and Canada between 2010 and 2018. We employ the Engle and Kroner (1995) AR(1)-diagonal BEKK(1,1) model. We utilize four trivariate models, each using S&P500, equity markets with the respective FOREX markets. We believe this is the first work that empirically investigates interdependence between equity and FOREX markets, by using our trivariate models and by taking into consideration the conditional second moments of the distribution (volatility spillovers).

Our main findings can be summarized as follows. (a) Using the diagonal BEKK modeling structure, first we measure own volatility spillovers. The main empirical results show that S&P500 exhibits the highest own volatility spillover effects, indicating that the USA's equity market has been affected to a smaller extend from the GFC of 2007. (b) Then, we take into consideration the DCCs. The analysis of DCCs confirms mounting evidence of the strongest contagion for the pairs of markets: S&P500-BOVESPA, S&P500-FTSEMIB, S&P500-DAX30 and S&P500-S&PTSX. (c) These results are of interest to institutions, to multinational corporations and to investors. Institutions can diversify their portfolios by taking into consideration international equity market. Multinational corporations can manage their FOREX market exposures effectively. Investors can built a profitable portfolio through equity and FOREX market investments.

References

Akar, C.: Dynamic Relationships between the Stock Exchange, Gold, and Foreign Exchange Returns in Turkey. Middle Eastern Finance and Economics. Vol. 12 (2011)

Ayayi, R. and Mougoue, M.: On the dynamic of the relation between stock prices and exchange rates. Journal of Financial Research. Vol. 19, 193-207 (1996)

Billio, M., Caporin, M.: Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion. Computational Statistics & Data Analysis. Vol. 54. No. 11, 2443-2458 (2010)

Bollerslev, T., Engle, R. F., Wooldridge, J.M.: A Capital Asset Pricing Model with Time Varying Covariances. Journal of Political Economy. Vol. 96, 116-131. (1988)

Bollerslev, T., Chou, R., Kroner, K. F.: ARCH modeling in finance: A review of the theory and empirical evidence. Journal of Econometrics. Vol. 52. No. 1-2, 5-59 (1992)

Burzała, M.: Wybrane metody badania efektów zarażania na rynkach kapitałowych. Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu (2014)

Burzala, M.: Did the crisis on the interbank market run parallel to the crisis on the capital market? A conspectral analysis. Safe Bank. Vol. 59. No. 2, 96-112 (2015)

Corsetti, G., Pericoli, M., Sbacia, M.: Some contagion, some interdependence": More pitfalls in tests of financial contagion. Journal of International Money and Finance. Vol. 25. No. 8, 1177-1199 (2005)

Dickey, D. A., Fuller, W. A.: Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association. Vol. 74, 427-431 (1979)

Dimitriou, D., Kenourgios, D,: Contagion of the global financial crisis and the real economy: Aregional analysis. Economic Modelling. Vol. 44, 283-293 (2015)

Engle, R. F., Kroner, K. F.: Multivariate Simultaneous Generalized ARCH. Econometric Theory. Vol. 11. No. 1, 122-150 (1995)

Forbes, K., Rigobon, R.: No contagion, only interdependence: Measuring stock market co-movements. Massachusetts Institute of Technology. Working Paper (2002)

Hosking, J. R. M.: The Multivariate Portmanteau Statistic. Journal of the American Statistical Association. Vol. 75. No. 371, 602-608 (1980)

Grambovas, C.: Exchange Rate Volatility and Equity Markets: evidence from the Czech Republic, Greece and Hungary. Eastern European Economics. Vol. 41. No. 5, 24-48. (2003)

Granger, C. W. J.: Investigating casual relations by econometric models and cross-spectral methods. Econometrica. Vol. 37. No. 3, 424−438 (1969)

Jiang, Y., Xing, Shu-guang: Dynamic Analysis of Foreign Exchange Reserve's Exchange Rate Risk Based on DCC-GARCH-CVaR Model. International Business. Vol. 4 (2010)

Joseph, N.: Modelling the impacts of Interest Rate and Exchange Rate Changes on UK Stock Returns. Derivatives Use, Trading and Regulation. Vol. 7. No. 4, 306-323 (2002)

Kanas, A.: Volatility Spillovers Between Stock Returns and Exchange Rate Changes: International Evidence. Journal of Business Finance and Accounting. Vol. 27. No. 3 & 4, (2000)

Kim, K.: Dollar Exchange Rate and Stock Price: Evidence from Multivariate Cointegration and Error Correction model. Review of Financial Economics. Vol. 12, 301-313 (2013)

Ku, Y., Wang, J. J.: Estimating portfolio value-at-risk via dynamic conditional correlation MGARCH model – an empirical study on foreign exchange rates. Applied Economic Letters. Vol. 15. No. 7, 533-538 (2008)

Kurihara, Y.: The Relationship between Exchange Rate and Stock Prices during the Quantitative Easing policy in Japan. International Journal of Business. Vol. 11. No. 4, 375-386 (2006)

Li, Y., Giles, D. E.: Modelling volatility spillover effects between developed stock markets and Asian emerging stock markets. International Journal of Finance and Economics. vol. 20, 155-177 (2015)

Massacci, D.: A two-regime threshold model with conditional skewed student t distribution for stock returns. Economic Modelling. Vol. 43, 9-20 (2014)

McLeod, A. I., Li, W. K.: Diagnostic checking ARMA time series models using squared-residual autocorrelations. Journal of Time Series Analysis. Vol. 4. No. 4, 269-273 (1983)

Pericoli, M., Sbracia, M.: A Primer on Financial Contagion. Journal of Economic Surveys. Vol. 17. No. 4 (2003)

Sehgal, S., Ahmad W., Deisting F.: An investigation of price discovery and volatility spillovers in India’s foreign exchange market. Journal of Economic Studies. Vol. 42. No. 2, 261-284 (2015)

Smith, C. E.: `Stock Markets and the Exchange Rate: A Multi-Country Approach', Journal of Macroeconomics. Vol. 14. No. 4, 607-629 (1992)

Vygodina, A. V.: Effects of size and international exposure of the US firms on the relationship between stock prices and exchange rates. Global Finance Journal. Vol. 17, 214–223 (2006)

Yau, H., Nieh, C.C.: Interrelations among Stock prices of Taiwan and Japan and NTD/Yen Exchange Rate. A. Journal of Asian Economics. Vol. 17, 535-552 (2006)

Yilmaz, T.: Improving Portfolio Optimization by DCC And DECO GARCH: Evidence from Istanbul Stock Exchange. Munich University Library Paper (2010)

Appendix

Table 1

Summary statistics of market returns, sample period: 13th April 2010 until 18th April 2018.

	EUR/USD	**CAD/USD**	**BRL/USD**	**S&P500**
Panel A: Basic statistics				
Mean	5,1117e-005	7,1609e-005	0,00025579	0,00045181
Minimum	-0,029954	-0,021192	-0,059464	-0,068958
Maximum	0,026528	0,025549	0,071608	0,046317
Std. deviation	0,005865	0,0052088	0,0095988	0,0090938
Panel B: Normality Test				
Skewness	0,029443	0,14277**	0,22159***	-0,47591***
t-Statistic	0,55005	2,6672	4,1397	8,8908
p-Value	0,58229	0,0076475	3,4773e-005	6,0658e-019
Excess Kyrtosis	1,6097***	1,4379***	3,8934***	5,2019***
t-Statistic	15,043	13,437	36,384	48,613
p-Value	3,8388e-051	3,6652e-041	0,00000	0,00000
Jarque-Bera	226,05***	187,23***	1337,8***	2436,5***
p-Value	8,1846e-050	2,2062e-041	3,1837e-291	0,00000
Panel C: Unit Root tests				
ADF	-27,5757	-26,4972	-27,8283	-28,031
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663
SCHMIDT-PHILLIPS Test Z(tau)	-44,807	-42,5879	-42,3001	-42,1005
Critical value: 1%	-3,56	-3,56	-3,56	-3,56
Critical value: 5%	-3,02	-3,02	-3,02	-3,02
Critical value: 10%	-2,75	-2,75	-2,75	-2,75
SCHMIDT-PHILLIPS Test Z(rho)	-2086,87	-2001,12	-1975,2	-1993,84
Critical value: 1%	-25,2	-25,2	-25,2	-25,2
Critical value: 5%	-18,1	-18,1	-18,1	-18,1
Critical value: 10%	-15	-15	-15	-15

Notes: Panel A shows the basic statistics of the FOREX and equity indexes returns, Panel B demonstates the normality test. Panel C presents the unit root tests. We used intercept and a time trend to generate ADF statistic with 2 lags. Additionally, we calculated SCHMIDT-PHILLIPS Z(tau) and Z((rho) statistics with the bandwidth parameter equal to zero.

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

Table 2

Summary statistics of market returns, sample period: 13th April 2010 until 18th April 2018.

	DAX30	**FTSEMIB**	**BOVESPA**	**S&PTSX**
Panel A: Basic statistics				
Mean	0,00039038	1,9795e-005	0,00010736	0,0001548
Minimum	-0,070673	-0,13331	-0,09211	-0,041227
Maximum	0,052104	0,10684	0,063874	0,03941
Std. deviation	0,012221	0,015983	0,014022	0,0077482
Panel B: Normality Test				
Skewness	-0,28160***	-0,35104***	-0,15874**	-0,35425***
t-Statistic	5,2607	6,5579	2,9656	6,6179
p-Value	1,4348e-007	5,4559e-011	0,0030213	3,6431e-011
Excess Kyrtosis	2,7823***	4,4818***	2,3173***	2,6357***
t-Statistic	26,002	41,884	21,656	24,632
p-Value	4,7432e-149	0,00000	5,3552e-104	5,8045e-134
Jarque-Bera	702,11***	1793***	476,64***	649***
p-Value	3,4565e-153	0,00000	3,1553e-104	1,1784e-141
Panel C: Unit Root tests				
ADF	-26,7387***	-27,4469***	-26,8204***	-27,4178***
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663
SCHMIDT-PHILLIPS Test Z(tau)	-39,2284***	-41,4633***	-26,9359***	-17,1964***
Critical value: 1%	-3,56	-3,56	-3,56	-3,56
Critical value: 5%	-3,02	-3,02	-3,02	-3,02
Critical value: 10%	-2,75	-2,75	-2,75	-2,75
SCHMIDT-PHILLIPS Test Z(rho)	-1786,73***	-1924,41***	-1056,99***	-497,156***
Critical value: 1%	-25,2	-25,2	-25,2	-25,2
Critical value: 5%	-18,1	-18,1	-18,1	-18,1
Critical value: 10%	-15	-15	-15	-15

Notes: Panel A presents the basic statistics of the equity indexes returns, Panel B shows the normality test. Panel C demonstrates the unit root tests. We used intercept and a time trend to generate ADF statistic with 2 lags. Additionally, we calculated SCHMIDT-PHILLIPS Z(tau) and Z((rho) statistics with the bandwidth parameter equal to zero.

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

Table 3
Estimated coefficients of conditional variance (H_t), for S&P500-BOVESPA-BRL/USD, sample period: 13th April 2010 until 18th April 2018.

Market i	S&P500 (i=1)	BOVESPA (i=2)	BRL/USD (i=3)
Panel A: coefficients $c_{i,j}$ of C matrix			
$c_{i,1}$	0,001228***		
t-Statistic	5,463		
p-Value	0,0000		
$c_{i,2}$	0,001062***	0,001764***	
t-Statistic	5,654	7,422	
p-Value	0,0000	0,0000	
$c_{i,3}$	-0,0003589***	-0,000218**	0,001015***
t-Statistic	-3,593	-2,112	5,149
p-Value	0,0003	0,0348	0,0000
Panel B: coefficients $a_{i,j}$ of A_1 matrix			
$a_{i,1}$	0,280096***		
t-Statistic	10,35		
p-Value	0,0000		
$a_{i,2}$		0,196338***	
t-Statistic		12,18	
p-Value		0,0000	
$a_{i,3}$			0,246544***
t-Statistic			8,929
p-Value			0,0000
Panel C: coefficients $g_{i,j}$ of G_1 matrix			
$g_{i,1}$	0,949038***		
t-Statistic	85,87		
p-Value	0,0000		
$g_{i,2}$		0,969544***	
t-Statistic		195,4	
p-Value		0,0000	
$g_{i,3}$			0,962461***
t-Statistic			116,7
p-Value			0,0000

Notes: Panel A presents the estimated coefficients of C upper triangular matrix, Panel B states the estimated coefficients of A diagonal matrix and Panel C demostrates the estimated coefficients of G diagonal matrix.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Conditional Variance matrix equation: $H_t = C^{'}C + A_1A_1^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'} + G_1G_1^{'}H_{t-1}$.

Table 4

Estimated coefficients of conditional variance (H_t), for S&P500-FTSEMIB-EUR/USD, sample period: 13th April 2010 until 18th April 2018.

Market i	S&P500 (i=1)	FTSEMIB (i=2)	EUR/USD (i=3)
Panel A: coefficients $c_{i,j}$ of C matrix			
$c_{i,1}$	0,001292***		
t-Statistic	6,574		
p-Value	0,0000		
$c_{i,2}$	0,000922***	0,001570***	
t-Statistic	4,843	6,113	
p-Value	0,0000	0,0000	
$c_{i,3}$	-0,0000434	0,0000384	0,000383**
t-Statistic	-0,9869	0,9098	2,793
p-Value	0,3238	0,3630	0,0053
Panel B: coefficients $a_{i,j}$ of A_1 matrix			
$a_{i,1}$	0,285548***		
t-Statistic	10,51		
p-Value	0,0000		
$a_{i,2}$		0,221053***	
t-Statistic		12,54	
p-Value		0,0000	
$a_{i,3}$			0,179050***
t-Statistic			11,21
p-Value			0,0000
Panel C: coefficients $g_{i,j}$ of G_1 matrix			
$g_{i,1}$	0,944325***		
t-Statistic	85,91		
p-Value	0,0000		
$g_{i,2}$		0,968154***	
t-Statistic		202,4	
p-Value		0,0000	
$g_{i,3}$			0,982227***
t-Statistic			263,8
p-Value			0,0000

Notes: Panel A presents the estimated coefficients of C upper triangular matrix, Panel B states the estimated coefficients of A diagonal matrix and Panel C demostrates the estimated coefficients of G diagonal matrix.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Conditional Variance matrix equation: $H_t = C^{'}C + A_1A_1^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'} + G_1G_1^{'}H_{t-1}$.

Table 5
Estimated coefficients of conditional variance (H_t), for S&P500-DAX30-EUR/USD, sample period: 13th April 2010 until 18th April 2018.

Market i	S&P500 (i=1)	DAX30 (i=2)	EUR/USD (i=3)
Panel A: coefficients $c_{i,j}$ of C matrix			
$c_{i,1}$	0,001255***		
t-Statistic	6,126		
p-Value	0,0000		
$c_{i,2}$	0,000780***	0,001016***	
t-Statistic	4,881	6,016	
p-Value	0,0000	0,0000	
$c_{i,3}$	-0,0000284	0,0000874	0,000385**
t-Statistic	-0,6671	1,867	2,418
p-Value	0,5048	0,0157	0,0157
Panel B: coefficients $a_{i,j}$ of A_1 matrix			
$a_{i,1}$	0,283861***		
t-Statistic	10,54		
p-Value	0,0000		
$a_{i,2}$		0,221872***	
t-Statistic		13,37	
p-Value		0,0000	
$a_{i,3}$			0,176711***
t-Statistic			9,890
p-Value			0,0000
Panel C: coefficients $g_{i,j}$ of G_1 matrix			
$g_{i,1}$	0,946426***		
t-Statistic	87,60		
p-Value	0,0000		
$g_{i,2}$		0,969181***	
t-Statistic		218,1	
p-Value		0,0000	
$g_{i,3}$			0,982827***
t-Statistic			233,3
p-Value			0,0000

Notes: Panel A presents the estimated coefficients of C upper triangular matrix, Panel B states the estimated coefficients of A diagonal matrix and Panel C demostrates the estimated coefficients of G diagonal matrix.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Conditional Variance matrix equation: $H_t = C^{'}C + A_1A_1^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'} + G_1G_1^{'}H_{t-1}$.

Table 6

Estimated coefficients of conditional variance (H_t), for S&P500-S&PTSX-CAD/USD, sample period: 13th April 2010 until 18th April 2018.

Market i	**S&P500 (i=1)**	**S&PTSX (i=2)**	**CAD/USD (i=3)**
Panel A: coefficients $\mathbf{c}_{i,j}$ of $\boldsymbol{C}$ matrix			
$c_{i,1}$	0,001014***		
t-Statistic	3,663		
p-Value	0,0003		
$c_{i,2}$	0,000478***	0,000615***	
t-Statistic	4,136	6,008	
p-Value	0,0000	0,0000	
$c_{i,3}$	-0,0001717**	0,0000805	0,000390**
t-Statistic	-2,446	1,531	2,668
p-Value	0,0145	0,1259	0,0077
Panel B: coefficients $\boldsymbol{a}_{i,j}$ of $\boldsymbol{A_1}$ matrix			
$a_{i,1}$	0,232658***		
t-Statistic	6,548		
p-Value	0,0000		
$a_{i,2}$		0,224026***	
t-Statistic		13,78	
p-Value		0,0000	
$a_{i,3}$			0,198611***
t-Statistic			9,360
p-Value			0,0000
Panel C: coefficients $\boldsymbol{g}_{i,j}$ of $\boldsymbol{G_1}$ matrix			
$g_{i,1}$	0,963201***		
t-Statistic	74,84		
p-Value	0,0000		
$g_{i,2}$		0,968704***	
t-Statistic		191,8	
p-Value		0,0000	
$g_{i,3}$			0,977131***
t-Statistic			153,3
p-Value			0,00000

Notes: Panel A presents the estimated coefficients of C upper triangular matrix, Panel B states the estimated coefficients of A diagonal matrix and Panel C demostrates the estimated coefficients of G diagonal matrix.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Conditional Variance matrix equation: $H_t = C^{'}C + A_1A_1^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'} + G_1G_1^{'}H_{t-1}$.

Table 7

Estimates of μ and AR(1), degrees of freedom and log-likelihood, for S&P500-BOVESPA-BRL/USD, sample period: 13th April 2010 until 18th April 2018.

	S&P500	BOVESPA	BRL/USD
Panel A: estimates of μ			
S&P500	0,000754***		
t-Statistic	6,052		
p-Value	0,0000		
BOVESPA		0,000481*	
t-Statistic		1,963	
p-Value		0,0498	
BRL/USD			-0,000013
t-Statistic			-0,09497
p-Value			0,9243
Panel B: estimates of AR(1)			
S&P500	-0,055905**		
t-Statistic	-2,934		
p-Value	0,0034		
BOVESPA		-0,037509**	
t-Statistic		-2,037	
p-Value		0,0418	
BRL/USD			-0,089926***
t-Statistic			-4,304
p-Value			0,0000
Panel C: degrees of freedom and log-likelihood			
degrees of freedom *(v)*	6,801400***		
t-Statistic	11,06		
p-Value	0,0000		
log-likelihood (l_t)	20995,064		

Notes: We used Full Information Maximum Likelihood methods to produce the maximum likelihood parameter.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.
Conditional mean equation: $(1 - fL)y_t = \mu + \varepsilon_t$, with $t = 1,\ldots,T$.
Log-Likelihood estimation: $l_t = log\frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{N}{2}}} - \frac{1}{2}log(|H_t|) - \left(\frac{N+\nu}{2}\right)log\left[1 + \frac{\varepsilon_t{}'H_t{}^{-1}\varepsilon_t}{\nu-2}\right]$.

Table 8
Estimates of μ and AR(1), degrees of freedom and log-likelihood, for S&P500-FTSEMIB-EUR/USD, sample period: 13th April 2010 until 18th April 2018.

	S&P500	FTSEMIB	EUR/USD
Panel A: estimates of μ			
S&P500	0,000825***		
t-Statistic	7,113		
p-Value	0,0000		
FTSEMIB		0,000562**	
t-Statistic		2,364	
p-Value		0,0182	
EUR/USD			0,0000359
t-Statistic			0,3703
p-Value			0,7112
Panel B: estimates of AR(1)			
S&P500	-0,099369***		
t-Statistic	-5,261		
p-Value	0,0000		
FTSEMIB		-0,070821***	
t-Statistic		-3,746	
p-Value		0,0002	
EUR/USD			-0,050431**
t-Statistic			-2,452
p-Value			0,0143
Panel C: degrees of freedom and log-likelihood			
degrees of freedom *(ν)*	6,292460***		
t-Statistic	12,98		
p-Value	0,0000		
log-likelihood (l_t)	21702,008		

Notes: We used Full Information Maximum Likelihood methods to produce the maximum likelihood parameter.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Conditional mean equation: $(1 - fL)y_t = \mu + \varepsilon_t$, with $t = 1,\ldots,T$.
Log-Likelihood estimation: $l_t = log\frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{N}{2}}} - \frac{1}{2}log(|H_t|) - \left(\frac{N+\nu}{2}\right)log\left[1 + \frac{\varepsilon_t{}'H_t{}^{-1}\varepsilon_t}{\nu-2}\right]$.

Table 9

Estimates of μ and AR(1), degrees of freedom and log-likelihood, for S&P500-DAX30-EUR/USD, sample period: 13th April 2010 until 18th April 2018.

	S&P500	DAX30	EUR/USD
Panel A: estimates of μ			
S&P500	0,000800***		
t-Statistic	7,290		
p-Value	0,0000		
DAX30		0,000795***	
t-Statistic		4,471	
p-Value		0,0000	
EUR/USD			0,0000749
t-Statistic			0,7830
p-Value			0,4337
Panel B: estimates of AR(1)			
S&P500	-0,143867***		
t-Statistic	-7,634		
p-Value	0,0000		
DAX30		-0,035510*	
t-Statistic		-0,1981	
p-Value		0,0477	
EUR/USD			-0,048676**
t-Statistic			-2,367
p-Value			0,0180
Panel C: degrees of freedom and log-likelihood			
degrees of freedom *(v)*	5,768043***		
t-Statistic	13,66		
p-Value	0,0000		
log-likelihood (l_t)	22424,786		

Notes: We used Full Information Maximum Likelihood methods to produce the maximum likelihood parameter.

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

Conditional mean equation: $(1 - fL)y_t = \mu + \varepsilon_t$, with $t = 1,\ldots,T$.

Log-Likelihood estimation: $l_t = log \frac{\Gamma\left(\frac{v+N}{2}\right)}{[v\pi]^{\frac{N}{2}}\Gamma\left(\frac{v}{2}\right)v-2^{\frac{N}{2}}} - \frac{1}{2}log(|H_t|) - \left(\frac{N+v}{2}\right)log\left[1 + \frac{\varepsilon_t{}'H_t{}^{-1}\varepsilon_t}{v-2}\right]$.

Table 10

Estimates of μ and AR(1), degrees of freedom and log-likelihood, for S&P500-S&PTSX-CAD/USD, sample period: 13th April 2010 until 18th April 2018.

