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Volatility Spillovers among Global Stock Markets: Measuring Total and Directional Effects*

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Abstract

In this study we construct volatility spillover indexes for some of the major stock market indexes in the world. We use a DCC-GARCH framework for modelling the multivariate relationships of volatility among markets. Extending the framework of Diebold and Yilmaz [2012] we compute spillover indexes directly from the series of returns considering the time-variant structure of their covariance matrices. Our spillover indexes use daily stock market data of Australia, Canada, China, Germany, Japan, the United Kingdom, and the United States, for the period January 2001 to August 2016. We obtain several relevant results. First, total spillovers exhibit substantial time-series variation, being higher in moments of market turbulence. Second, the net position of each country (transmitter or receiver) does not change during the sample period. However, their intensities exhibit important time-variation. Finally, transmission originates in the most developed markets, as expected. Of special relevance, even though the Chinese stock market has grown importantly over time, it is still a net receiver of volatility spillovers.

Key Words. Volatility spillovers; DCC-GARCH model; Global stock market linkages; financial crisis.
JEL Classification. G01; G15; C32.

1 Introduction

International financial market integration has importantly increased over the last two decades. Different factors have contributed to this observed globalization, including the implementation of policies favoring financial market deregulation, the development of new trading technologies, and the interest of global investors in diversifying their financial portfolios in world asset markets. Financial integration can potentially yield many benefits for

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market participants and even for countries. The former obtain larger investment opportunities and better chances for risk sharing, while the latter benefit from the effects that deeper financial markets have on their economic stability and resilience.

Risk sharing is a key channel through which financial integration improves the resilience of the global financial system. Financial openness has proven effective in increasing consumption opportunities and income risk-sharing, and in reducing the volatility of consumption growth Bekaert et al. [2006]. Similarly, integration promotes new investment opportunities and new sources for funding investment plans. Hence, financial integration is beneficial for allocative efficiency and economic diversification.

However, the benefits of financial integration are not cost-free. In a more financially integrated world, national policies and relevant financial events may have important cross-border effects. Over the past two decades crises have propagated more rapidly than in the past and have proven to be more persistent and disruptive.

Perhaps one of the most salient features of recent financial crises has been the occurrence of volatility spillovers. This fact has motivated the emergence of a large and growing literature on financial contagion and volatility transmission (e.g. Forbes and Rigobon [2002]; Bradley and Taqqu [2004]; Diebold and Yilmaz [2009]; Caccioli et al. [2014]; andAït-Sahalia et al. [2015]). The measurement of volatility spillovers has gained attention recently in the literature. Diebold and Yilmaz [2012] presented an interesting way of measuring spillovers through forecast error variance decomposition from vector autoregressions. Their framework is useful for measuring volatility transmission within markets after the occurrence of a shock in a transmitter market. With their method, both total and directional spillovers can be calculated, facilitating the identification of individual and systemic volatility effects. Their methodology, however, has a limitation. They construct spillover indexes within a VAR system in which the covariance matrix is assumed to be time-invariant, and compute volatilities through a particular definition involving daily high and low prices.

Gamba-Santamaria et al. [2016] present an extension in which a DCC-GARCH model is used for modelling the multivariate relationships of volatility among different assets. This extension allows for a better representation of observable volatility clusters (e.g. Bollerslev [1990] and Engle [1993]) and time-varying asset price correlations (e.g. Yang [2005]) in financial time series. They apply their method to stock market indexes of the United States and four major Latin American economies, finding that total spillovers exhibit important time variation, and that the United States and Brazil are net volatility transmitters for the whole sample period used in their study.

In this paper we study stock market volatility spillovers among Australia, Canada, China, Germany, Japan, the United Kingdom, and the United States, for the period between November 10th, 2004 and August 26th, 2016. We compute both total and directional spillovers for these market indexes. We obtain several relevant results. Total spillovers exhibit substantial variation over time, being considerably higher in moments of market turbulence. For instance, they are substantially higher between the third quarter of 2008 and the second quarter of 2012, a highly volatile period corresponding to the United States subprime crisis and the European sovereign bond crisis. Additionally, total spillovers have remained thereof in higher levels than those registered between 2001 and 2007.