	S&P500	S&PTSX	CAD/USD
Panel A: estimates of μ			
S&P500	0,000733***		
t-Statistic	5,826		
p-Value	0,0000		
S&PTSX		0,000453***	
t-Statistic		3,647	
p-Value		0,0003	
CAD/USD			-0,0000528
t-Statistic			-0,6234
p-Value			0,5331
Panel B: estimates of AR(1)			
S&P500	-0,052292***		
t-Statistic	-3,165		
p-Value	0,0016		
S&PTSX		0,037753**	
t-Statistic		2,084	
p-Value		0,0373	
CAD/USD			-0,060243***
t-Statistic			-3,167
p-Value			0,0016
Panel C: degrees of freedom and log-likelihood			
degrees of freedom *(v)*	7,053835***		
t-Statistic	12,13		
p-Value	0,0000		
log-likelihood (l_t)	24051,712		

Notes: We used Full Information Maximum Likelihood methods to produce the maximum likelihood parameter.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Conditional mean equation: $(1 - fL)y_t = \mu + \varepsilon_t$, with $t = 1,\ldots,T$.
Log-Likelihood estimation: $l_t = log\frac{\Gamma\left(\frac{v+N}{2}\right)}{[v\pi]^{\frac{N}{2}}\Gamma\left(\frac{v}{2}\right)v-2^{\frac{N}{2}}} - \frac{1}{2}log(|H_t|) - \left(\frac{N+v}{2}\right)log\left[1 + \frac{\varepsilon_t{}'H_t{}^{-1}\varepsilon_t}{v-2}\right]$.

Table 11

Diagnostic tests and information criteria of AR(1)-diagonal-BEKK(1,1) model for S&P500-BOVESPA-BRL/USD and S&P500-FTSEMIB-EUR/USD, sample period: 13th April 2010 until 18th April 2018.

	S&P500-BOVESPA-BRL/USD	**S&P500-FTSEMIB-EUR/USD**
Panel A: diagnostic tests		
$x^2(6)$	748,63**	451,06**
p-Value	0,0000	0,0000
Hosking (50)	470,965	490,887
p-Value	0,2285799	0,0840035
Hosking^2 (50)	464,454	459,849
p-Value	0,2859338	0,3391994
Li-McLeod (50)	470,540	491,150
p-Value	0,2327593	0,0827379
Li-McLeod^2 (50)	465,080	460,731
p-Value	0,2790323	0,3286732
Panel B: Information Criteria		
Akaike	-20,072788	-20,749290
Schwarz	-20,021471	-20,697973

Notes: Panel A presents diagnostic tests of Hosking (1980) and McLeod and Li (1983). In Panel B we see the information criteria of AR(1)-diagonal-BEKK(1,1) model, using 1 lag. P-values have been corrected by 2 degrees of freedom for Hosking^2 (50) and Li-McLeod^2 (50) statistics and by 1 degree of freedom for Hosking (50) and Li-McLeod (50) statistics.
** denote statistical significance at the 5% level.

Table 12

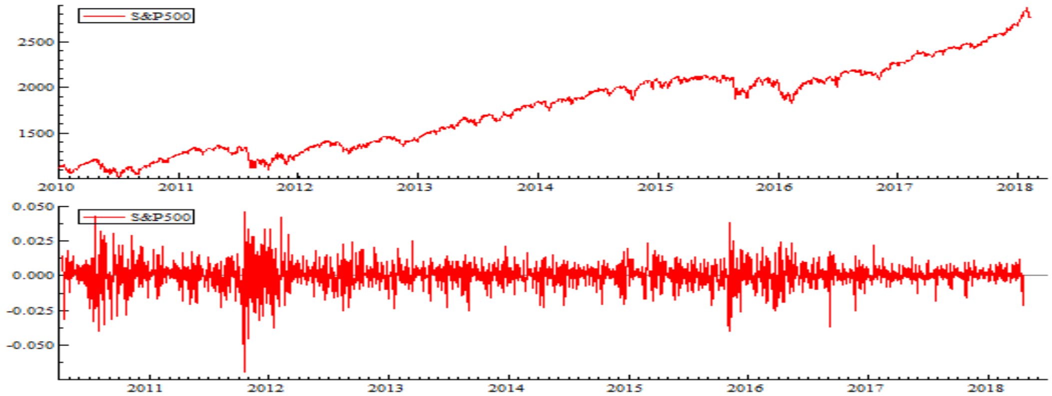
Estimated results of AR(1)-diagonal-BEKK(1,1) model for S&P500-S&PTSX-CAD/USD and S&P500-DAX30-EUR/USD, sample period: 13th April 2010 until 18th April 2018.

	S&P500-S&PTSX-CAD/USD	**S&P500-DAX30-EUR/USD**
Panel A: diagnostic tests		
$x^2(6)$	277,04**	360,65**
p-Value	0,0000	0,0000
Hosking (50)	210,130	554,021**
p-Value	0,0555485	0,0005093
Hosking^2 (50)	329,114**	497,055
p-Value	0,0000000	0,0542896
Li-McLeod (50)	210,161	553,972**
p-Value	0,553808	0,0005119
Li-McLeod^2 (50)	328,994**	497,867
p-Value	0,0000000	0,0515587
Panel B: Information Criteria		
Akaike	-22,997811	-21,440944
Schwarz	-22,946493	-21,389626

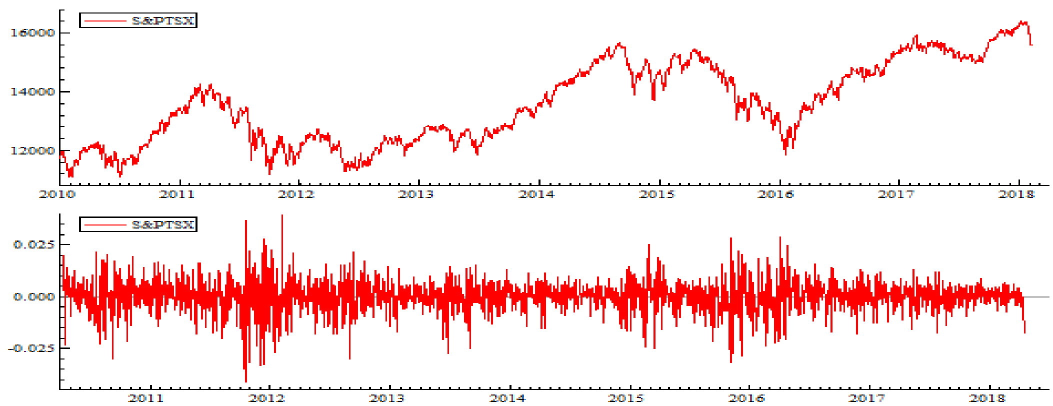
Notes: Panel A presents diagnostic tests of Hosking (1980) and McLeod and Li (1983). In Panel B we see the information criteria of AR(1)-diagonal-BEKK(1,1) model, using 1 lag. P-values have been corrected by 2 degrees of freedom for Hosking^2 (50) and Li-McLeod^2 (50) statistics and by 1 degree of freedom for Hosking (50) and Li-McLeod (50) statistics.
** denote statistical significance at the 5% level.

Figure 1. Actual series and logarithmic returns of the markets.

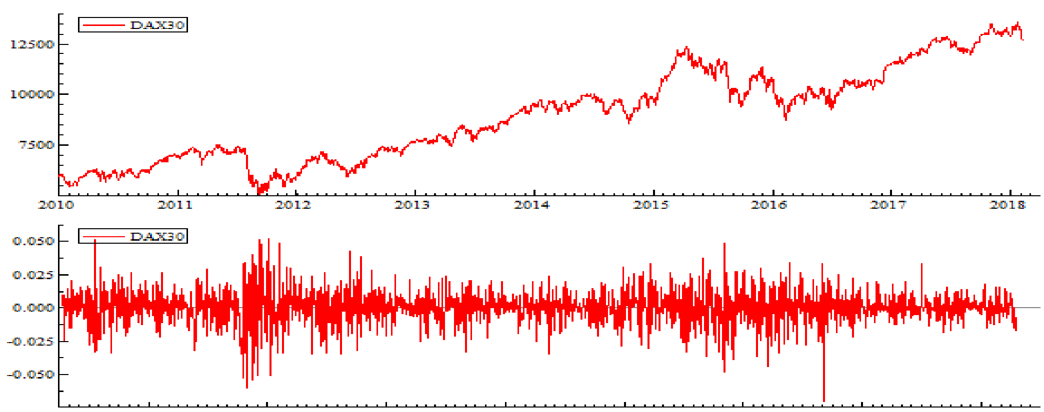
Graph A. ***S&P500***



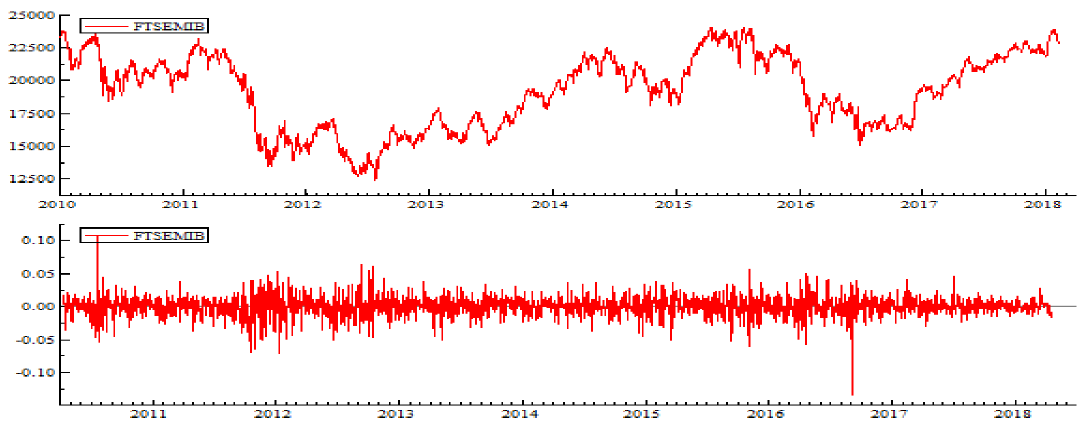
Graph B. ***S&PTSX***



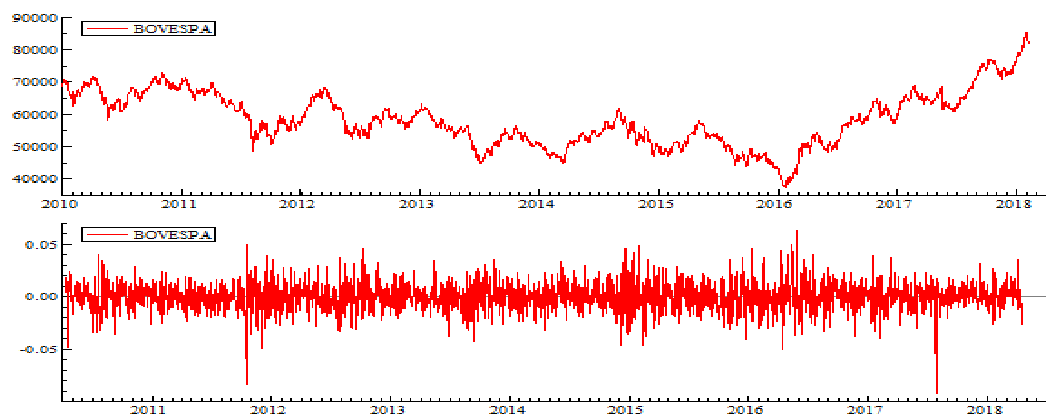
Graph C. ***DAX30***



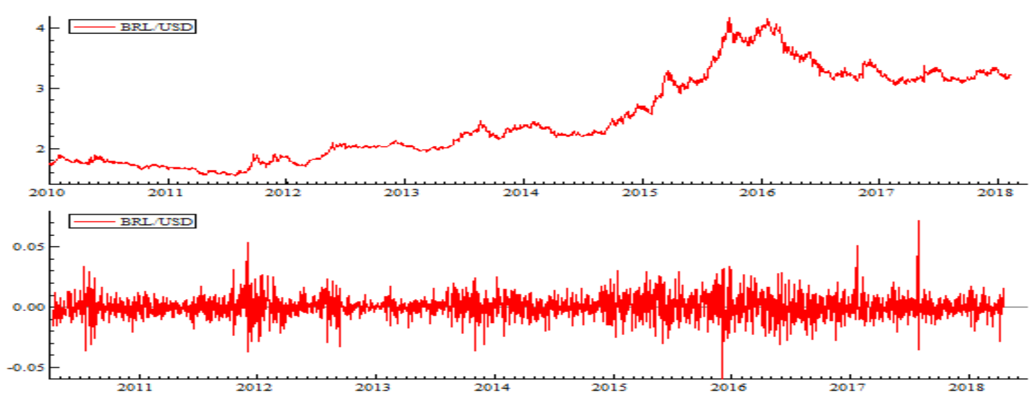
Graph D. FTSEMIB



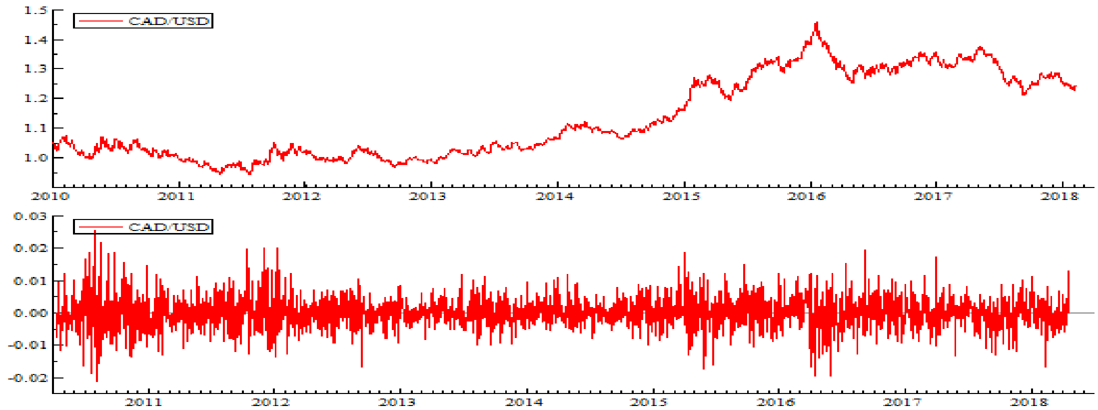
Graph E. BOVESPA



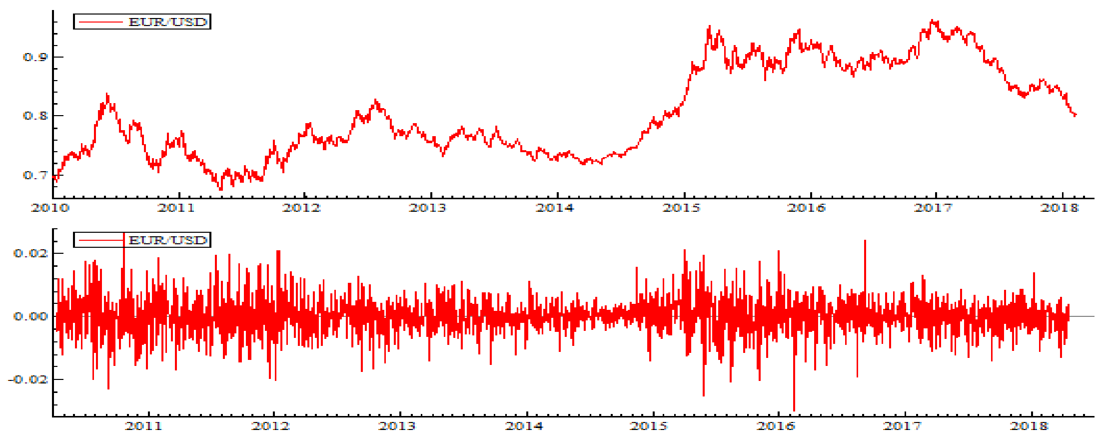
Graph F. BRL/USD



Graph G. *CAD/USD*



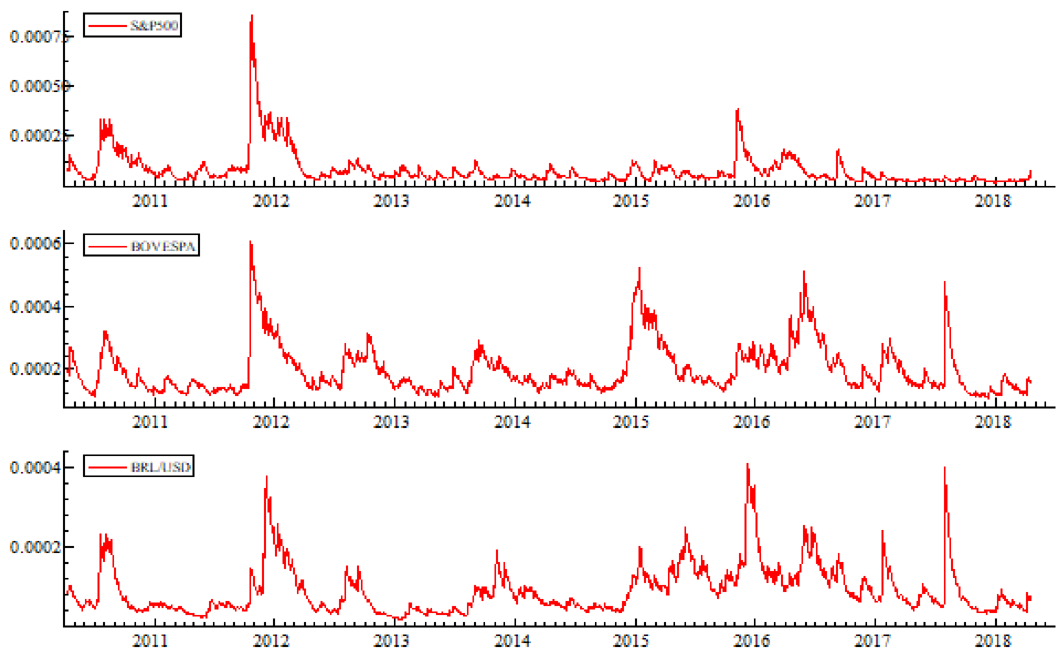
Graph H. *EUR/USD*



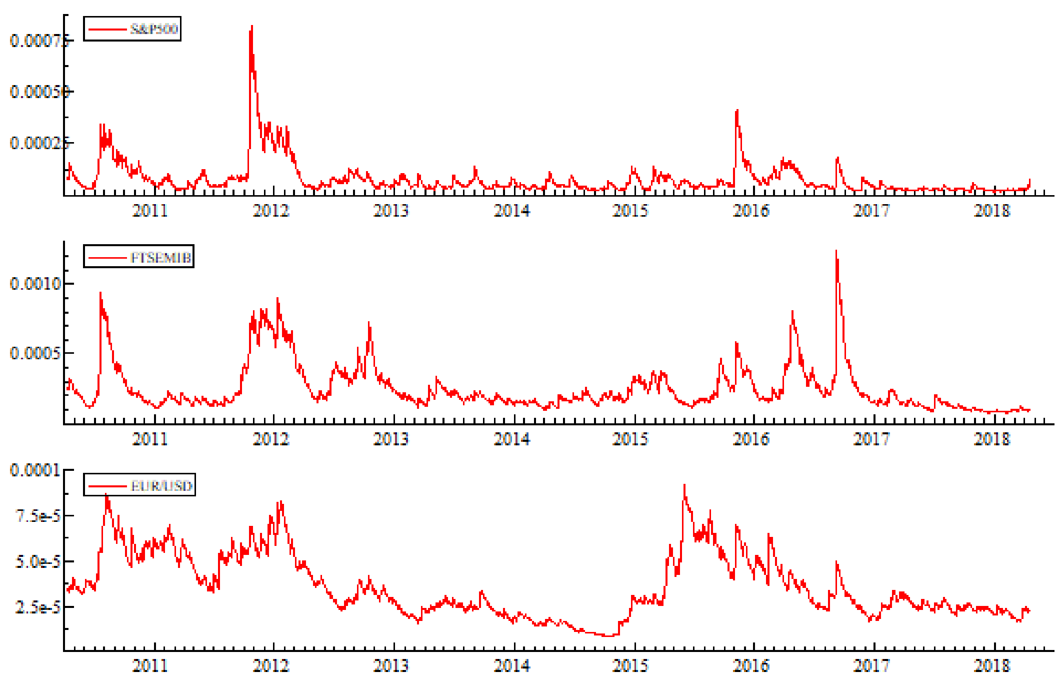
Notes: Logarithmic returns are generated by using the following equation: $r_t = log(p_t) - log(p_{t-1})$.

Figure 2. Conditional variances of the AR(1)-Diagonal-BEKK(1,1) model.

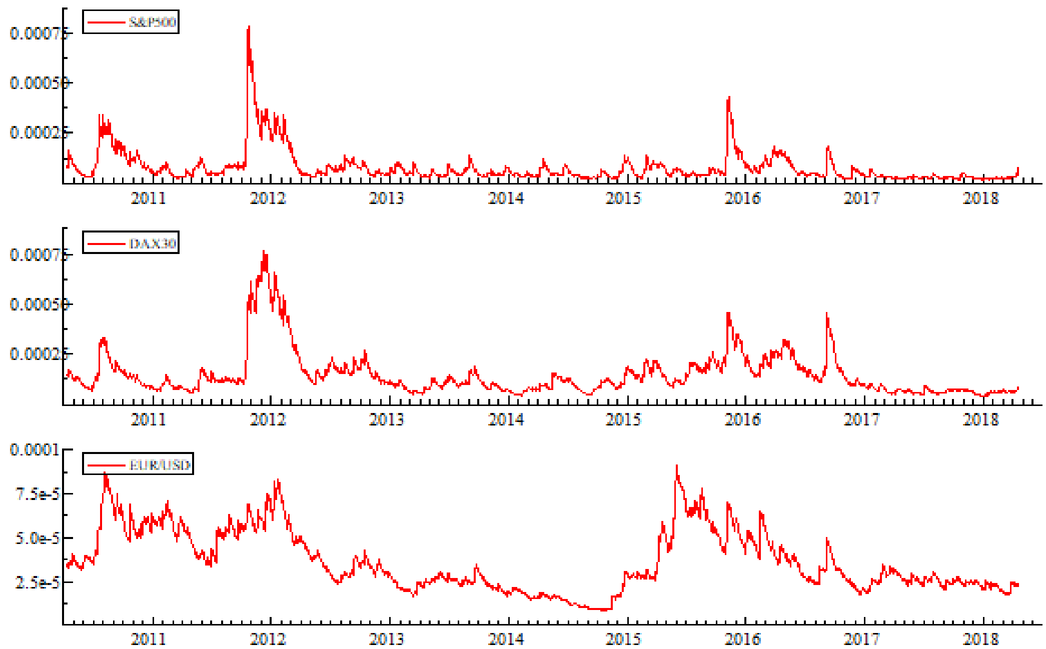
Graph A. ***S&P500, BOVESPA and BRL/USD***



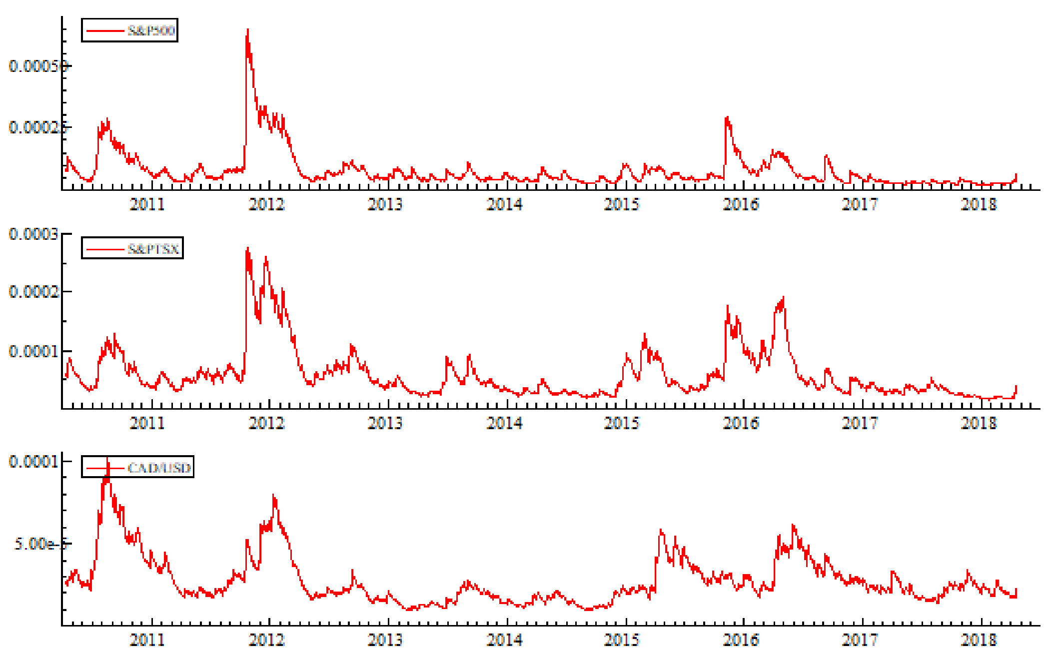
Graph B. ***S&P500, FTSEMIB and EUR/USD***



***Graph C.** S&P500, DAX30 and EUR/USD*



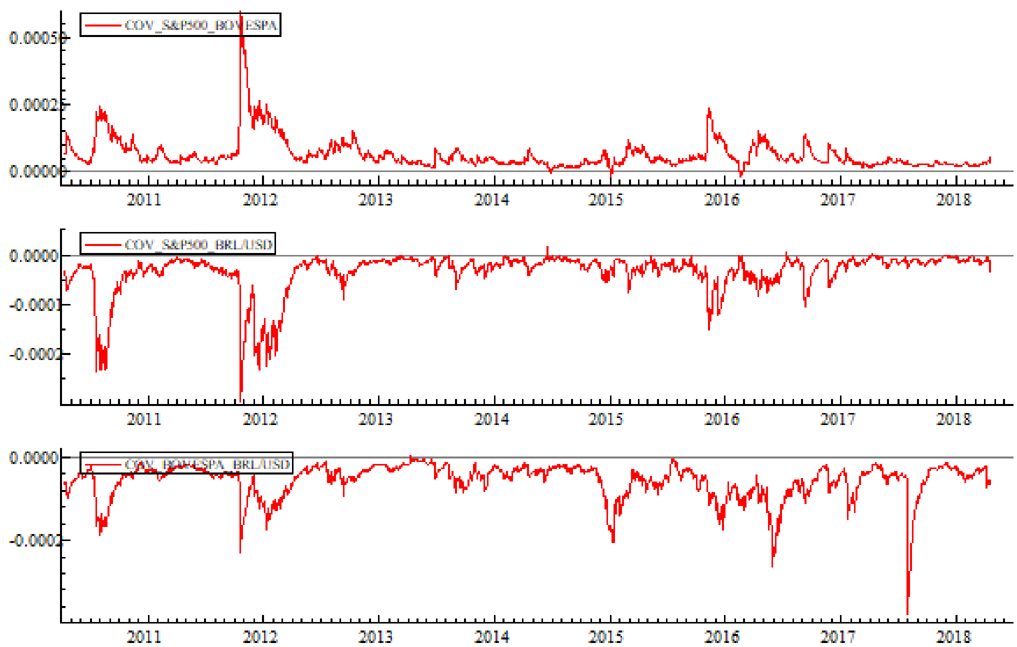
***Graph D.** S&P500, S&PTSX and CAD/USD*



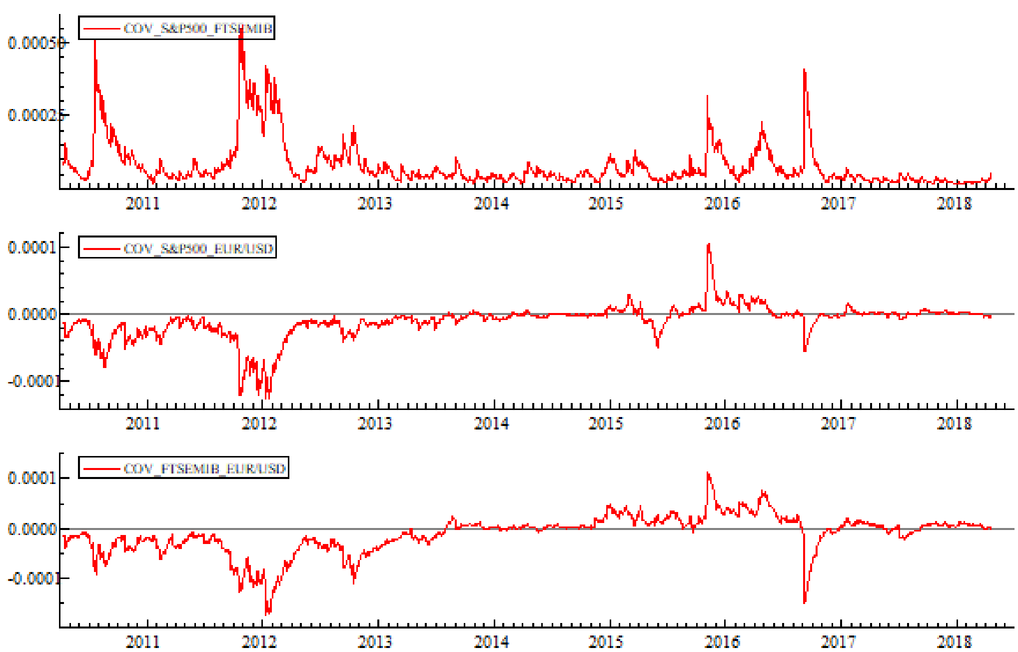
Notes: The red lines represent the conditional variances of the trivariate conditional variance matrix (H_t) for all markets, generated by Equation 3.

Figure 3. Conditional covariances of the AR(1)-Diagonal-BEKK(1,1) model.

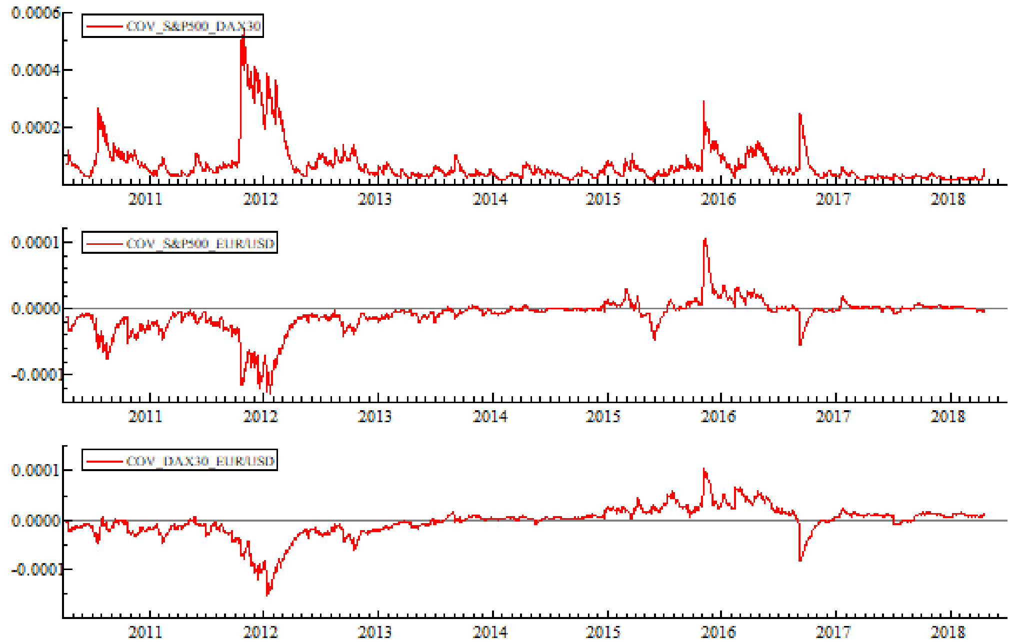
Graph A. ***S&P500, BOVESPA and BRL/USD***



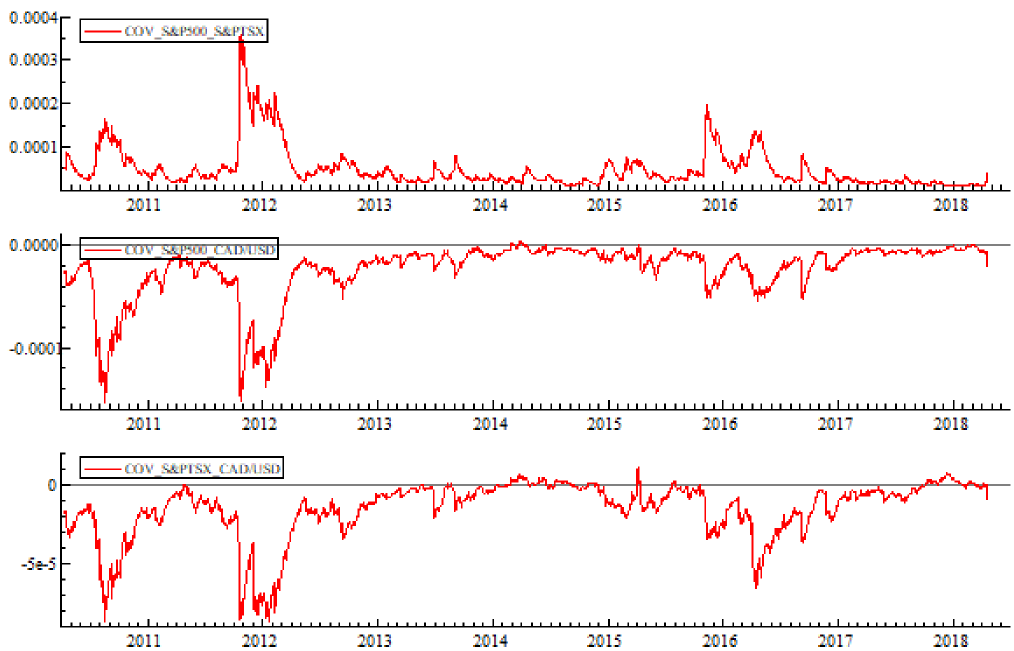
Graph B. ***S&P500, FTSEMIB and EUR/USD***



Graph C. ***S&P500, DAX30 and EUR/USD***



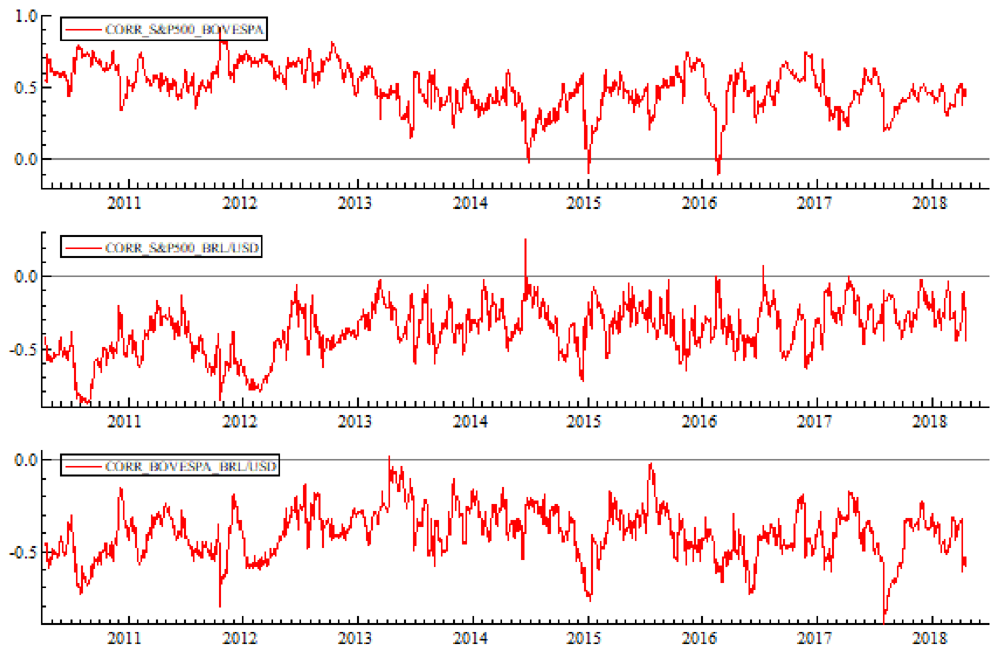
Graph D. ***S&P500, S&PTSX and CAD/USD***



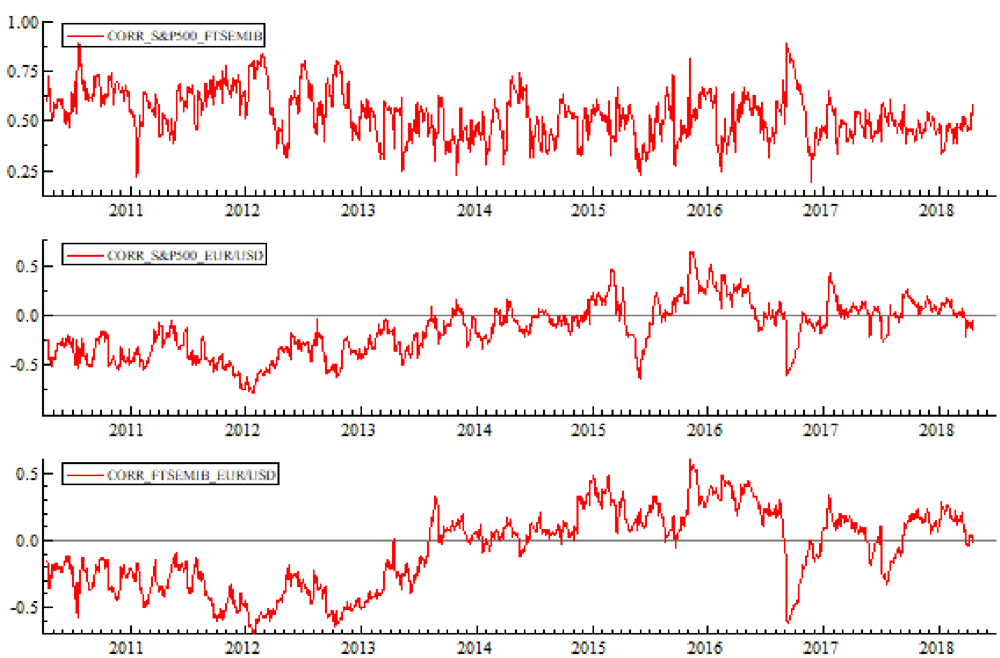
Notes: The red lines represent the conditional covariances of the trivariate conditional variance matrix (H_t) for all the pairs of markets, generated by Equation 3.

Figure 4. Dynamic conditional correlations (DCCs) of the AR(1)-Diagonal-BEKK(1,1) model.

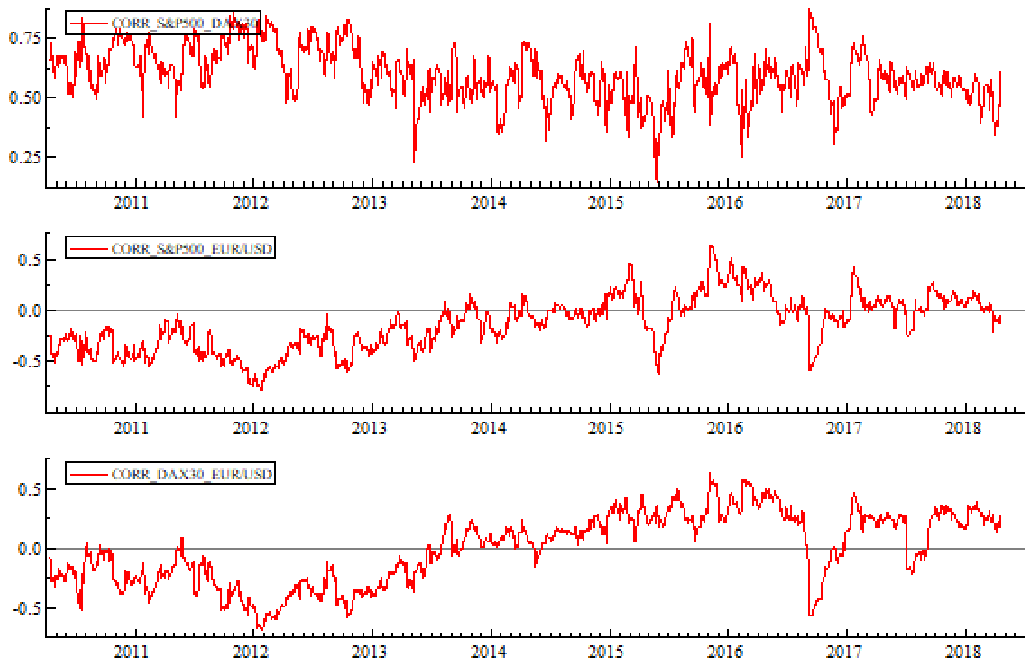
Graph A. S&P500, BOVESPA and BRL/USD



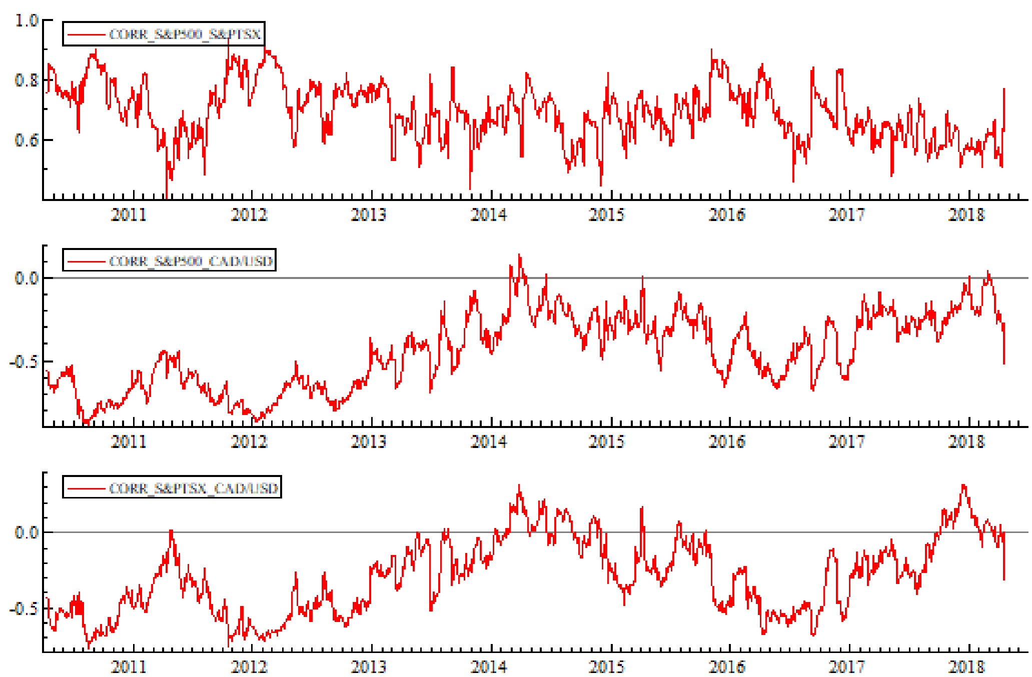
Graph B. S&P500, FTSEMIB and EUR/USD



Graph C. ***S&P500, DAX30 and EUR/USD***



Graph D. ***S&P500, S&PTSX and CAD/USD***



Notes: The red lines illustrate the pairwise DCCs for all the triplets of markets, generated by the Oxmetrics.

Chapter 3

FOREX markets response in the aftermath of the Global Financial Crisis: evidence from EUR/USD, JPY/USD, CHW/USD and GBP/USD

Abstract

The purpose of this study is to investigate the volatility transmission among four major FOREX markets, namely: EUR/USD, JPY/USD, CHW/USD and GBP/USD, in the aftermath of Global Financial Crisis (GFC) (2007). We employ a fourvariate DCC-GARCH model in order to capture potential contagion effects between the markets. According to dynamic conditional correlations (DCCs), we do not reject contagion for all the pairs of markets. Additionally, EUR/USD and GBP/USD present the strongest contagion effects, while CHW/USD show the lowest contagion levels with the rest markets. Our results are important for any investor, since strong contagion effects suggest a risky correlation from an investor's perspective.

1. Introduction

In 1997, Thailand government broke the fixed exchange rate of local currency to USD[25], generating global financial market declines, leading to the Asian financial crisis (AFC) of 1997. However, in terms of extension and consequences, global financial crisis (GFC) of 2007 is characterized as the worst financial crisis since the Great Depression of 1929 (Sehgal, Ahmad and Deisting 2015). That time (2007), investors[26] started to have negative expectations about FOREX markets (Akar 2011), considering the huge losses in FOREX market investments. The investigation of the FOREX markets integration is of great importance today, since a bull or a bear FOREX market can transfer very easy the risk to another financial market, ending to an economic crisis (Forbes and Rigobon 2002; Pericoli and Sbracia 2003).

In this paper, we provide empirical arguments, supporting the integration (contagion[27]) among four major FOREX markets (EUR/USD, JPY/USD, CHW/USD, GBP/USD). We examine the period after the end of the recent global financial crisis (GFC) of 2007, and specifically from 19th April 2011 until 5th February 2018. In addition, we employ a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) model[28] (Engle 2002).

A section of the existing empirical literature has focused on FOREX market integration (Hong 2001; Lee[29] 2010), although This section is less frequent than those covering other financial markets (Soriano and Climent 2006). Hong (2001) examines the volatility spillovers between two weekly nominal U.S. dollar exchange rates—Deutschemark and Japanese yen during the period 1976 -1995. He employs a class of asymptotic N(0,1) tests for volatility spillover. He finds that for causality in mean, there exists only strong simultaneous interaction

[25] Until 1997, Thailand used a currency peg, which means an attached Thailand's central bank's rate of exchange to USA currency, leading to a stabilized exchange rate between the two countries.

[26] FOREX rate volatility was used by traders to manage their inventory positions, evaluate their trading risk and price FOREX derivatives.

[27] Forbes and Rigobon (2002) argued that the term contagion entail a dynamic increased correlation. Moreover, contagion entails four different types of transmission channels: the correlated information channel (Furstenberg and Jeon 1989), the liquidity challen (Forbes 2004), the cross-market hedging channel (Kodres and Pritsker 2002) and the wealth effect channel (Kyle and Xiong 2001).

[28] DCC-GARCH model has various advantages: it estimates correlation coefficients of the standardized residuals and thus accounts for heteroskedasticity directly and can be used to examine multiple asset returns without adding too many parameters (Engle 2002).