Regarding directional spillovers, the net position of each country does not change during the sample period. Some countries are net transmitters (the United States, the United Kingdom, Canada, and Germany) while others are net receivers (Australia, China, and Japan) for the whole time. However, their intensities exhibit important time-variation. Similar to the behavior of total spillovers, directional spillovers are higher during periods of financial turbulence.

Although the empirical finance literature counts with several studies on the linkages and transmission dynamics among stock markets, our study distinguishes from others in three key aspects. First, we study volatility spillovers in a framework that avoids the need of sticking to a particular contagion definition that has to be tested in ad-hoc time-periods. Second, instead of studying spillovers only among developed stock markets, or between the United States and emerging markets, we analyse spillovers among six developed markets from different regions and a large emerging stock market. Finally, contrasting to the related literature, we do not need to distinguish between return and volatility spillovers because our volatility measure is directly estimated from the covariance matrix of a multivariate GARCH model.

Section 2 shows the methodological framework in which our extension is introduced. Section 3 describes the data used in our empirical application. Section 4 shows our main results, and finally Section 5 concludes.

2 Methodology

Consider the following VAR(p) model

$$Y_t = \Phi_0 + \sum_{l=1}^{p} \Phi_l Y_{t-l} + \varepsilon_t \tag{1}$$

where Y_t is a vector of size N, containing all stock market returns at time t, and $\varepsilon_t | t-1 \sim F(0, H_t)$ and F is the multivariate conditional probability distribution of errors. In this way, H_t is the conditional covariance matrix of errors.

Given a set of initial conditions, the model can be solved recursively to obtain its VMA(∞) expression

$$Y_t = \Phi_0^* + \sum_{p=0}^{\infty} \Theta_p \varepsilon_{t-p} \tag{2}$$

Its h-periods ahead forecast error is given by

$$\begin{aligned} e_{t+h}|t = \; & \Theta_0 \varepsilon_{t+h} + \Theta_1 \varepsilon_{t+h-1} + \dots \\ & + \Theta_{h-1} \varepsilon_{t+1} \end{aligned} \tag{3}$$

with covariance matrix given by

$$\begin{aligned} \Sigma^e_{t+h}|t = \; & \Theta_0 H_{t+h} \; \Theta_0' + \Theta_1 H_{t+h-1} \; \Theta_1' + \dots \\ & + \Theta_{h-1} H_{t+1} \; \Theta_{h-1}' \end{aligned} \tag{4}$$

Each element of the diagonal of $\Sigma^e_{t+h}|t$ is a summation that includes terms of the covariance matrices of the error term ε_t in (1), H_{t+i} for all $i = 1, 2, \dots h$. Therefore, variance decompositions $\Psi_{ij,t}(h)$ are defined in a way such that they contain the proportion of the h-step ahead forecast error variance of i coming from j at time t

$$\Psi_{ij,t}(h) = \frac{\sum_{k=0}^{h-1} \frac{\left(d_i' \;\; \Theta_k \;\; \Sigma^e_{t+k}|t \;\; d_j\right)^2}{\sqrt{d_j' \;\; \Sigma^e_{t+k}|t \;\; d_j}}}{\sum_{k=0}^{h-1} \left(d_i' \;\; \Theta_k \;\; \Sigma^e_{t+k}|t \;\; \Theta_k' \;\; d_i\right)} \tag{5}$$

where d_i and d_j are extraction vectors, i.e. zero vectors that are one in the i^{th} and j^{th} positions, respectively.