[29] Lee (2010) used the multivariate formulation of the M-GARCH model proposed by Elyasiani and Mansur (1998).

between the two exchange rates. In addition, for causality in variance, there exists strong simultaneous interaction between the two exchange rates. Lee (2010) investigates the volatility transmission among ten emerging foreign exchange markets in Asia and Latin America, together with potential spillovers from major external stock and foreign currency markets. He uses daily data during the period from 1st September 2001 until 31st August 2008. He employs a modified EGARCH-M model, finding evidence of volatility spillover effects from the major currency and stock markets to all ten markets, with particularly strong influences exerted by the Japanese yen on Asian currency markets, and the US SP500 on most of the currency markets. Although, studies of volatility transmission analysing FOREX markets are based mostly on low-frequency data (Kearney and Patton 2000), there are studies using intraday FOREX data (Baillie and Bollerslev 1991; Melvin and Melvin 2003). Kearney and Patton (2002) examine the volatility transmission among the important European Monetary System (EMS) currencies including the French franc, the German mark, the Italian lira, and the European Currency Unit. They construct a series of 3-, 4- and 5-variable multivariate GARCH, using daily and weekly data from April 1979 to March 1997. They find that increased temporal aggregation reduces observed volatility transmission and that the mark plays a dominant position in terms of volatility transmission. Baillie and Bollerslev (1991) investigate the volatility transmission among GBP/USD, DM/USD, SF/USD and JPY/USD for the period from 2nd January 1986 until 15th July 1986. They use hourly data. By employing a robust LM tests, they didn't find significant evidence of volatility spillovers between the markets. Melvin and Melvin investigate the volatility spillovers of the DM/$ and ¥/$ exchange rate across regional markets, using high frequency data (15 minutes) during the period from 1st December 1993 until 28th April 1995. Daily models of integrated volatility are then built and estimated for each region. They find that estimates differ across regions, lending support to the notion that regions have unique characteristics such as institutions or relationships with other regions that are only revealed through individual regional modelling.

This article takes into consideration key contributions. Our first contribution is to contact our empirical analysis for the period after the recent global financial crisis[30] (GFC) of 2007. This

[30] The after GFC period has no heteroskedasticity problem when measuring dynamic correlations, in contrast to GFC period due to volatility increase.

period is very important considering the new financial determinants (McKinsey Global Institute 2018). Second, we use daily data for four of the most important FOREX markets. Our third important contribution is to investigate the contagion[31] (Forbes and Rigobon 2002) by employing a fourvariate DCC-GARCH model.

We organize the rest of the paper as follows. Section two provides a macro-analysis of the markets and Section three presents the data. Section four discusses the econometric methodology. Section five gives the empirical results from DCC-GARCH model. Section six concludes.

2. Overview of the Markets

In this section, we present major macroeconomic figures of Germany, UK, China, Japan and USA from 2011 until 2017 (Table 1). We present the following macroeconomic figures: GDP per capita growth (annual %), unemployment rate (% of total labor force), exports of goods and services (% of GDP), imports of goods and services (% of GDP) and inflation, consumer prices (annual %), downloaded from World Bank.

2.1 Germany macro-conditions

Germany (Panel A) presents the most unaffected exports and imports after GFC. In addition, inflation remains positive all over the years. Unemployment has significantly declined until 2017. Moreover, we observe a small but positive GDP growth the rest years.

2.2 UK macro-conditions

UK (Panel B) has a positive but low GDP growth during the period. Unemployment and inflation are positive in the whole period but seem to be volatile. The imports and the exports seem to be steady as they don't exhibit violate fluctuations all over the years. UK economy characterized by no serious economic problems as London is traditionally the world financial center. Interestingly after the BREXIT announcement we don't observe striking fluctuations in the selected macroeconomic figures.

[31] Other studies investigate contagion focusing on different assets (e.g. crude oil price, metal, etc) using DCC-GARCH models during GFC (Singhal and Ghosh 2016).

2.3 Japan macro-conditions

Japan (Panel C) presents a decreased unemployment at the end of 2017. In addition, Japan exhibits the highest imports and exports in 2014 and 2015 respectively. The inflation is negative in 2011, 2012 and 2016. In a general point of view, Japan exhibits steady economic conditions, considering the technological innovations. In addition, Japan and has the third-largest economy in the world by nominal GDP.

2.4 China macro-conditions

China (Panel D) has the highest levels of GDP growth. Moreover, unemployment rate has increased in the end of 2017 in contrast to the decreased unemployment rate that all the other markets state. The inflation presents fluctuations with a decreasing tendency. GFC of 2007 did not slow down China exports, and China became the largest exporter among the four under investigation markets.

2.5 USA macro-conditions

USA (Panel E) presents the highest exports in 2013. Interestingly, USA does not exhibit the highest unemployment rate all over the years under investigation. In addition. inflation is positive all over the years.

3. Data description and summary statistics

Our data consists of daily currencies (obs. 1776) for EUR, CHW, JPY and GBP denominated in USD. The data set is sourced from *Thomson Financial (Datastream)*, for a period from 19th April 2011 to 5th February 2018. We set the beginning of the period of observation in April 2011, four months before the sharp drop in stock prices in August 2011 across the USA, Middle East, Europe and Asia. Daily logarithmic returns for each FOREX market are calculated as: $r_t = log(p_t) - log(p_{t-1})$, where p_t the price of FOREX market at the day *t*.

Table 2 states the summary statistics. According to standard deviation, lowest minimum and the second highest maximum return prices, JPY/USD returns experience the largest fluctuations. In addition, CHW/USD and GBP/USD returns present a positive skewness, while JPY/USD and EUR/USD returns are negatively skewed. Kurtosis, for all markets, exceeds three (fat tails), indicating a leptokurtic distribution (Billio and Caporin 2010; Burzala 2015). Jarque-Bera statistic rejects the null hypothesis of normality for all market returns. Skewness ($\neq$0), Kurtosis (>3) and Jarque-Bera test results suggest the use of student-t distribution for the empirical analysis. Augmented Dickey Fuller test (ADF) (Dickey and Fuller 1979) and SCHMIDT-PHILLIPS test with the two statistiscs (Z(tau) and Z(rho)) indicate the rejection of the null hypotheses of a unit root at the 1% level.

Figure 1 plots the actual series for EUR/USD (Graph A), JPY/USD (Graph B), CHW/USD (Graph C) and GBP/USD (Graph D) and their respective logarithmic returns during the period from 19th April 2011 to 5th February 2018. According to the actual series, the figure reveals strong co-movements for all the markets. In addition, we observe the effects of crucial economic facts: (1) in June 2013, the Bank of England announcement of continuing the Quantitative Easy (QE), (2) in October 2011, Spain lost credit rating to AA- with a negative outlook from Standard & Poor. Based on the logarithmic returns, we observe that all markets exhibit high levels of volatility, indicating the presence of heteroskedasticity[32] and appropriate the use of DCC-GARCH model.

4. Methodology

This section lays out the theoretical framework for the GARCH(p,q) - DCC model. It is employed in two stages. In §(4.1.), we define the univariate GARCH model. In §(4.2.), we set the fourvariate framework of DCC. In §(4.3.), we define the log-likelihood function.

4.1 Univariate GARCH framework

In the first stage, we generate the daily logarithmic returns:

$$y_t = \mu + \varepsilon_t, \text{ with } t = 1, \ldots, T \tag{1}$$

where μ is constant and ε_t is standardized residuals defined as follows:

$$\varepsilon_t = \sqrt{h_t} u_t, \text{ where } \varepsilon_t \sim N(0, H_t) \text{ and } u_t \text{ are i.i.d.} \tag{2}$$

[32] A time series is said to be heteroscedastic if its variance changes over time, otherwise it is called homoscedastic.

where u_t is standardized errors and h_t is conditional variance depending on h_t and ε_t for each market lagged one period, generated by the univariate GARCH(1,1) model (Bollerslev 1986):

$$h_t = \omega + a\varepsilon_{t-1}^2 + bh_{t-1} \tag{3}$$

where ω is constant, a and b are ARCH and GARCH effects.

4.2 Fourvariate DCC framework

In the second stage, we employ the Engle (2002) representation of the fourvariate GARCH model in order to estimate the fourvariate conditional variance matrix (H_t is $N\ x\ N$ matrix, with N the number of markets, $i = 1,\ldots,N$) as follows:

$$H_t = D_t R_t D_t \tag{4}$$

D_t is the conditional variance matrix given by:

$$D_t = diag\left(h_{11t}^{\frac{1}{2}} \ldots h_{NNt}^{\frac{1}{2}}\right) \tag{5}$$

R_t is the condition correlation matrix of $N\ x\ N$ dimension, and is defined as follows:

$$R_t = (\rho_{iit}) = diag(q_{11,t}^{-\frac{1}{2}} \ldots q_{NN,t}^{-\frac{1}{2}})Q_t diag(q_{11,t}^{-\frac{1}{2}} \ldots q_{NN,t}^{-\frac{1}{2}}) \tag{6}$$

where the $N\ x\ N$ symmetric positive definite matrix $Q_t = (q_{ii,t})$ is given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1}, \tag{7}$$

$\bar{Q}$ is the $N\ x\ N$ unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.

4.3 Log-likelihood function

We estimate the model using Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors. We maximize the log-likelihood as follows:

$$\sum_{t=1}^{T}\left[log\frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{N}{2}}} - \frac{1}{2}\log\left(|H_t|\right) - \left(\frac{N+\nu}{2}\right)log\left[1 + \frac{\varepsilon_t{}'H_t{}^{-1}\varepsilon_t}{\nu-2}\right]\right] \tag{8}$$

where N is the number of markets, $\Gamma(.)$ is the Gamma function and v is the degrees of freedom.

5. Empirical results

§(5.1.) states the results from DCC-GARCH(1,1) model, while §(5.2.) provides a preliminary analysis of contagion. In §(5.3.), we see the estimates of simple correlation analysis, while in §(5.4.), we observe the mean values of conditional variances and covariances. §(5.5.) presents an economic analysis of DCCs and §(5.6.) demonstrates the diagnostic tests.

5.1. Results of the DCC-GARCH(1,1) model

Panel A of table 3 provides the estimated values for the mean equation (Equation 1) and the univariate GARCH(1,1) model (Equation 3). According to the mean equation, we observe statistically insignificant μ for all markets. In addition, in the variance equation, we see statistically insignificant ω. ARCH *(a)* and GARCH *(b)* terms are highly significant, implying strong ARCH and GARCH effects.

Panel B of table 3 exhibits the estimated fourvariate DCC model. In line with other several studies, (Cosetti, Pericoli and Sbracia 2005; Tolgahan 2010; Sehgal and Ghosh 2016), parameter estimates α and β are statistically significant and different from zero, indicating the presence of strong ARCH and GARCH effects. The above results state that the four under investigation markets are integrated. Additionally, we state the estimated degrees of freedom (5,133630) and the log-likelihood (36389,857).

In panel C of table 3, we observe the estimated Ljuing-Box of Hosking (1980) and Li-McLeod (1983) diagnostic tests results, revealing no autocorrelation and indicating evidence of no misspecification in the standardized residuals. We used $x^2(8)$ statistic to examine the hypothesis of no spillover effects, suggesting the existence of spillovers.

In addition, in panel D of table 3, we state the estimated AIC and SIC information criteria.

5.2. DCCs preliminary test for contagion

We calculate and store the DCCs of the DCC-GARCH(1,1) model. Next, we employ a regression equation for the DCCs on a constant and a trend. The rise in DCCs is measured by the term $\widehat{\Delta\rho}$, which is equal to the difference between the last and the first fitted values[33].

Table 4 reports the regression results, indicating a significant rise of DCCs for the pairs of markets EUR/USD-JPY/USD (Δρ=25,17%), EUR/USD-CHW/USD (Δρ=23,2%) and JPY/USD-GBP/USD (Δρ=18,55%). In addition, we observe a lower rise in DCCs for the pairs of markets CHW/USD-GBP/USD (Δρ=11,11%) and JPY/USD-GBP/USD (Δρ=4,5%). The significant decrease of DCCs between EUR/USD and GBP/USD (Δρ=-9,47%), suggests that those markets have become less inter-correlated over time.

5.3 Simple Correlation Analysis

We employ Spearman's rank correlation to quantify potential transmission mechanisms. For a sample size of T observations, the T raw scores i_t, j_t ($i \neq j = 1,\dots,N$ markets and $t = 1,\dots,T$ observations) are converted to ranks rg_i, rg_j.

Using the covariance of the rank variables $cov(rg_i, rg_j)$ and the standard deviations of the rank variables (σ_{rg_i} and σ_{rg_j}), Spearman's rank correlation (ρ_{rg_i,rg_j}) is generated as follows:

$$\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}} \tag{9}$$

In table 5, we see the results of the Spearman's rank correlation. Results suggest the strongest rank correlation for the pairs of markets EUR/USD-GBP/USD (ρ_{rg_1,rg_4}), JPY/USD-GBP/USD (ρ_{rg_2,rg_4}) and EUR/USD-JPY/USD (ρ_{rg_1,rg_2}). The above markets present a level of integraion for three main reasons: (1) the above markets are highly exposed to USA financial markets, (2) EU and UK are economically interdependent, and (3) during the GFC Japan started to invest into European financial assets. Moreover, China presents the lowest rank correlation with the rest markets. China is not highly exposed to USA financial markets

[33] We applied DCC-GARCH(1,1) model for the under examination markets. Thus, we stored the fitted values of dynamic conditional correlations and lastly, we calculated Δρ, which is equal to the difference between the last and the first fitted values.

because China preferred to buy USA's treasury debt via bonds[34] due to its export industries enormous earnings of foreign currency.

5.4 Mean values of conditional variances and covariances

Table 6 reports the estimated mean values ($\overline{h_{ij}}$, with $i, j = 1, \ldots, N$) of conditional variances and conditional covariances. Results state that $\overline{h_{2,2}} > \overline{h_{4,4}} > \overline{h_{1,1}} > \overline{h_{3,3}}$, suggesting JPY/USD's the strongest own spillovers. In addition, we observe that $\overline{h_{1,4}} > \overline{h_{1,2}} > \overline{h_{2,4}} > \overline{h_{3,4}} > \overline{h_{1,3}} > \overline{h_{2,3}}$. The pairs of markets EUR/USD-JPY/USD ($\overline{h_{1,2}}$), JPY/USD-GBP/USD ($\overline{h_{2,4}}$) and EUR/USD-GBP/USD ($\overline{h_{1,4}}$) exhibit stronger spillover effects. The above is interpretable for two major reasons: (1) Japan's and China's economies are directly linked, and (2) Japan in highly exposed to European financial assets.

Figure 2 presents the evolution of conditional variances for EUR/USD (graph A), JPY/USD (graph B), CHW/USD (graph C) and GBP/USD (graph D). We observe a tremble trend for all markets. In addition, important economic shocks are observable i.e. the Brexit decision in June 2016 caused bear financial markets in UK, leading to a sharp rise of conditional variance of GBP/USD, among others.

In figure 3, we report the estimates of conditional covariances, generated by DCC-GARCH(1,1) model for the pairs of markets: EUR/USD-JPY/USD (graph A), EUR/USD-CHW/USD (graph B), EUR/USD-GBP/USD (graph C), JPY/USD-CHW/USD (graph D), JPY/USD-GBP/USD (graph E) and CHW/USD-GBP/USD (graph F). Results state clearly the behavior of spillovers, as we can notice the existence of extreme volatility levels.

5.5. Economic analysis of dynamic conditional correlations (DCCs)

The DCCs for the pairs of markets EUR/USD-JPY/USD (Graph A of figure 5) and JPY/USD-GBP/USD (Graph E of figure 5) demonstrate strong co-movements. While, DCCs have mostly positive values, they are extremely volatile suggesting increasing riskiness from an investor's perspective. In addition, DCCs present some common extreme jumps over time generated by short-term global market drops: i.e. (a) the day The President of the Catalonia, Artur Mas i Gavarró dropped plans for a referendum on independence on 9/11/2014 from Spain

[34] China buys US treasury debt, means that China is lending money to the USA government.

(14/10/2014), and (b) the United Kingdom European Union membership referendum (23/06/2016), among others.

Additionally, the DCCs for the pairs of markets EUR/USD-CHW/USD (Graph B of figure 5), JPY/USD-CHW/USD (Graph D of figure 5), CHW/USD- GBP/USD (Graph F of figure 5) exhibit strong co-movements. In addition they have mostly positive values and extreme volatility, suggesting the correlations risky for any investor. Moreover, DCCs demonstrate two common extreme jumps (12/12/2014, 23/06/2016) that can be attributed to: (a) S&P 500 had a sharp fall (12/12/2014), and (b) the United Kingdom European Union membership referendum (23/06/2016).

Graph C of figure 5 show that the DCC between EUR/USD and GBP/USD has positive values and is extremely volatile, revealing a low stability of the correlation. Additionally, we notice some extreme jumps over time generated by major economic events, i.e. (a) plans to liquidate IBRC are abruptly announced and get underway in dramatic circumstances (06/02/2013), and (b) the UK EU membership referendum (23/06/2016), among others.

6. Conclusions

In this paper, we empirically investigated potential spillover effects among EUR/USD, CHW/USD, GBP/USD and JPY/USD. The under investigation period is defined after the recent GFC of 2007. We used a fourvariate DCC-GARCH model, in order to examine volatility transmission among the FOREX markets.

We extract several important contributions from our empirical analysis. According to summary statistics, JPY/USD experiences the largest fluctuations. Interestingly, the results of preliminary analysis show that EUR/USD and GBP/USD become less inter-correlated over time. The Spearman's correlation analysis reveal that CHW/USD is the most immune market and a level of integration for the pairwise rank correlation of EUR/USD, GBP/USD and JPY/USD, supported from the estimated mean values of conditional variances and covariances. Results of the estimated DCCs show that all the pairs of markets exhibit contagion effects, with the strongest contagion between EUR/USD and GBP/USD. Furthermore, macroeconomic figures are not related to conditional volatility results.

The above conclusions are important for risk managers, policy markets, banks and investors. Risk managers can use the above information for hedging purposes. Policy makers, can analyze the movements among the markets and determine a potential future crisis on a global level. Banks may use FOREX market spillover effects as a factor of three different things: (1) balance of payments for a country, (2) corporate earnings, (3) macro-analysis (inflation). Investors should be cautious about investing into financial assets, which present contagion effects.

References

Akar, C.: Dynamic Relationships between the Stock Exchange, Gold, and Foreign Exchange Returns in Turkey. Middle Eastern Finance and Economics. Vol. 12, 109-115 (2011)

Baillie, R., Bollerslev, T.: Intra-day and inter-market volatility in foreign exchange rates. Review of Economic Studies. Vol. 58, 565–585 (1991)

Billio, M., Caporin, M.,: Market linkages, variance spillovers, and correlation stability: Empirical evidence of financial contagion. Computational Statistics & Data Analysis. Vol. 54. No. 11, 2443-2458 (2010)

Bollerslev, T.: Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics. Vol. 31. No. 3, 307-327 (1986)

Burzala, M.: Did the crisis on the interbank market run parallel to the crisis on the capital market? A conspectral analysis. Safe Bank. Vol. 59. No. 2, 96-112 (2015)

Corsetti, G., Pericoli, M., Sbacia, M.: Some contagion, some interdependence': More pitfalls in tests of financial contagion. Journal of International Money and Finance. Vol. 25. No. 8, 1177-1199 (2005)

Dickey, D., Fuller, W. A.: Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association. Vol. 74, 427-431 (1979)

Elyasiani, E., Mansur, I.: Sensitivity of the bank stock returns distribution to chances in the level and volatility of interest rates: A GARCH-M model. Journal of Banking and Finance. Vol. 22, 535-563 (1998)

Engle, R. F.: Dynamic conditional correlation-a simple class of multivariate GARCH models. J. Bus. Econ. Stat.. Vol. 20, 339-350 (2002)

Forbes, K., Rigobon, R.: No contagion, only interdependence: Measuring stock market comovements. Working Paper. Massachusetts Institute of Technology (2002)

Forbes, K.: The Asian flu and Russian virus:firm-level evidence on how crises are transmitted internationally. Journal of International Economics. Vol. 63. No. 1, 59-92 (2004)

Furstenberg, G., Jeon, B. N.: International stock price movements: links and messages. Brookings Papers on Economic Activity. Vol. 1, 125-167 (1989)

Hong, Y.: A Test for Volatility Spillover with Application to Exchange Rates. Journal of Econometrics. Vol. 103, 183–224 (2001)

Hosking, J. R. M.: The multivariate portmanteau statistic. Journal of the American Statistical Association. Vol. 75, 602-608 (1980)

Kearney, C., Patton, A.J.: Multivariate GARCH modeling of exchange rate volatility transmission in the European monetary system. The Financial Review. Vol. 41, 29–48 (2000)

Kodres, L. E., Pritsker, M.: A rational expectations model of financial contagion. Journal of Finance. Vol. 57. No. 2, 769-799 (2002)

Koutmos, G., Booth, G. G.: Asymmetric volatility transmission in international stock markets. Journal of International Money and Finance. Vol. 14, 747-762 (1995)

Kyle, A., Xiong, W.: Contagion as a wealth effect. Journal of Finance. Vol. 56. No. 4, 1401-1440 (2001)

Lee, J.: Currency risk and volatility spillover in emerging foreign exchange markets. International Research Journal of Finance and Economics. Vol. 42, 37-45 (2010)

Melvin, M., Melvin, B.P.: The global transmission of volatility in the foreign exchange market. The Review of Economics and Statistics. Vol. 85, 670–679 (2003)

McLeod, A.J., Li, W.K.: Diagnostic checking ARMA time series models using squaredresidual autocorrelations. Journal of Time Series Analysis. Vol. 4, 269-273 (1983)

Pericoli, M., Sbracia, M.: A Primer on Financial Contagion. Journal of Economic Surveys. Vol. 17. No. 4, 571-608 (2003)

Sehgal, S., Ahmad, W., Deisting, F.: An investigation of price discovery and volatility spillovers in India's foreign exchange market. Journal of Economic Studies. Vol. 42. No. 2, 261-284 (2015)

Singhal S., Ghosh, S.: Returns and volatility linkages between international crude oil price, metal and other stock indices in India: Evidence from VAR-DCC-GARCH models. Resources Policy. Vol. 50, 276-288 (2016)

Soriano, P., Climent, F.J.: Volatility transmission models: a survey. Revista de Economía Financiera. Vol. 10, 32–81 (2006)

Tolgahan, Y.: Improving Portfolio Optimization by DCC And DECO GARCH: Evidence from Istanbul Stock Exchange. Munich University Library Paper (2010)

Appendix

Table 1

GDP per capita growth, Unemployment Rate, Investment in financial assets, Exports, Imports and Stock Trade of Germany, UK, Japan, China and USA, sample period: 2011-2018.

	2011	2012	2013	2014	2015	2016	2017
Panel A: Germany							
GDP per capita growth (annual %)	5,599	0,303	0,215	1,505	0,866	1,124	1,794
Unemployment, total (% of total labor force)	5,82	5,38	5,23	4,98	4,619	4,119	3,736
Exports of goods and services (% of GDP)	44,81	45,98	45,39	45,70	46,87	46,11	47,23
Imports of goods and services (% of GDP)	39,92	39,89	39,43	38,78	38,88	38,14	39,66
Inflation, consumer prices (annual %)	2,075	2,008	1,504	0,906	0,234	0,483	NA
Panel B: UK							
GDP per capita growth (annual %)	0,662	0,778	1,371	2,28	1,535	1,21	1,129
Unemployment, total (% of total labor force)	8,039	7,889	7,53	6,11	5,3	4,809	4,322
Exports of goods and services (% of GDP)	30,51	29,73	29,66	28,24	27,38	28,25	30,52
Imports of goods and services (% of GDP)	32,04	31,71	31,68	30,25	29,09	30,32	31,93
Inflation, consumer prices (annual %)	4,484	2,821	2,554	1,46	0,05	0,641	NA
Panel C: Japan							
GDP per capita growth (annual %)	0,069	1,657	2,147	0,507	1,461	1,054	1,88
Unemployment, total (% of total labor force)	4,55	4,349	4,03	3,579	3,329	3,13	2,831
Exports of goods and services (% of GDP)	14,92	14,54	15,91	17,54	17,58	16,11	NA
Imports of goods and services (% of GDP)	15,46	16,09	18,23	20	18	15,14	NA
Inflation, consumer prices (annual %)	-0,26	-0,05	0,346	2,761	0,789	-0,11	NA
Panel D: China							
GDP per capita growth (annual %)	9,012	7,332	7,226	6,755	6,358	6,123	6,303
Unemployment, total (% of total labor force)	4,34	4,469	4,539	4,592	4,605	4,649	4,675
Exports of goods and services (% of GDP)	26,49	25,40	24,50	23,49	21,34	19,65	19,75
Imports of goods and services (% of GDP)	24,10	22,69	22,06	21,38	18,10	17,37	18,04
Inflation, consumer prices (annual %)	5,41	2,643	2,628	2	1,437	2	NA
Panel E: USA							
GDP per capita growth (annual %)	0,849	1,459	0,956	1,8	2,087	0,742	1,546
Unemployment, total (% of total labor force)	8,949	8,069	7,38	6,17	5,28	4,849	4,438
Exports of goods and services (% of GDP)	13,57	13,60	13,63	13,62	12,49	11,89	NA
Imports of goods and services (% of GDP)	17,31	17,10	16,58	16,54	15,39	14,68	NA
Inflation, consumer prices (annual %)	3,156	2,069	1,464	1,622	0,118	1,261	NA

Notes: This table presents the key annual macroeconomics market of Germany, UK, Japan, China and USA during the period 2008 to 2017. Per capita GDP growth the GDP growth of a country divided by the number of people in every country. Unemployment rate is generated by the number of unemployed persons as a percentage of the labor force. Exports and imports are generated as a percentage of GDP. Inflation reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services of a country.

Table 2
Summary statistics of daily FOREX returns, sample period: 19th April 2011 – 5th February 2018.

	EUR/USD	JPY/USD	CHW/USD	GBP/USD
Panel A: Basic statistics				
Mean	7,9132e-005	0,00016225	-2,0137e-005	8,1481e-005
Minimum	-0,029954	-0,037675	-0,011898	-0,0299
Maximum	0,024191	0,034693	0,018382	0,084081
Std. deviation	0,0055857	0,0059209	0,0015426	0,0055322
Panel B: Normality Test				
Skewness	-0,006646	-0,10991	0,54949***	1,9781***
t-Statistic	0,11435	1,8910	9,4537	34,033
p-Value	0,90896	0,058621	3,2704e-021	7,3300e-254
Excess Kyrtosis	1,8701***	4,2077***	17,575***	31,132***
t-Statistic	16,096	36,216	151,27	267,96
p-Value	2,7091e-057	3,3563e-287	0,0000	0,0000
Jarque-Bera	258,38***	1311,5***	22907***	72756***
p-Value	7.8427e-057	1.6144e-285	0,0000	0,0000
Panel C: Unit Root tests				
ADF	-24,9446***	-24,4111***	-22,8547***	-25,1344***
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663
SCHMIDT-PHILLIPS Test Z(tau)	-26,2961***	-37,7412***	-36,4892***	-27,5229***
Critical value: 1%	-3,56	-3,56	-3,56	-3,56
Critical value: 5%	-3,02	-3,02	-3,02	-3,02
Critical value: 10%	-2,75	-2,75	-2,75	-2,75
SCHMIDT-PHILLIPS Test Z(rho)	-981,027***	-1615***	-1497,62***	-1052,38***
Critical value: 1%	-25,2	-25,2	-25,2	-25,2
Critical value: 5%	-18,1	-18,1	-18,1	-18,1
Critical value: 10%	-15	-15	-15	-15

Notes: Panel A presents the basic statistics of daily FOREX returns. Panel B shows the normality test and panel C demonstrates the unit root tests. We used intercept and a time trend to generate ADF statistic with lags equal to zero. Additionally, we calculated SCHMIDT-PHILLIPS Z(tau) and Z((rho) statistics with the bandwidth parameter equal to zero.
*** denote statistical significance at the 1% level.

Table 3

Estimates of DCC-GARCH(1,1) model, sample period: 19th April 2011 – 5th February 2018.

	EUR/USD	JPY/USD	CHW/USD	GBP/USD
Panel A: estimates of GARCH(1,1) model				
Constant (μ)	0,000014	0,000190	-0,0000333	0,000026
t-Statistic	0,1208	1,468	-0,9119	0,2276
p-Value	0,9039	0,1423	0,3619	0,8200
Constant (ω)	0,123455	0,454605	0,408752	0,495938
t-Statistic	1,179	1,608	0,9327	1,491
p-Value	0,2386	0,1079	0,3511	0,1360
ARCH (a)	0,029584***	0,049908**	0,133232**	0,087466*
t-Statistic	4,790	2,729	2,353	1,928
p-Value	0,0000	0,0064	0,0187	0,0540
GARCH (b)	0,966194***	0,938617***	0,697667***	0,902342***
t-Statistic	134,3	42,41	3,311	21,25
p-Value	0,0000	0,0000	0,0009	0,0000
Panel B: estimates of DCC model				
Alpha (α)	0,031906***			
t-Statistic	5,216			
p-Value	0,0000			
Beta (β)	0,938977***			
t-Statistic	62,43			
p-Value	0,0000			
df (v)	5,133630***			
t-Statistic	20,51			
p-Value	0,0000			
Log-likelihood	36389,857			
Panel C: diagnostic tests				
$x^2(8)$	8603,7**			
p-Value	0,0000			
Hosking (50)	888,877			
p-Value	0,0153437			
Hosking^2 (50)	747,685			
p-Value	0,8979872			
Li-McLeod (50)	888,474			
p-Value	0,0157102			
Li-McLeod^2 (50)	748,784			
p-Value	0,8927797			
Panel D: Information Criteria				
Akaike	-34,322375			
Schwarz	-34,245099			

Notes: Panel A presents the results of univariate GARCH(1,1), panel B shows the results of the dynamic conditional correlation driving process Q_t and panel C demonstrates the diagnostic tests of Hosking (1980) and McLeod and Li (1983). In panel D we see the information criteria of DCC-GARCH(1,1) model. P-values have been corrected by 2 degrees of freedom for Hosking^2 (50) and Li-McLeod^2 (50) statistics and by 1 degree of freedom for Hosking (50) and Li-McLeod (50) statistics.
*, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively

Mean equations: $y_{it} = \mu_{it} + \varepsilon_{it}$, where $y_{it} = (y_{1t}, \dots, y_{4t})$, $\mu_{it} = (\mu_{1t}, \dots, \mu_{4t})$, $\varepsilon_{it} = (\varepsilon_{1t}, \dots, \varepsilon_{4t})$, $\varepsilon_{it} \sim N(0, H_t)$.

Variance equations: $h_{iit} = \omega + a_i \varepsilon_{t-i}^2 + b_i h_{ii,t-1}$ $i = 1,\dots,4$.

Conditional correlation dricing process equation of standardized residuals (u_t): $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}' + \beta Q_{t-1}$.

Log-likelihood equation: $\sum_{t=1}^{T} \left[log \frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}} \Gamma\left(\frac{\nu}{2}\right) \nu - 2^{\frac{N}{2}}} - \frac{1}{2} log\,(|H_t|) - \left(\frac{N+\nu}{2}\right) log\left[1 + \frac{\varepsilon_t{}' H_t{}^{-1} \varepsilon_t}{\nu - 2}\right] \right]$

Table 4

DCC preliminary test for contagion, sample periods: 19th April 2011 – 5th February 2018.

	EUR/USD-JPY/USD	**EUR/USD-CHW/USD**	**EUR/USD-GBP/USD**
Constant	0,201737***	0,00422231	0,579773***
t-Statistic	29,1	0,818	133
p-Value	0,0000	0,4135	0,0000
Trend	0,000142046***	0,000131026***	-5,35274e-005***
t-Statistic	21	26	-12,5
p-Value	0,0000	0,0000	0,0000
$\widehat{\Delta\rho}$%	25,17%	23,2%	-9,47%
	JPY/USD-CHW/USD	**JPY/USD-GBP/USD**	**CHW/USD-GBP/USD**
Constant	0,00128204	0,185168***	0,0660661***
t-Statistic	0,259	26,1	14,3
p-Value	0,7954	0,0000	0,0000
Trend	0,000104790***	2,99051e-005***	6,27367e-005***
t-Statistic	21,7	4,32	13,9
p-Value	0,0000	0,0000	0,0000
$\widehat{\Delta\rho}$%	18,55%	4,5%	11,11%

Notes: We applied GARCH(1,1)-DCC model and we stored DCC's. Trend is the slope coefficient of a regression of DCC's, on a constant and a time trend. The rise of DCC's is measured by $\widehat{\Delta\rho}$ which is equal to the difference between the last and the first fitted values of a regression of DCCs on a constant and a zero-mean time trend.
*** denote statistical significance at the 1% level.

Table 5

Estimates of Spearman's rank correlation coefficient (ρ_{rg_i,rg_j}), sample period: 19th April 2011 – 5th February 2018.

	EUR/USD (i=1)	**JPY/USD (i=2)**	**CHW/USD (i=3)**	**GBP/USD (i=4)**
ρ_{rg_i,rg_1}	1	-	-	-
t-Statistic	-			
p-Value	-			
ρ_{rg_i,rg_2}	0,323939***	1	-	-
t-Statistic	7,860	-		
p-Value	0,0000	-		
ρ_{rg_i,rg_3}	0,099372**	0,091542**	1	-
t-Statistic	2,334	2,002	-	
p-Value	0,0197	0,0454	-	
ρ_{rg_i,rg_4}	0,501683***	0,214507***	0,108108**	1
t-Statistic	15,60	4,681	2,508	-
p-Value	0,0000	0,0000	0,0122	-

Notes: Table 5 exhibits the estimates of elements (ρ_{rg_i,rg_j}) of rank correlation.
** and *** denote statistical significance at the 5% and 1% levels, respectively.
Spearman's rank correlation equation: $\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}}$.

Table 6

Average values of conditional variance and covariance $(\overline{h_{ij}})$, sample period: 19th April 2011 – 5th February 2018.

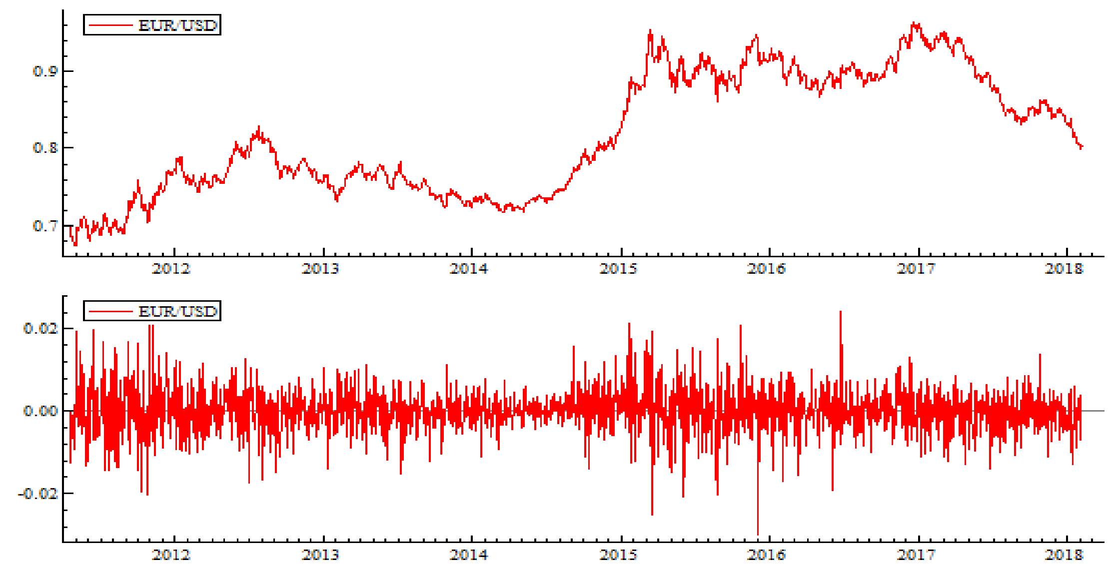
Market i	**EUR/USD (j=1)**	**JPY/USD (j=2)**	**CHW/USD (j=3)**	**GBP/USD (j=4)**
$(\overline{h_{i,1}})$	3,11337e-005	-	-	-
$(\overline{h_{i,2}})$	1,04415e-005	3,60199e-005	-	-
$(\overline{h_{i,3}})$	1,00300e-006	8,80869e-007	2,39531e-006	-
$(\overline{h_{i,4}})$	1,63382e-005	5,72715e-006	1,24555e-006	3,23996e-005

Notes: $\overline{h_{ij}}$, with i, j = 1,…,N, denotes the average values of conditional variances and conditional covariances.

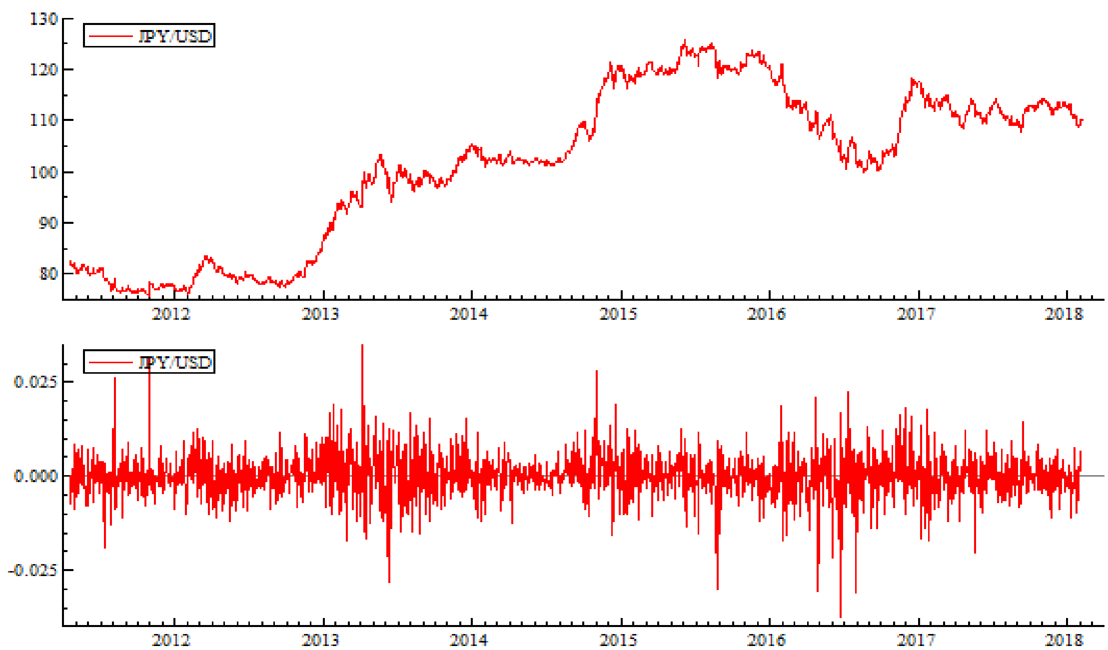
Multivariate conditional variance equation: $H_t = D_t R_t D_t$.

Figure 1. Actual series and the respective logarithmic returns of FOREX markets.

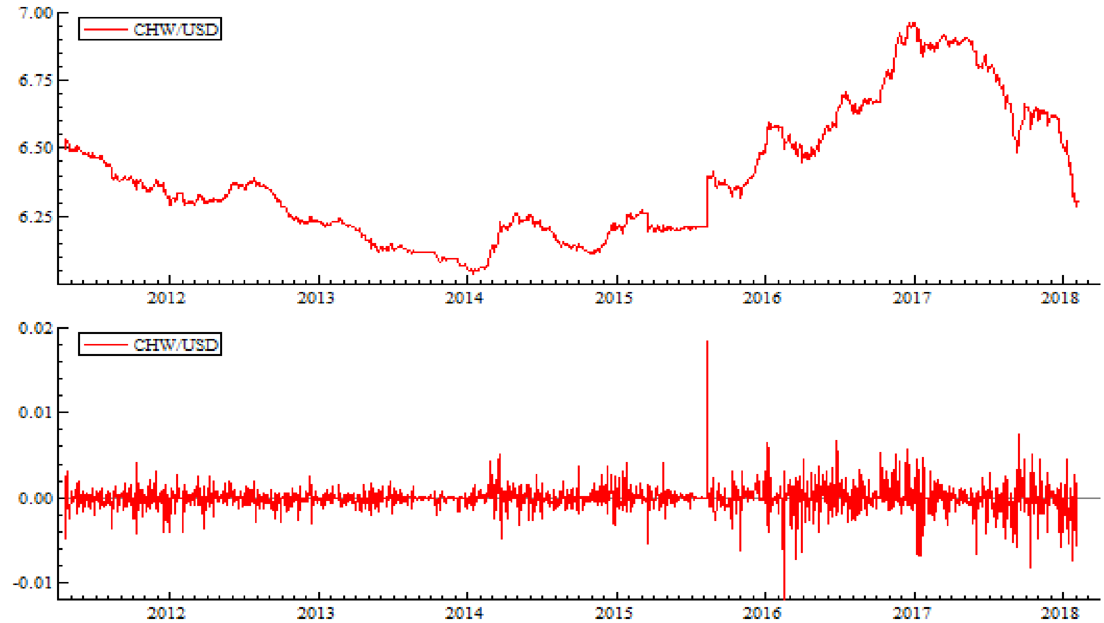
Graph A. EUR/USD



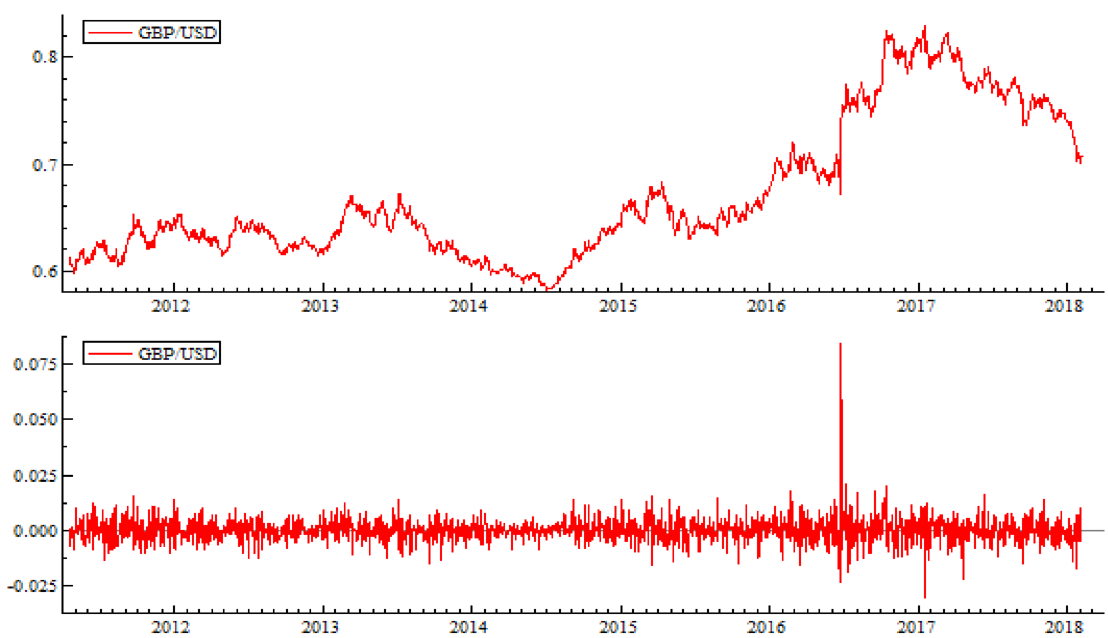
Graph B. JPY/USD



Graph C. CHW/USD



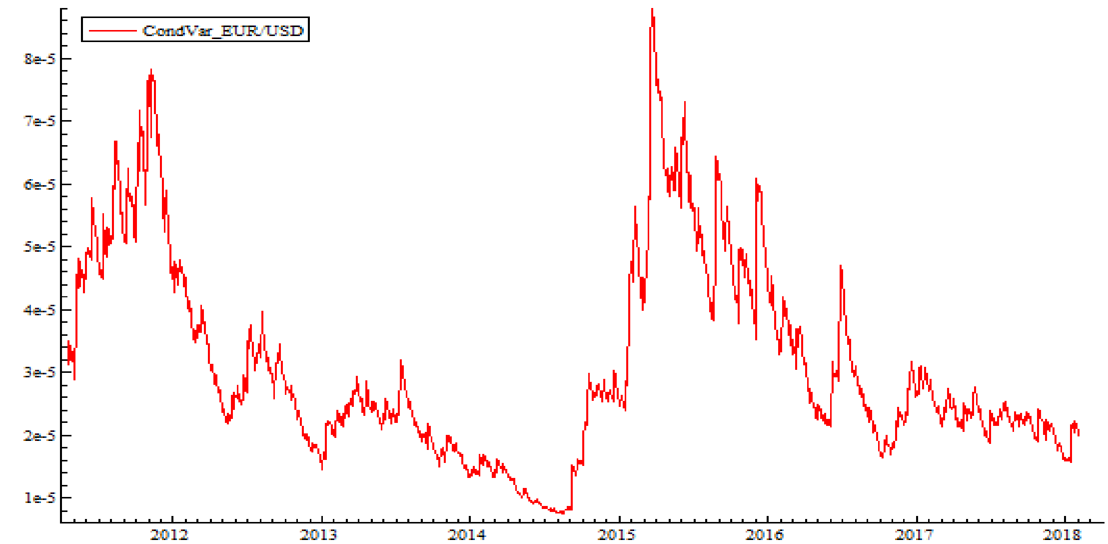
Graph D. JPY/USD



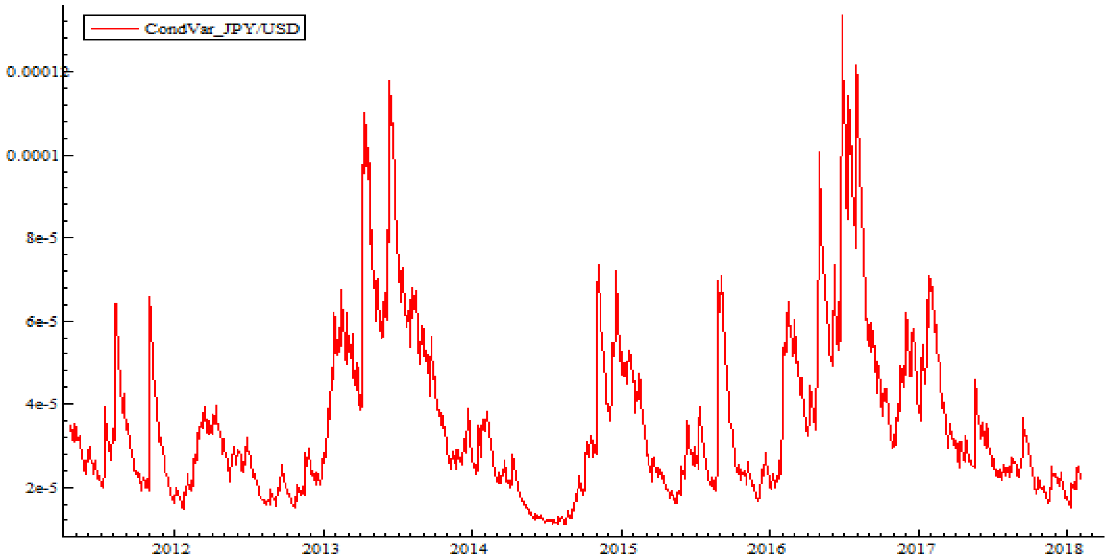
Notes: FOREX market logarithmic returns are generated by $r_t = ln(p_t) - ln(p_{t-1})$,

Figure 2. Conditional variances of the DCC-GARCH (1,1) model.