Following Gamba-Santamaria et al. [2016], we allow for a time-varying covariance matrix, H_t. We normalize these indexes in order to interpret them as variance shares. Let $\widetilde{\Psi}_{ij,t}(h)$ be the h-step ahead forecast error variance share of i generated by shocks in j at time t.

$$\widetilde{\Psi}_{ij,t}(h) = \frac{\Psi_{ij,t}(h)}{\sum_{j=1}^{N} \Psi_{ij,t}(h)} \tag{6}$$

We compute two different types of indexes, total spillover index and directional spillover indexes. The former measure the contribution of spillovers on the system's forecast error variance, and is computed in the following way

$$S_t(h) = \frac{\sum_{i=1, i\neq j}^{N} \sum_{j=1, j\neq i}^{N} \widetilde{\Psi}_{ij,t}(h)}{N} \tag{7}$$

Regarding directional spillovers, both transmission-directional and reception-directional spillover indexes are calculated for each market. The former contains the spillover contributions caused by market i on the rest of the system, while the latter incorporates the summation of other markets' spillovers on market i. The transmission-directional spillover index is defined as

$$S_{\cdot i,t}(h) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\Psi}_{ji,t}(h)}{N} \tag{8}$$

and the reception-directional spillover index is given by

$$S_{i\cdot,t}(h) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\Psi}_{ij,t}(h)}{N} \tag{9}$$

Net spillover indexes can be calculated as the difference between the transmission and reception spillover indexes

$$S_{i,t}(h) = S_{\cdot i,t}(h) - S_{i\cdot,t}(h) \tag{10}$$

Pairwise indexes can also be computed as the difference between the volatility spillover from i to j and the volatility spillover from j to i

$$S_{ij,t}(h) = \frac{\widetilde{\Psi}_{ji,t}(h) - \widetilde{\Psi}_{ij,t}(h)}{N} \tag{11}$$

Our extension to this framework consists in modelling the time-varying structure of the covariance matrix of the error term ε_t in (1), H_t. We follow the approach of Engle [2002], namely the DCC-GARCH model.

In this multivariate model the conditional covariance matrix of ε_t is given by

$$H_t = D_t R_t D_t \tag{12}$$

D_t is a diagonal matrix of time varying standard deviations of each element in ε_t and R_t is the time varying correlation matrix.

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} & \cdots & h_{1Nt} \\ h_{21t} & h_{22t} & \cdots & h_{2Nt} \\ \vdots & \vdots & \ddots & \vdots \\ h_{N1t} & h_{N2t} & \cdots & h_{NNt} \end{bmatrix}$$

$$D_t = \begin{bmatrix} \sqrt{h_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{22t}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{h_{NNt}} \end{bmatrix}$$

$$R_t = \begin{bmatrix} 1 & \rho_{12t} & \cdots & \rho_{1Nt} \\ \rho_{21t} & 1 & \cdots & \rho_{2Nt} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{N1t} & \rho_{N2t} & \cdots & 1 \end{bmatrix}$$

where h_{iit} is the variance of ε_{it}, h_{ijt} is the covariance of ε_{it} and ε_{jt}, and ρ_{ij} is the Pearson correlation

Table 1: Summary Descriptive Statistics on the Daily Series of Stock Market Returns

	United States	United Kingdom	Germany	Canada	Japan	Australia	China
Mean	0.01094	0.00875	0.02219	0.01996	0.01047	0.01724	0.0219
Std. Dev.	1.15994	1.21759	1.54344	1.08933	1.55643	1.01363	1.49
Skewness	-0.1007	-0.1661	-0.0646	-0.6584	-0.3834	-0.4661	-0.0591
Kurtosis	8.60124	6.33745	4.3491	10.13603	5.97662	5.49981	8.40492
LB test	40.814	67.115	26.242	56.404	15.15	7.835	39.728
LB2 test	3170.343	2959.994	2181.668	4042.358	3024.136	2967.542	3047.794
JB test	12569.515	6839.628	3215.779	17739.277	6166.253	5284.823	11998.194
ADF test	-16.128	-16.639	-15.704	-16.178	-16.06	-16.806	-15.331

LB stands for Ljung-Box test statistics over the returns, while LB2 does it for Ljung-Box test statistics on the squared returns. JB represents the Jarque-Bera test statistics and ADF means Augmented Dickey-Fuller test. All four null hypothesis are rejected for each one of the markets at a 1% level of significance.

between ε_{it} and ε_{jt}.

In this methodology, squared elements of the diagonal of D_t which are the variances of each ε_{it} are modelled like independent univariate GARCH processes

$$h_{iit} = \omega_i + \sum_{l=1}^{P_i} \alpha_{il}\varepsilon_{it-l}^2 + \sum_{l=1}^{Q_i} \beta_{il} h_{iit-l} \tag{13}$$

Now, for the R_t dynamics, the next decomposition is needed

$$R_t = Q_t^{*-1} Q_t \, Q_t^{*-1} \tag{14}$$

where Q_t^* is a diagonal matrix whose diagonal is the square root of the diagonal of Q_t and Q_t is a covariance matrix that has the following dynamic

$$\begin{aligned} Q_t = & \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\bar{Q} \\ & + \sum_{m=1}^{M} a_m \left(\varepsilon_{t-m}\varepsilon_{t-m}'\right) + \sum_{n=1}^{N} b_n Q_{t-n} \end{aligned} \tag{15}$$

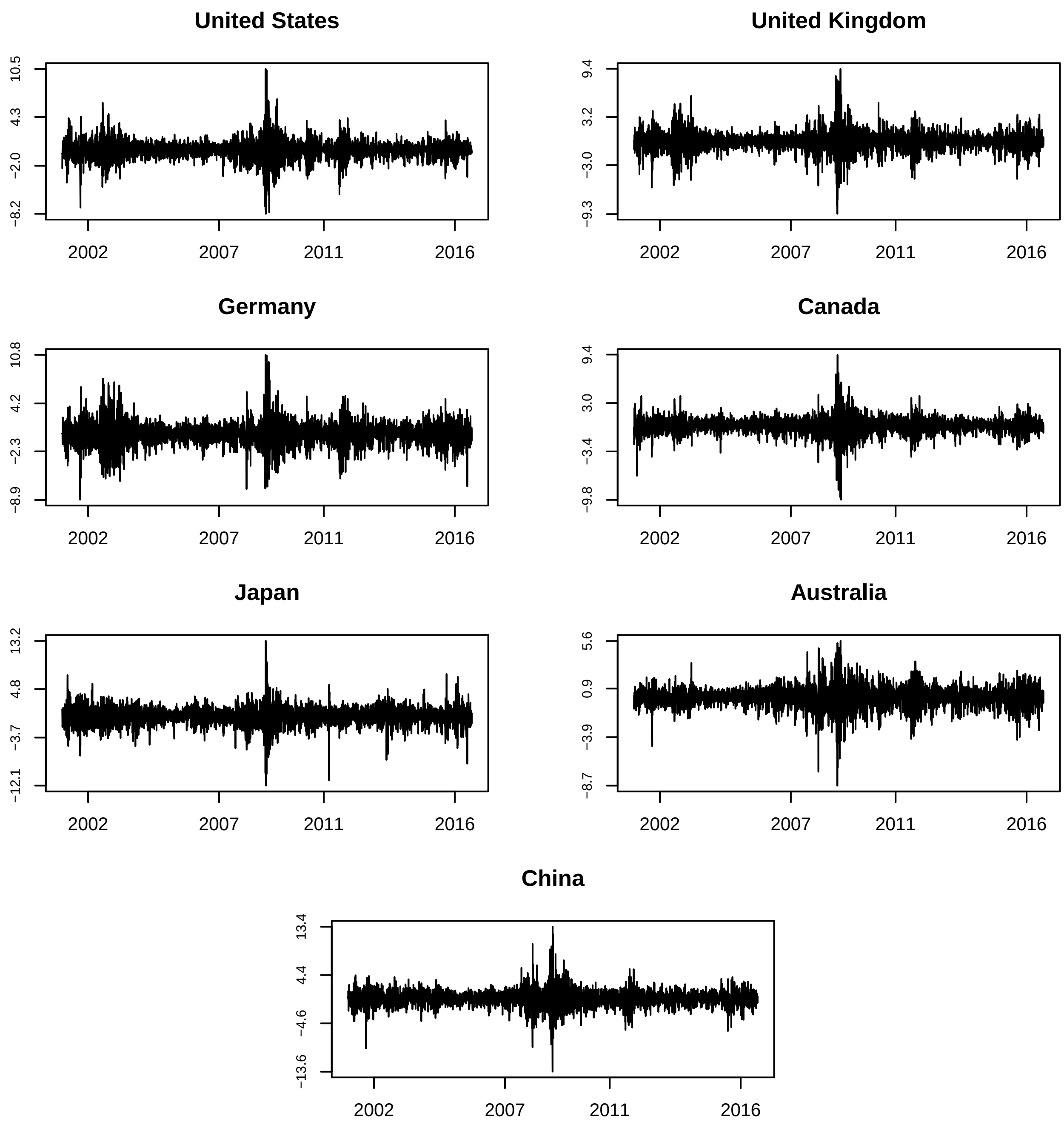
where $\bar{Q}$ is the unconditional expected value of Q_t.