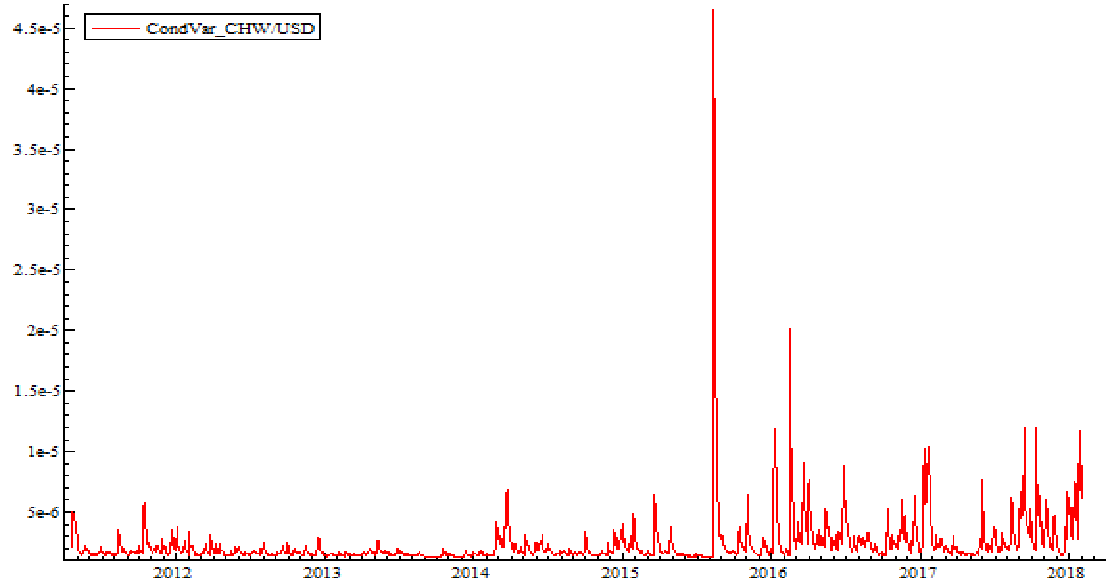
Graph A. EUR/USD



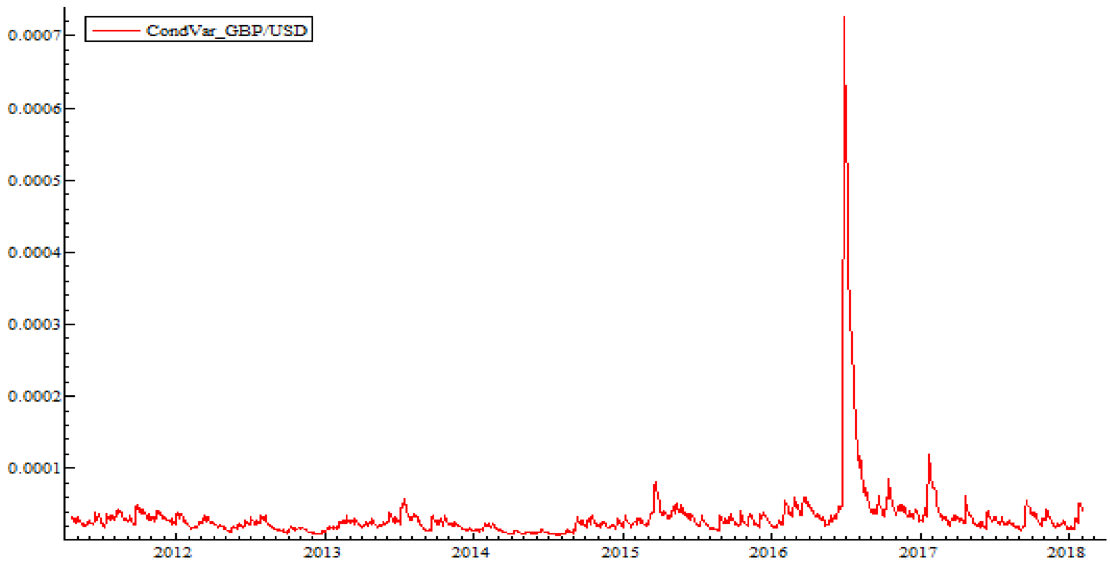
Graph B. JPY/USD



Graph C. CHW/USD



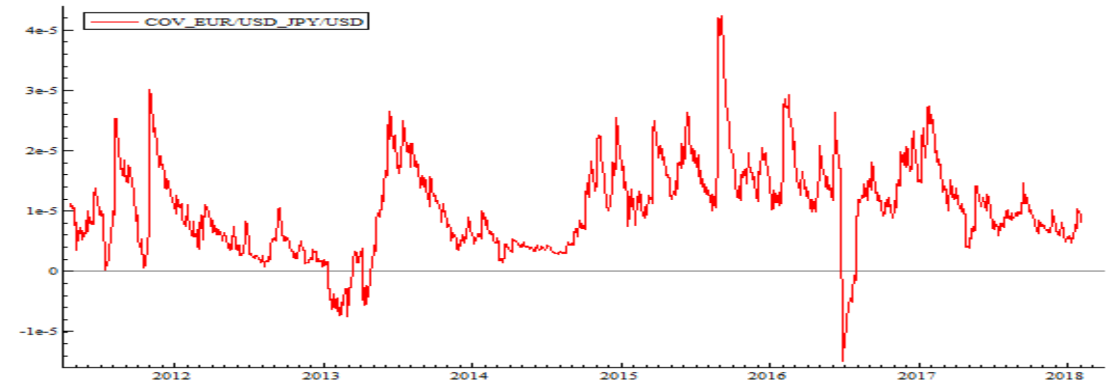
Graph D. GBP/USD



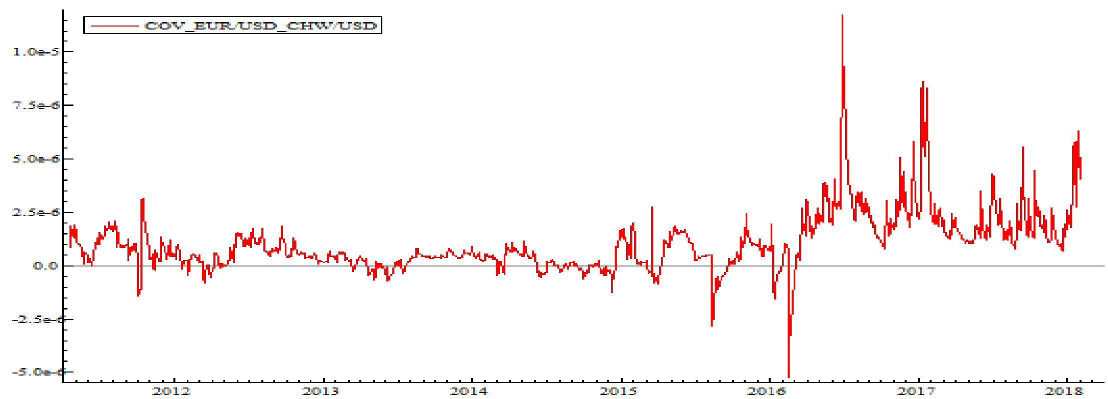
Notes: The red lines represent the conditional variances (h_t) for all markets, generated by Eq.(3).

Figure 3. Conditional covariances of the DCC-GARCH (1,1) model.

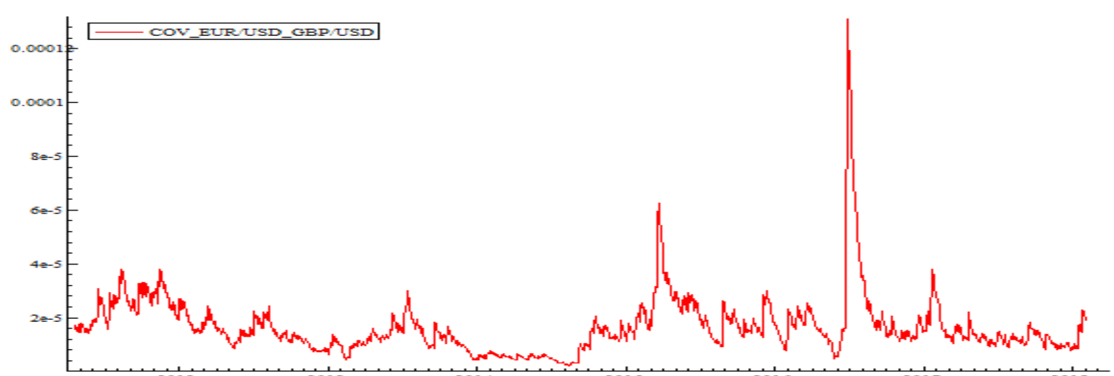
Graph A. EUR/USD-JPY/USD



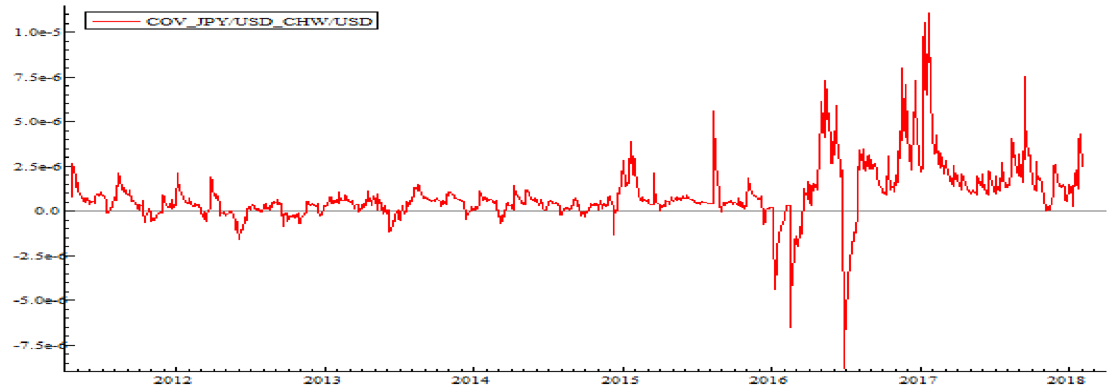
Graph B. EUR/USD-CHW/USD



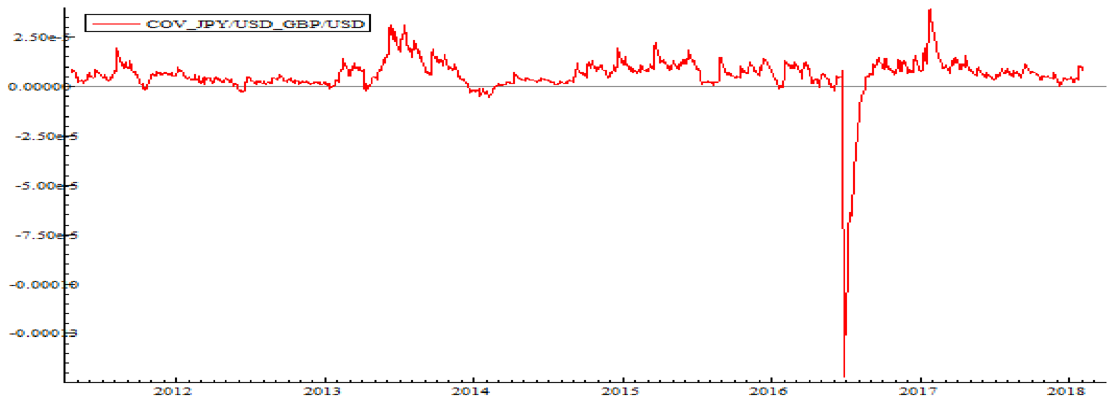
Graph C. EUR/USD-GBP/USD



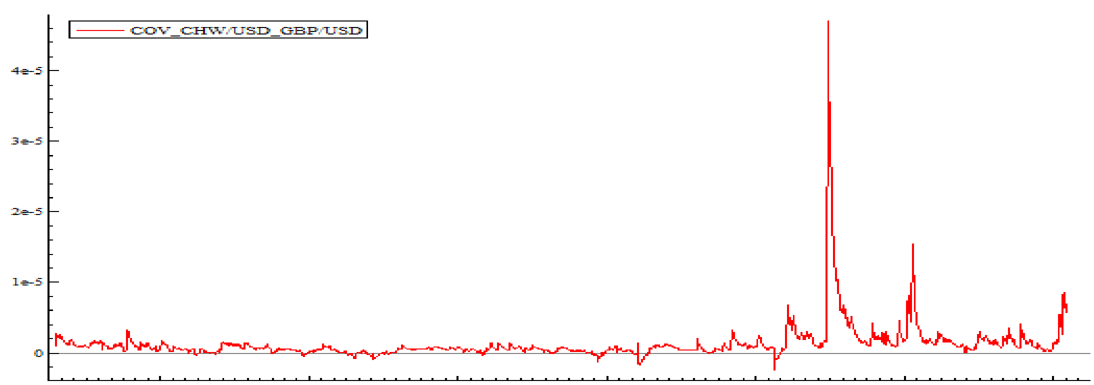
Graph D. JPY/USD-CHW/USD



Graph E. JPY/USD-GBP/USD



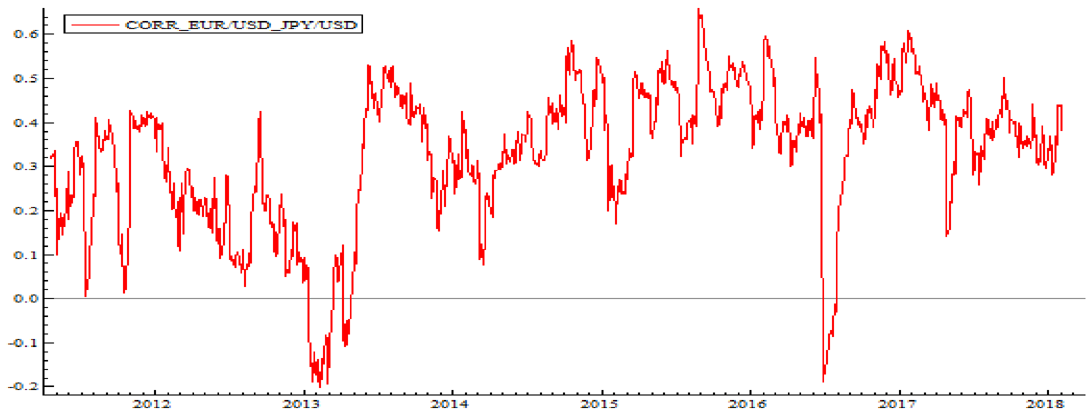
Graph F. CHW/USD-GBP/USD



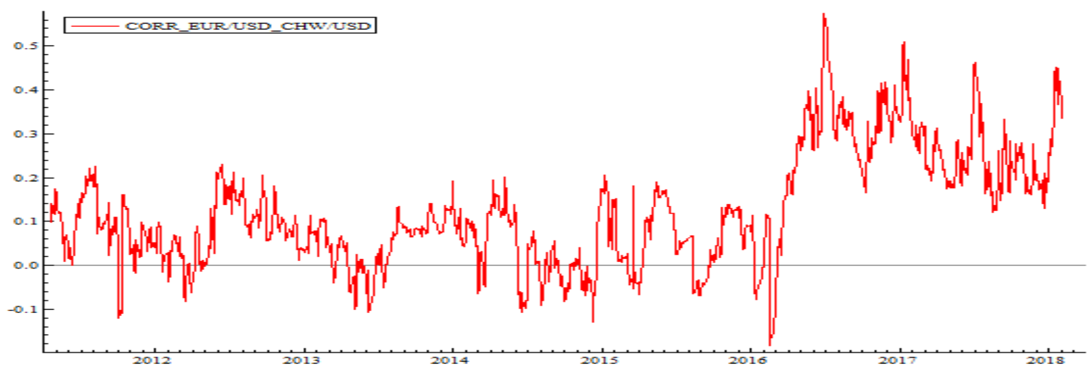
Notes: The red lines represent the conditional covariances of the fourvariate conditional variance matrix (H_t) for all the pairs of markets, generated by Eq.(4).

Figure 4. Dynamic conditional correlations of the DCC-GARCH (1,1) model.

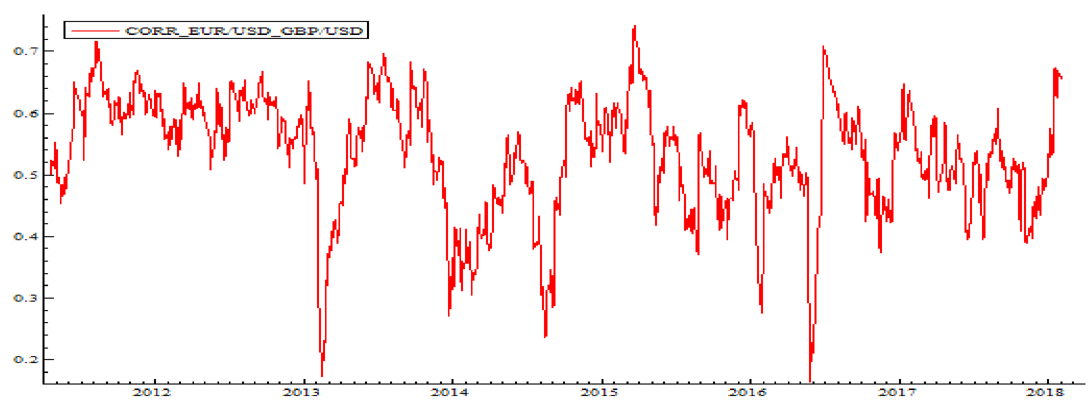
Graph A. EUR/USD-JPY/USD



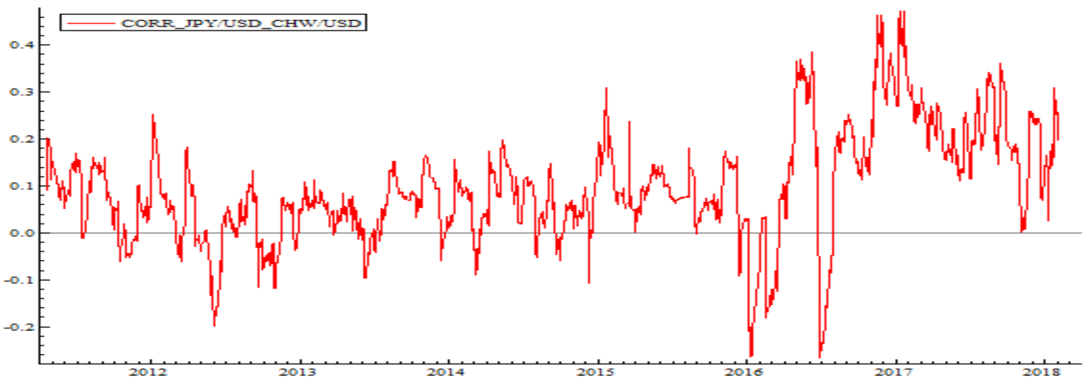
Graph B. EUR/USD-CHW/USD



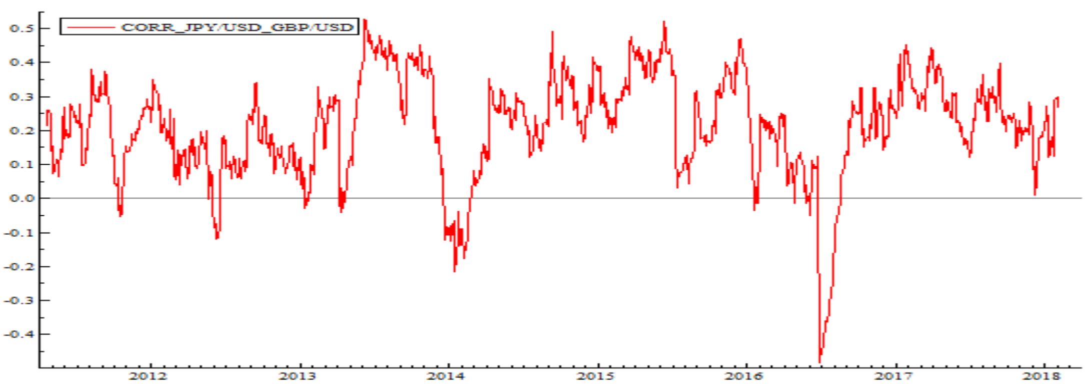
Graph C. EUR/USD-GBP/USD



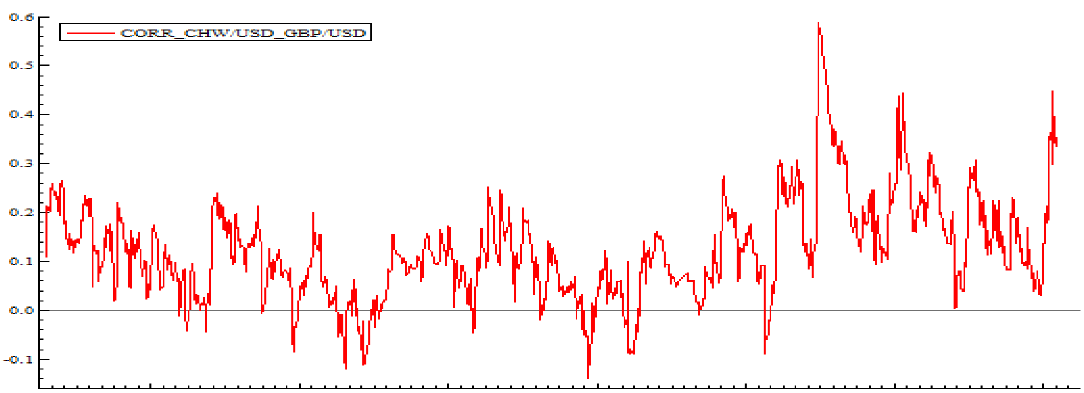
Graph D. JPY/USD-CHW/USD



Graph E. JPY/USD-GBP/USD



Graph F. CHW/USD-GBP/USD



Notes: The red lines illustrate the dynamic conditional correlations of the correlation matrix (R_t) generated by Eq.(6) for all the pairs of markets.

Chapter 4

Volatility spillover effects from MSCI global index to Japan, China and USA national indexes from 2008 to 2018

Abstract

This paper analyses the contagion effects of equity markets for MSCI (global index), NIKKEI 400 (Japan), CSI 300 (China) and S&P 500 (USA) by taking into account a portfolio analysis. In particular, we employ a trivariate MGARCH model and we use daily data for the period 2008-2018. Results of portfolio analysis indicate that MSCI has a significant positive influence on equity market returns. MGARCH results reveal significant spillovers among the three national equity markets. In addition, rank correlation results suggest that the three national equity markets are integrated. Lastly, based on dynamic conditional correlations, we observe contagion effects for the pairs of markets NIKKEI 400-CSI 300, NIKKEI 400-S&P 500 and S&P 500-CSI 300, suggesting risky correlations for any investor.