3 Data

In this paper we compute stock market volatility spillovers between Australia, Canada, China, Germany, Japan, the United Kingdom (UK), and the United States (US), using data from January 2nd, 2001 to August 26th, 2016. For this purpose we use daily data on stock market indexes for these seven countries.[1] Returns are calculated taking first differences of the stock indexes' natural logarithms. Figure 1 shows the series of returns for the countries included in our sample. Volatility hikes are a common salient feature for the time period around

[1] The stock market indexes used are S&P/ASX 200 (AS51), S&P/Toronto Stock Exchange Composite Index (SPTSX), Hang Seng Index (HSI), German Stock Index (DAX), Nikkei-225 stock average (NKY), FTSE 100 Index (UKX) and Dow Jones Industrial Average (INDU), respectively.

Figure 1: Stock Market Index Returns



the Lehman Brother's failure of September 2008.

Table 1 presents some descriptive statistics of the series of stock market returns for our seven countries. It shows sample means, standard deviations, skewness, kurtosis, Jarque-Bera (JB) tests for normality, Ljung-Box (LB) tests for autocorrelation, and Augmented Dickey-Fuller (ADF) unit roots tests. In all cases the null hypothesis of a unit root in the data is rejected in favor of stationary time series on stock market returns. Hence, they can be used in the VAR analysis. All series exhibit a high kurtosis and serial correlation, as is often the case in financial time series.

While under the null hypothesis of normal distribution excess kurtosis should be three, for our sample data all kurtosis are way higher. The JB test shows that none of the returns is normally distributed.

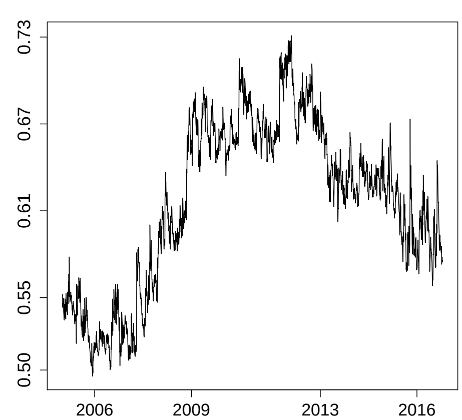
Important to mention, Ljung-Box statistics for the squared errors (LB2) of the series show that a GARCH specification might be adequate in this context due to the presence of volatility clusters in the data.

4 Results

We focus in a ten-day horizon ($h = 10$ days) in our empirical analysis. The method presented above is applied using a rolling estimation, with a window of size 1000. In other words, we compute spillover indexes for 3070 time periods, spanning from November 10th, 2004 to August 26th, 2016. Table 2 shows the volatility spillover estimates for the seven countries over the entire sample period.[2] The ij^{th} entry represents the estimated contribution to the forecast error variance of country i generated by an innovation in country j. The US is the most important volatility transmitter, followed by the UK and Germany. The system's total spillover is 61.5%, a percentage way higher than the 39.3% computed by Gamba-Santamaria et al. [2016] for a set of Latin American countries and the US. This shows the importance of volatility spillovers among the countries included in our sample.

The total system's spillover is depicted in Figure 2. This spillover, computed as the sum of all transmissions and receptions for the seven countries included in this study, varies considerably over time. Note that the total spillover is increasing from 2007 to 2009, and remains in high levels up to the end of 2011. During that period of time, corresponding to the international financial crisis, the total spillover reaches levels above 17%. From that moment on it reduces, but remains in higher levels than those that prevailed before the US subprime financial crisis (around one percentage point above).

Figure 2: Total Spillover Index



[2] Table 4 in Appendix A contains specification tests of the DCC-GARCH results of the last rolling estimation.

Table 2: Volatility Spillover Table

	United States	United Kingdom	Germany	Canada	Japan	Australia	China	Directional FROM Others
United States	0.063	0.023	0.026	0.029	0.004	0.004	0.005	0.091
United Kingdom	0.025	0.057	0.039	0.020	0.005	0.007	0.008	0.104
Germany	0.027	0.041	0.059	0.019	0.005	0.006	0.008	0.106
Canada	0.029	0.021	0.019	0.063	0.004	0.004	0.006	0.083
Japan	0.018	0.014	0.014	0.012	0.047	0.009	0.010	0.077
Australia	0.018	0.015	0.015	0.016	0.007	0.045	0.009	0.080
China	0.015	0.013	0.012	0.013	0.010	0.011	0.050	0.074
Directional TO Others	0.132	0.127	0.125	0.109	0.035	0.041	0.046	**Total Spillover**
Directional including own	0.195	0.184	0.184	0.162	0.082	0.086	0.096	0.615

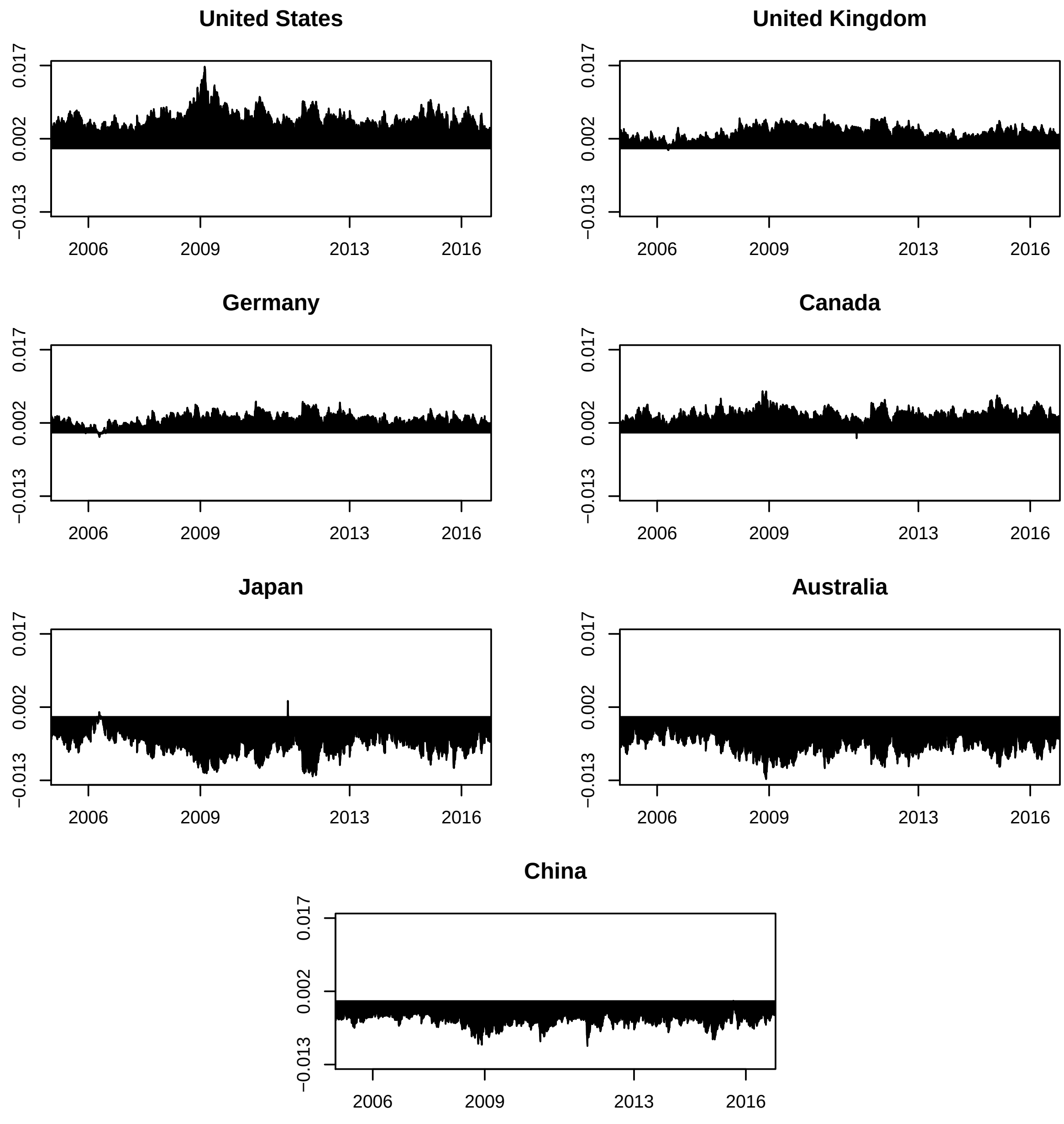
Figure 3 shows total net volatility spillovers for individual countries. They are computed as the difference between spillover transmission and reception. Positive (negative) values at time t correspond to a net transmitter (receiver) position at that time. An interesting result is that while transmission intensities vary over time, the net position of each country does not change along the sample period. Countries are always either net transmitters (the US, the UK, Canada, and Germany) or net receivers (Australia, China, and Japan). Even though the Chinese stock market has grown importantly during the last few decades, it is still a net volatility receiver from the most developed financial markets. Regarding time variation, the highest spillovers are observed around the Lehman Brothers' event in September 2008, and around the european sovereign bond crisis of late 2011. The US was the main transmitter during the former while Germany and the UK were the main volatility originators during the latter.