1. Introduction

This paper contributes to the financial markets' contagion effects by investigating the contagion hypothesis among one of the most important global equity index (Morgan Stanley Capital International or MSCI)[35] and three of the most important national equity indexes (China Securities Index 300 or CSI 300, NIKKEI 400, Standard & Poors 500 or S&P 500). We set the period from 21st January 2008 to 5th January 2018. Additionally, we use the diagonal model for portfolio analysis of Sharpe (1964) to calculate the standardized residuals and we fit a trivariate cDCC-GARCH model (Aielli 2009) to the estimated standardized residuals in order to examine potential spillovers.

Recent studies on risk transmission suggest that national equity markets have become more inter-correlated the last decades (Syriopoulos 2007; Bartram and Bodnar 2009; Dooley and Hutchinson 2009; Pesaran and Pesaran 2010; Arouri, Nguyen and Pukthuanthong 2012). Much of the extant literature in the field of risk transmission has focused on the way that major world and national equity markets spill over. For instance, Bekaert and Harvey (1995) investigate spillover effects from 1969 until 1992 among twelve national equity indexes from MSCI and IFC including both developed and emerging markets. They use a conditional CAPM model and average annualized returns. They conclude that the under investigation period is characterized by spillover effects among the equity markets. Ng (2000) investigates the linkages among equity markets, considering that the markets are geographically and economically correlated. He uses weekly data from USA, Japan and Pacific Basin equity markets and he employs a bivariate GARCH(1,1) model, finding evidence of integration. The starting date for the markets are different, although the ending day is the last week of December 1996. Miyakoshi (2003) and Liu and Pan (1997) investigate the level of integration among USA and Japanese equity markets to four Asian equity markets. The under investigation periods are from 1st January 1998 to 30th April 2000 and from 3rd January 1984 to 30th December 1991, respectively. The frequency of the data is daily. They use a bivariate EGARCH(1,1) and an ARMA(1)–GARCH(1,1) models, respectively. They find evidence of

[35] The MSCI world equity index is a broad global equity index that represents large and mid-cap equity performance across 23 developed markets countries. It covers approximately 85% of the free float-adjusted market capitalization in each country.

spillover effects. Moreover, they highlight the dominant place of USA equity markets among others.

In terms of influential empirical studies on contagion effects, numerous researchers have highlighted the importance of integration among global and national equity markets (Sharma and Wongbangpo 2002; Wang and Firth 2004). Although the idea that global and equity markets do influence each other is well known, still, there is a huge gap in the literature of multivariate MGARCH models. Additionally, there is a new trend to forecast volatility in the aftermath of GFC (2007) (Dooley and Hutchison 2009).

In this paper we comprise the following important aspects, followed by the empirical analysis. First, we examine an important period from 2008 to 2018. Second, we use daily data for one of the most important global equity index (MSCI) and the three of the most important national equity markets: S&P 500 (USA), NIKKEI 400 (Japan) and CSI 300 (China). Third, we examine volatility transmission using an trivariate cDCC-GARCH model by taking into consideration the effects of MSCI on the national equity indexes. Fourth, we employ a trivariate cDCC-GARCH model, which uses a reformulated driving process of standardized residuals

The remainder of the paper is organized as follows: Chapter 2 provides information for the data and gives the summary statistics. Chapter 3 describes the empirical methodology. Chapter 4 contains the results. Chapter 5 concludes the paper.

2. Data description and summary statistics

We use daily data for one of the most important global equity index (MSCI) and three of the most important national equity indexes for Japan (CSI 300), China (NIKKEI 400) and USA (S&P 500), downloaded from *Thomson Financial (Datastream)*. We use the price index form for all equity indexes. We define the period, from 21st January 2008 until 5th January 2018 (2622 obs). We transform the daily data into a logarithmic form using the equation: $r_{i,t} = log(p_t) - log(p_{t-1})$ where p_t is the price of equity market (*i*) on day *t*.

Table 1 presents the summary statistics of equity returns. MSCI returns exhibit the highest mean value (0,00025395). According to the highest maximum (0,059705) and the lowest minimum (-0,13566) and the highest std. deviation (0,0098211) value, MSCI returns demonstrate the largest flunctuations. All market returns are negatively skewed, except the case of MSCI returns. In addition, all market returns state excess kurtosis, indicating leptokurtic behavior. Jarque-Bera statistic results reject the null hypothesis of normality for all market returns. ADF (Dickey and Fuller, 1979) test results, reject the null hypotheses of a unit root at the 1% level. Estimates of ARCH-Lagrange Multiplier tests suggest the existence of heteroskedasticity.

Figure 1 visualizes the raw series and the logarithmic returns for equity markers for MSCI (Graph A), CSI 300 (Graph B), NIKKEI 400 (Graph C) and S&P 500 (Graph D), during the whole period. The market returns are following a tremble trend, suggesting evidence of heteroskedasticity[36] and rationalizing the use of multivariate MGARCH model.

3. Econometric methodology

For our investigation, we use the diagonal model for portfolio analysis of Sharpe (1964). Simply stated, the model postulates a linear relationship between the returns on any security (γ_{it}) and a general market factor (γ_{Mt}) as follows:

$$\gamma_{it} = \theta_i + \delta_i \gamma_{Mt} + \varepsilon_{it},\ i = 1,...,N \text{ and } t = 1,\ldots,T \tag{1}$$

Our model is slightly different from the diagonal model analyzed by Sharpe (1964). γ_{Mt} is the MSCI index returns, θ_i and δ_i are constants and ε_{it} are standardized residuals where $\varepsilon_t = \sqrt{h_t}u_t$, and $\varepsilon_t \sim N(0, H_t)$ with u_t are $\mathrm{i.i.d.}$

Since the main purpose of this work is to investigate the integration among the global and national indexes, we fit the standardized residuals (ε_t) of equation 1 in a GARCH (1,1) model (Bollerslev 1986) to generate the conditional variance (h_t). h_t is depending on h_t and ε_t for each market lagged one period. The equation of h_t can be expressed as:

$$h_t = \omega + a\varepsilon_{t-1}^2 + bh_{t-1} \tag{2}$$

where $\omega > 0$, $a \geq 0$ and $b \geq 0$ is sufficient for the conditional variance to be positive.

In the second stage, we use the standard deviations from the first stage to transform the standardized residuals. Then, we use them to estimate the parameters of the conditional

[36] A time series is said to be heteroscedastic if its variance changes over time, otherwise it is called homoscedastic.

correlation. We define the trivariate conditional variance matrix (H_t) ($N\,x\,N$ matrix), using the cDCC model of Aielli (2009) as follows:

$$H_t = D_t R_t D_t \tag{3}$$

where $D_t = diag\left(h_{11t}^{\frac{1}{2}} \dots h_{NNt}^{\frac{1}{2}}\right)$ is the conditional variance obtained from the univariate GARCH(1,1) model, and the conditional correlation matrix, with N is the number of markets (i = 1,…,N) is given by:

$$R_t = diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}})Q_t diag(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}) \tag{4}$$

To obtain cDCC model, first, we define $P_t = diag\left(q_{11,t}^{-\frac{1}{2}} \dots q_{NN,t}^{-\frac{1}{2}}\right)$ and $u_t^* = P_t u_t$. The cDCC model of Aielli (2009) is an extension of the DCC model of Engle (2002). In the cDCC model, $Q_t = (q_{ij,t})$ ($N\,x\,N$ symmetric positive definite matrix) is defined as follows:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u_{t-1}^* u_{t-1}^{*\prime} + \beta Q_{t-1} \tag{5}$$

where $\bar{Q}$ is the $N\,x\,N$ unconditional variance matrix of u_t^* (since $\mathrm{E}[u_t^* u_t^{*\prime} | \Omega_{t-1}] = Q_t$)[37]. α and β are nonnegative scalar parameters, satisfying $\alpha + \beta < 1$.

For the cDCC model, the estimation of the matrix $\bar{Q}$ and the parameters α and β are intertwined, since $\bar{Q}$ is estimated sequentially by the correlation matrix of the u_t^*. To obtain u_t^* we need however a first step estimator of the diagonal elements of Q_t. Thanks to the fact that the diagonal elements of Q_t do not depend on $\bar{Q}$ (because $\overline{Q_{ii}} = 1$ for i = 1,…,N), Aielli (2009) proposed to obtain these values $q_{11,t}$,.., $q_{NN,t}$ as follows:

$$q_{ii,t} = (1-\alpha-\beta) + \alpha u_{i,t-1}^2 + \beta q_{ii,t-1} \tag{6}$$

for i = 1,…,N. In short, given α and β, we can compute $q_{11,t}$,.., $q_{NN,t}$ and thus u_t^*, then we can estimate $\bar{Q}$ as the empirical covariance of u_t^*.

Additionally, we use Full Information Maximum Likelihood (FIML) methods with student's t-distributed errors to estimate the model as follows:

$$\sum_{t=1}^{T}\left[log\frac{\Gamma\left(\frac{\nu+N}{2}\right)}{[\nu\pi]^{\frac{N}{2}}\Gamma\left(\frac{\nu}{2}\right)\nu-2^{\frac{N}{2}}} - \frac{1}{2}\log\left(|H_t|\right) - \left(\frac{N+\nu}{2}\right)log\left[1+\frac{\varepsilon_t{}' H_t{}^{-1}\varepsilon_t}{\nu-2}\right]\right] \tag{7}$$

[37] Aielli (2009) has shown that the estimation of $\bar{Q}$ as the empirical correlation matrix of u_t is inconsistent because: $\mathrm{E}[u_t\ u_t\ ] = \mathrm{E}[\mathrm{E}[u_t' u_t\ |\Omega_{t-1}] = \mathrm{E}[R_t\ ] \neq \mathrm{E}[Q_t\ ]$.

where $\Gamma(.)$ is the Gamma function, N is the number of markets, v is the degrees of freedom and ε_t is the vector of standardized residuals.

4. Empirical results

4.1 Coefficient estimates of Sharpe's (1964) diagonal model

We use the diagonal model for portfolio analysis of Sharpe (1964) (Equation 1) to determine the effect of the partial effect of the independent variable (MSCI) on the dependent variable (NIKKEI 400, S&P 500, CSI 300). Table 2 presents the above results. Results state significant θ_i only for NIKKEI 400. In addition, we see significant value (p-Value = 0,0000 < 0,05) of MSCI (δ_i) on NIKKEI 400, S&P 500 and CSI 300, suggesting that MSCI has a significant positive influence on equity market returns.

4.2 Estimates of the univariate GARCH(1,1) model and Box/Pierce test

Panel A of table 3 presents the estimated GARCH(1,1) model (Equation 2). Estimates of the variance equation reveal statistical significant constant (ω) for NIKKEI 400 and CSI 300. All ARCH (α) and GARCH effects (b) are statistically significant. Panel B of table 3 shows the estimates of Box/Pierce tests. Results suggest evidence of no serial autocorrelation and consequently no misspecification errors.

4.3 Estimates of the trivariate cDCC model, diagnostic tests and information criteria

Table 4 presents the estimates of cDCC model, the diagnostic tests and the information criteria. Estimates of cDCC model (Equation 5) reveal that all the ARCH (α) and GARCH effects (β) are statistically significant. In addition, we see the estimates of log-likelihood. Estimates of $x^2(8)$ statistics suggest the rejection of the null hypothesis of no spillovers at 1% significance level. Ljuing-Box test results (Hosking 1980; Li-McLeod 1983) show evidence of no serial autocorrelation, suggesting no misspecification errors. Additionally, estimates of the AIC and SIC information criteria are stated.

In figure 2, we graph the conditional variances for NIKKEI 400 (Graph A), CSI 300 (Graph B), S&P 500 (Graph C) during the whole time period. Conditional variances demonstrate strong co-movements. In addition, we observe significant peaks and troughs, indicating extreme volatility levels.

Figure 3 illustrates the conditional covariances for the pairs of markets: NIKKEI 400-CSI 300 (Graph A), S&P 500-CSI 300 (Graph B) and NIKKEI 400-S&P 500 (Graph C) during the whole period. According to the graphs, the conditional covariances follow a tremble and are extreme volatile. Additionally, we observe the effects of major economic events, i.e. (1) the bankruptcy of Lehman brothers (15/09/2008), (2) the USA presidential elections (04/11/2008), (3) S&P's downgraded the long-held AAA rating of USA securities (05/08/2011), and (4) Greek domestic conditions e.g. legislative elections (20/09/2015), among others.

4.4. Estimates of Spearman's rank correlation

We use Spearman's rank correlation to measure the financial contagion phenomenon by computing the mean correlations. Given the T observations, the T raw scores i_t, j_t ($i \neq j$ = 1,…,N markets and t = 1,…,T observations) are converted to ranks rg_i, rg_j.

Using the covariance of the rank variables ($cov(rg_i, rg_j)$) and the standard deviations of the rank variables (σ_{rg_i} and σ_{rg_j}), we calculate the correlation coefficients (ρ_{rg_i,rg_j}) as follows:

$$\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}} \tag{8}$$

The empirical results are summarized in table 5. Results reveal the highest rank correlation for the pairs of markets: NIKKEI 400-CSI 300 (ρ_{rg_1,rg_3}), NIKKEI 400-S&P 500 (ρ_{rg_1,rg_2}) and S&P 500-CSI 300 (ρ_{rg_2,rg_3}). Additionally, all the rank correlations are almost the same, indicating a level of integration for the three markets.

4.5 Dynamic conditional correlations (DCCs) analysis

Figure 4 shows that the DCCs (Equation 4) for the pairs of markets NIKKEI 400-CSI 300, S&P 500-CSI 300 and NIKKEI 400-S&P 500 have mostly positive values and they are extremely volatile, suggesting contagion and risky correlations from an investor's perspective. We can clearly see the effects of major economic events: (1) the bankruptcy of Lehman brothers (15/09/2008), (2) the USA presidential elections (04/11/2008), (3) S&P's downgraded the long-held triple-A rating of USA securities (05/08/2011), and (4) worries about Russian economy, due the rise of interest rate to prevent the collapse of rubble's value and stabilize the Russian economy (15/12/2014), among others.

5. Conclusions

In this paper, we investigate two main issues: (1) the partial effect of MSCI on the NIKKEI 400, S&P 500 and CSI 300 using Sharpe's (1964) diagonal model, and (2) we use standardized residuals from the above model into a trivariate cDCC-GARCH framework in order to quantify the volatility transmission among the three of the most important national equity indexes. We use daily data for the time period 21st January 2008 until 5th January 2018. Our results can help investors to maximize their profits and policymakers to build profitable strategies for their investments portfolios.

Important contributions can be extracted based on our analysis. To contact a portfolio analysis, we first use the diagonal model of Sharpe (1964). Empirical results suggest that MSCI has a significant positive influence on equity market returns. Next, we employ a trivariate cDCC-GARCH model to prove the existence of spillovers. Empirical results support evidence of significant spillover effects among the three national equity markets. Moreover, we use Sprearman's rank correlation to measure the financial contagion phenomenon. Results reveal a level of integration for the three markets. Then, we analysed the DCCs. The main empirical findings indicate the existence of financial contagion between all the pairs of markets (NIKKEI 400-CSI 300, NIKKEI 400-S&P 500, S&P 500-CSI 300), suggesting for any investor risky correlations.

References

Aielli, G. P., 2009: "Dynamic conditional correlations: on properties and estimation", Technical report, Department of Statistics, University of Florence.

Arouri, A.E.H., Nguyen, D.K., Pukthuanthong, K.: An international CAPM for partially integrated markets: theory and empirical evidence. J. Bank. Finan. Vol. 36, 2473–2493 (2012)

Bartram, S., Bodnar, G.: No place to hide: the global crisis in equity markets in 2008/2009. J. Int. Money Financ. Vol. 28, 1246–1292 (2009)

Bekaert, G., Harvey, C.R.: Time-varying world market integration. Journal of Finance. Vol. 50, 403−444 (1995)

Bollerslev, T.: Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics. Vol. 31. No. 3, 307-327 (1986)

Bollerslev, T., Chou, R., Kroner, K. F.: ARCH modeling in finance: A review of the theory and empirical evidence. Journal of Econometrics. Vol. 52. No. 1-2, 5-59 (1992)

Dickey, D. A., & Fuller, W. A., 1979: "Distribution of the Estimators for Autoregressive Time Series with a Unit Root", *Journal of the American Statistical Association*, vol. 74: 427-431.

Dimitriou, D, Kenourgios, D., Simos, T.: Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH-DCC approach. International Review of Financial Analysis. Vol. 30, 46-56 (2013)

Dooley, M., Hutchison, M.: Transmission of the U.S. subprime crisis to emerging markets: Evidence on the decoupling–recoupling hypothesis. Journal of Empirical Finance. Vol. 28, 1331-1349 (2009)

Engle, R. F., 2002: "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models" *Journal of Business and Economic Statistics*, vol. 20: 339-350.

Hosking, J. R. M.: The Multivariate Portmanteau Statistic. Journal of the American Statistical Association. Vol. 75. No. 371, 602-608 (1980)

Liu, Y. A., Pan, M.: Mean and volatility spillover effects in the U.S. and Pacific-Basin stock markets. Multinational Finance Journal. Vol. 1, 47−62 (1997)

McLeod, A. I., Li, W. K.: Diagnostic checking ARMA time series models using squared-residuals autocorrelations. Journal of Time Series Analysis. Vol. 4. No. 4, 269-273 (1983)

Miyakoshi, T.: Spillovers of stock return volatility to Asian equity markets from Japan and the US. Journal of International Financial Markets, Institutions and Money. Vol. 13, 383−399 (2003)

Ng, A.: Volatility spillover effects from Japan and the US to the Pacific Basin. Journal of International Money and Finance. Vol. 19, 207–233 (2000)

Pesaran, B., Pesaran, M.H.: Conditional volatility and correlations of weekly returns and the VaR analysis of 2008 stock market crash. Econ. Model. Vol. 27, 1398–1419 (2010)

Sharma, S. C., Wongbangpo, P.: Long-term trends and cycles in ASEAN stock markets. Review of Financial Economics. Vol. 11. No. 4, 299-315 (2002)

Sharpe, W.F.: Capital Asset Pricing: A Theory of Market Equilibrium under Conditions of Risk. J. Finance. Vol 19, 425–42 (1964)

Syriopoulos, T.: Dynamic linkages between emerging European and developed stock?: has the EMU any impact? Int. Rev. Financ. Anal. Vol. 16, 41–60 (2007)

Wang, S. S., Firth, M.: Do bears and bulls swim across oceans? Market information transmission between greater China and the rest of the world. Journal of International Financial Markets, Institutions and Money. Vol. 14. No. 3, 235-254 (2004)

Appendix

Table 1

Summary statistics of the equity indexes returns, sample period: 21st January 2008 until 5th February 2018.

	MSCI	**CSI 300**	**NIKKEI 400**	**S&P500**
Panel A: Basic statistics				
Mean	0,00025395	6,7827e-006	5,7387e-005	0,0001214
Minimum	-0,13566	-0,041582	-0,044903	-0,041126
Maximum	0,059705	0,038883	0,056635	0,047586
Std. deviation	0,0098211	0,0075048	0,0062677	0,0054673
Panel B: Normality Test				
Skewness	1,0782***	-0,43457***	-0,36298***	-0,34797***
t-Statistic	22,543	9,0861	7,5894	7,2756
p-Value	1,5718e-112	1,0263e-019	3,2141e-014	3,4484e-013
Excess Kyrtosis	19,897***	4,4205***	8,4344***	11,795***
t-Statistic	208,09	46,230	88,209	123,36
p-Value	0,00000	0,00000	0,00000	0,00000
Jarque-Bera	43727***	2215,6***	7823,5***	15241***
p-Value	0,00000	0,00000	0,00000	0,00000
Panel C: Unit Root tests				
ADF	-31,9594***	-29,5001***	-31,3829***	-31,5577***
Critical value: 1%	-2,56572	-2,56572	-2,56572	-2,56572
Critical value: 5%	-1,94093	-1,94093	-1,94093	-1,94093
Critical value: 10%	-1,61663	-1,61663	-1,61663	-1,61663
Panel D: ARCH-Lagrange Multiplier tests				
ARCH 1-2 test	43,161**	68,961**	337,79**	277,99**
p-Value	0,0000	0,0000	0,0000	0,0000
ARCH 1-5 test	21,842**	47,766**	166,75**	170,98**
p-Value	0,0000	0,0000	0,0000	0,0000
ARCH 1-10 test	13,409**	34,056**	96,572**	105,57**
p-Value	0,0000	0,0000	0,0000	0,0000

Notes: We used intercept and a time trend to generate ADF statistic with 2 lags.
** and *** denote statistical significance at the 5% and 1% levels, respectively.

Table 2

Coefficient estimates of diagonal model for portfolio analysis of Sharpe (1964), sample period: 21st January 2008 until 5th February 2018.

	NIKKEI 400 (i=1)	S&P 500 (i=2)	CSI 300 (i=3)
θ_i	3,81033e-005**	3,55785e-005	-1,33264e-005
t-Statistic	0,7542	0,420	-0,0913
p-Value	0,0000	0,6746	0,9272
δ_i	0,0759354***	0,339295***	0,0791847***
t-Statistic	6,13	39,3	5,33
p-Value	0,0000	0,0000	0,0000

Notes: *** denote statistical significance at the 1% level.

Diagonal model equation: $\gamma_{it} = \theta_i + \delta_i \gamma_{Mt} + \varepsilon_{it}$, i = 1,...,N and t = 1,…,T.

Table 3

Estimates of the univariate GARCH(1,1) model and Box/Pierce tests results, sample period: 21st January 2008 until 5th February 2018.

	NIKKEI 400	S&P 500	CSI 300
Panel A: GARCH (1,1) results			
constant *(ω)*	0,790737***	0,287288	0,156002**
t-Statistic	3,125	1,938	2,099
p-Value	0,0018	0,0528	0,0359
ARCH *(a)*	0,114224***	0,068857***	0,056976***
t-Statistic	5,842	3,692	5,385
p-Value	0,0000	0,0002	0,0000
GARCH *(b)*	0,864930***	0,914172***	0,941401***
t-Statistic	38,86	45,99	92,84
p-Value	0,0000	0,0000	0,0000
Panel B: Box/Pierce tests			
Q (50) on Standardized Residuals	45,1671	45,3563	65,8705
p-Value	0,6673175	0,6599494	0,0655460
Q (50) on Squared Standardized Residuals	46,1193	2,71736	45,9673
p-Value	0,6298379	1,0000000	0,6358783

Notes: ** and *** denote statistical significance at the 5% and 1% levels, respectively

Variance equation: $h_t = \omega + a\varepsilon_{t-1}^2 + bh_{t-1}$.

Table 4

Estimates of the trivariate cDCC model, log-likelihood, diagnostic tests and information criteria, sample period: 21st January 2008 until 5th February 2018.

Panel A: estimates of cDCC model	
alpha *(α)*	0,023858**
t-Statistic	2,000
p-Value	0,0456
beta *(β)*	0,523647**
t-Statistic	2,210
p-Value	0,0272
degrees of freedom (v)	6,326386***
t-Statistic	15,60
p-Value	0,0000
log-likelihood	30871,651
Panel B: diagnostic tests	
$x^2(8)$	7720,5**
p-Value	0,0000
Hosking^2 (50)	351,478
p-Value	0,9997376
Li-McLeod^2 (50)	352,517
p-Value	0,9996948
Panel C: Information Criteria	
Akaike	0,001692
Schwarz	0,033064

Notes: The symmetric positive definite matrix Q_t is generated using one lag of Q and of u^*. P-values have been corrected by 2 degrees of freedom for Hosking^2 (50) and Li-McLeod^2 (50) statistics.
** and *** denote statistical significance at the 5% and 1% levels, respectively
Conditional correlation driving process equation of standardized residuals (u_t): $Q_t = (1-\alpha-\beta)\bar{Q} + \alpha u^*_{t-1} u^{*\prime}_{t-1} + \beta Q_{t-1}$.
Log-likelihood equation: $\sum_{t=1}^{T}\left[log\frac{\Gamma\left(\frac{v+N}{2}\right)}{[v\pi]^{\frac{N}{2}}\Gamma\left(\frac{v}{2}\right)v-2^{\frac{N}{2}}} - \frac{1}{2}log\left(|H_t|\right) - \left(\frac{N+v}{2}\right)log\left[1+\frac{\varepsilon_t' {H_t}^{-1}\varepsilon_t}{v-2}\right]\right]$.

Table 5

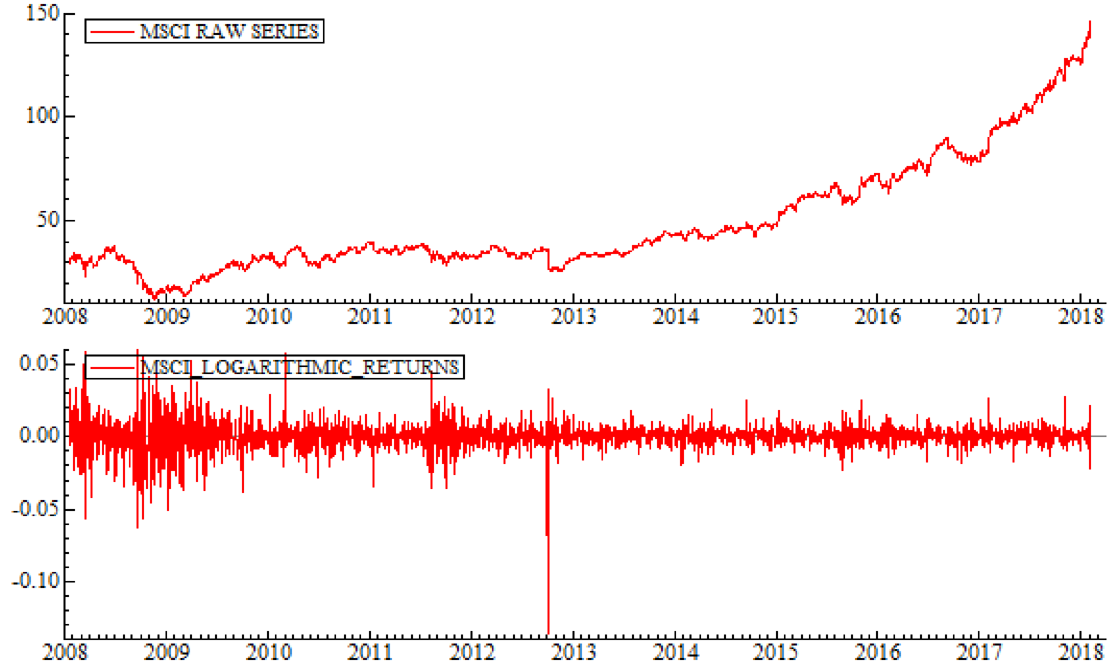
Estimates of Spearman's rank correlation coefficient (ρ_{rg_i,rg_j}), sample period: 21st January 2008 until 5th February 2018.

Market i	**NIKKEI 400** **(i=1)**	**S&P 500** **(i=2)**	**CSI 300** **(i=3)**
ρ_{rg_i,rg_1}	**1**		
t-Statistic	-		
p-Value	-		
ρ_{rg_i,rg_2}	0,108730***	**1**	
t-Statistic	4,891	-	
p-Value	0,0000	-	
ρ_{rg_i,rg_3}	0,250135***	0,063451***	**1**
t-Statistic	13,17	3,003	-
p-Value	0,0000	0,0027	-

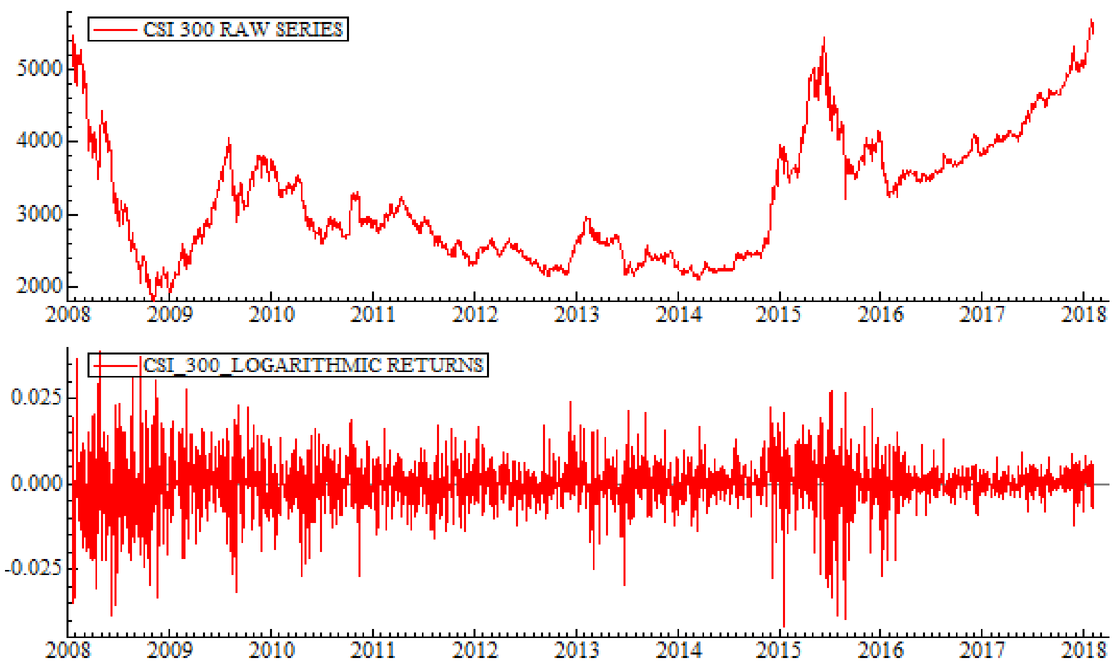
Notes: Table 5 exhibits the estimates of elements (ρ_{rg_i,rg_j}) of rank correlation.
*** denote statistical significance at the 1% level.
Spearman's rank correlation equation: $\rho_{rg_i,rg_j} = \frac{cov(rg_i,rg_j)}{\sigma_{rg_i}\sigma_{rg_j}}$.

Figure 1. Raw series and logarithmic returns of the markets, sample period: 22nd January 2008 until 29th July 2011.

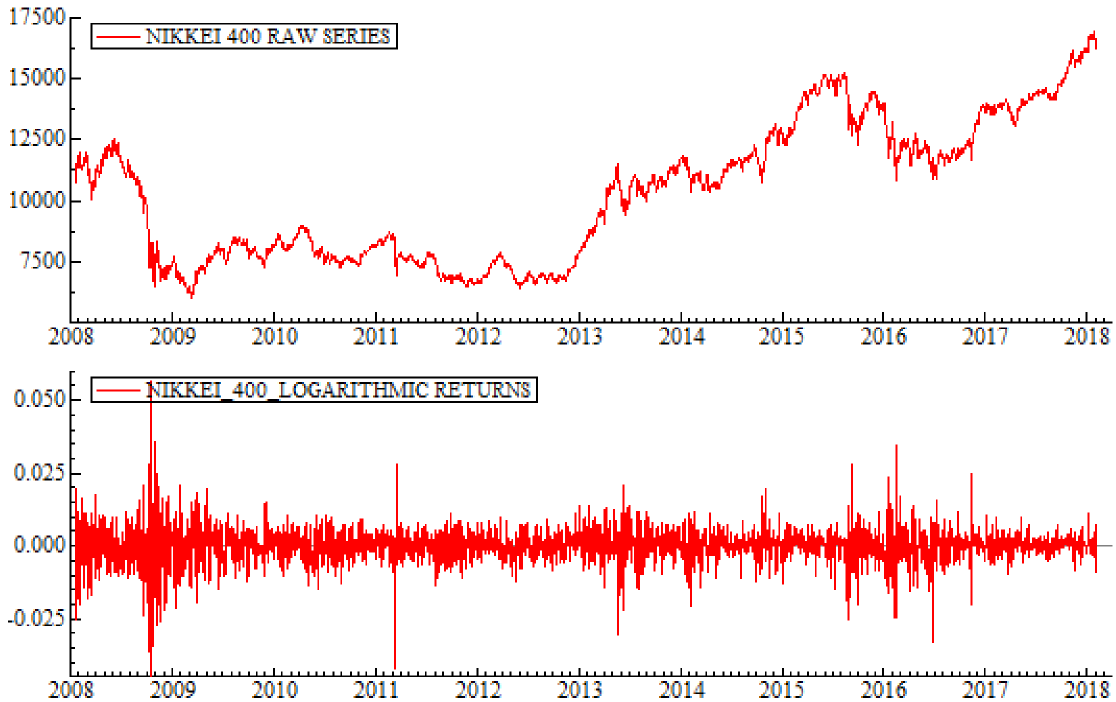
Graph A. MSCI



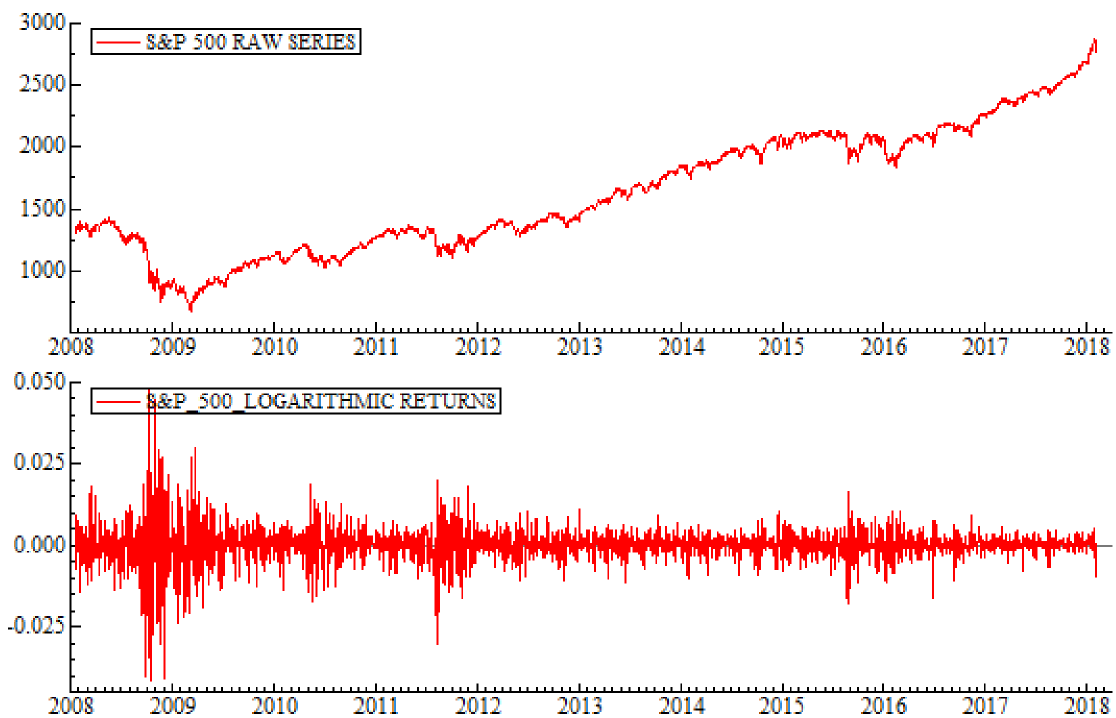
Graph B. CSI 300



Graph C. NIKKEI 400



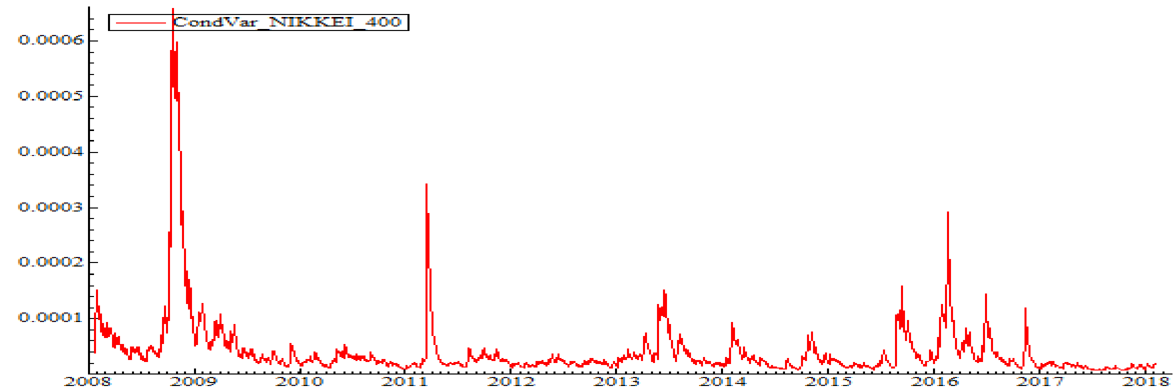
Graph D. S&P 500



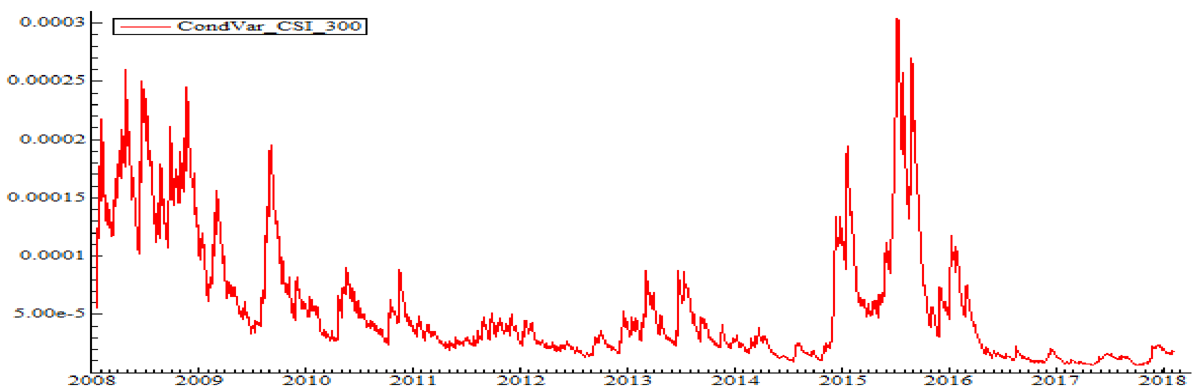
Notes: The equity index returns are generated by the equation: $r_t = log(p_t) - log(p_{t-1})$.

Figure 2. Conditional variances of the univariate GARCH (1,1) model, sample period: 21st January 2008 until 5th February 2018.

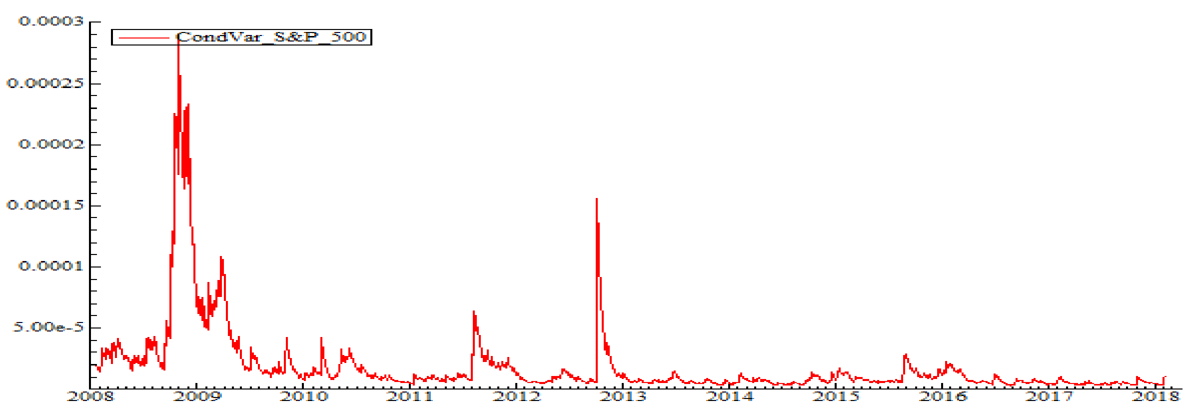
Graph A. NIKKEI 400



Graph B. CSI 300



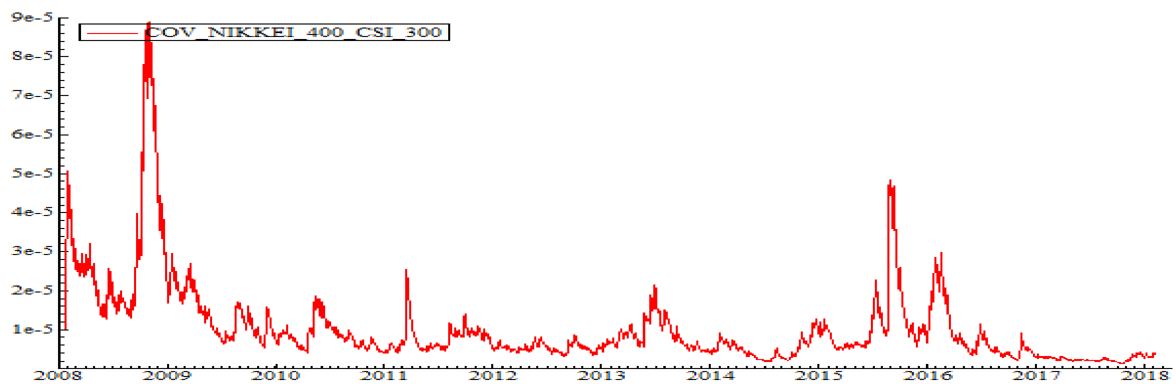
Graph C. S&P 500



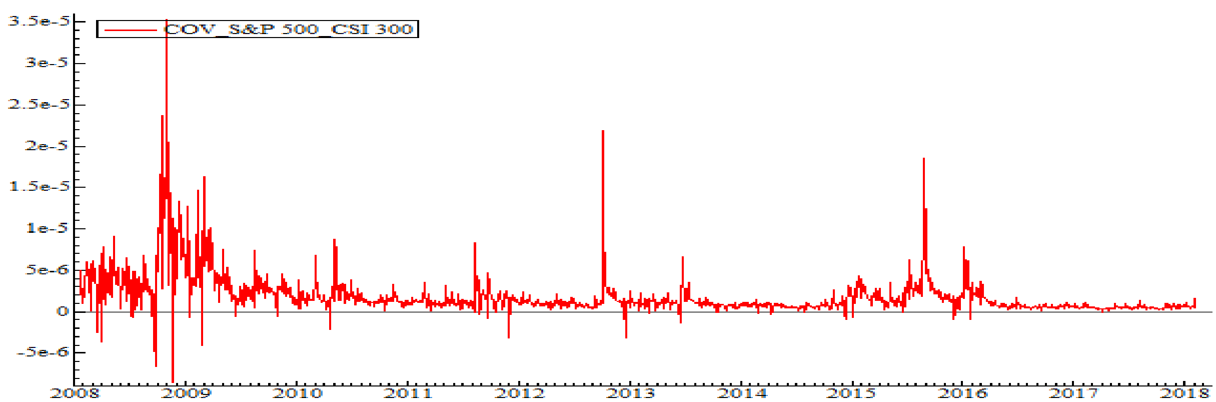
Notes: The red lines represent the conditional variances (h_t) for all markets, generated by Equation 2.

Figure 3. Conditional covariances of the trivariate cDCC-GARCH (1,1) model, sample period: 21st January 2008 until 5th February 2018.

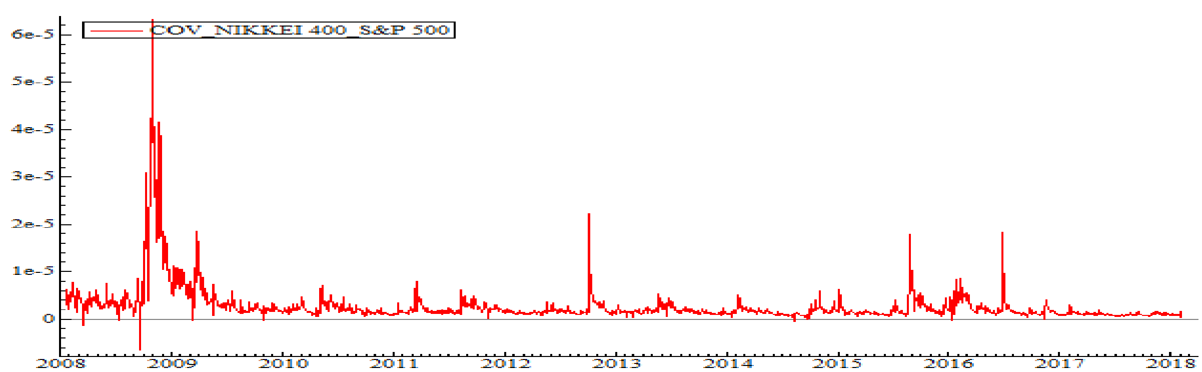
Graph A. NIKKEI 400-CSI 300



Graph B. S&P 500-CSI 300



Graph C. NIKKEI 400-S&P 500

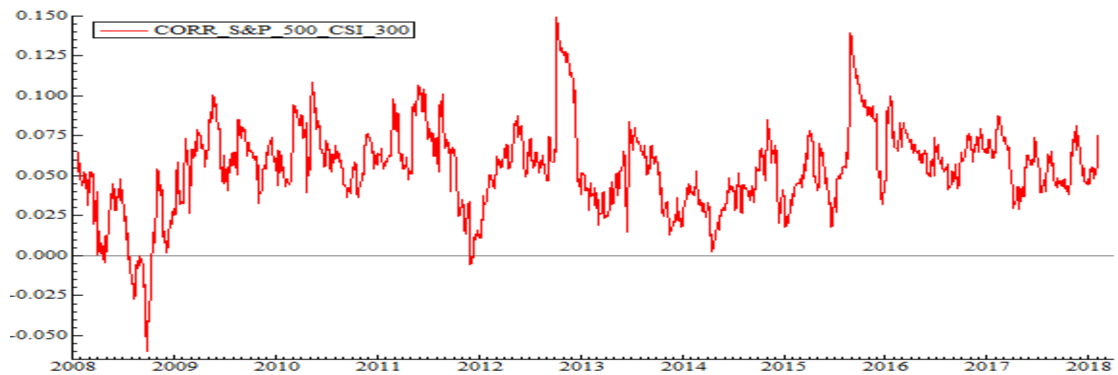


Notes: The red lines illustrate the conditional covariances of the trivariate conditional variance matrix (H_t) for all the pairs of markets, generated by Equation 3.

Figure 4. Dynamic conditional correlations of the trivariate cDCC-GARCH (1,1) model, sample period: 21st January 2008 until 5th February 2018.

Graph A. NIKKEI 400-CSI 300

Graph B. S&P 500-CSI 300



Graph C. NIKKEI 400-S&P 500

Notes: The red lines illustrate the dynamic conditional correlations (R_t), generated by Equation 4 for all the pairs of markets.