Pairwise spillovers provide further information on the dynamics of transmission. Figures 4, 5 and 6 in Appendix B presents all possible pairs of transmissions for the set of countries in our sample. An interesting feature is that spillover transmission is stronger from the most developed economies (the US, the UK, and Germany) to the rest of the countries, except Canada. Any other pairwise transmission is of lower magnitude. This result shows that volatility spillovers are stronger from central countries to peripheral ones. The case of Canada is interesting, as spillovers to/from the US, the UK, and Germany are quite low. Canada is a net transmitter to China and Japan, and a net receiver from Australia.

Note that the US is a spillover transmitter to all other countries, except for very short and particular time periods in which it receives volatility spillovers from Germany or the UK. Transmission from the US to the UK were particularly strong during the fourth quarter of 2008, at the highest point of the recent subprime financial crisis.

Given the US is the most important volatility trans-

Figure 3: Net Directional Spillover Index



Net directional spillover indexes are the difference between the volatility transmitted from one market to the system and the volatility received by that one market from the system. Hence when the index is positive the market is a net transmitter of volatility, whereas it is negative, it is a net receiver of volatility.

mitter of the countries in our sample, an interesting question is whether spillovers from the US to the other six countries were significantly higher during the recent international financial crisis. In order to answer this question, we perform a similar exercise as those of Chiang et al. [2007], Syllignakis and Kouretas [2011], and Gamba-Santamaria et al. [2016]. We use the following regression equation

$$S_{ij,t} = \omega_{ij} + \alpha_{ij} DM_t + \eta_{ij,t} \tag{16}$$

where $i = \{Australia, Canada, China, Germany, Japan, UnitedKingdom\}$ and $j = \{UnitedStates\}$. We regress pairwise spillovers ($S_{ij,t}$) on a constant term (ω_{ij}) and a dummy variable DM_t, taking on the value of one during the period of the United States subprime financial crisis and zero otherwise. As the exact period of this crisis is not precisely defined, we use the same period used by Syllignakis and Kouretas [2011] and Gamba-Santamaria et al. [2016]: September 26th, 2008 - September 29th, 2009. Results are qualitatively identical when July 2nd, 2007 is taken as the initial date, as in Wang et al. [2016a] and Wang et al. [2016b].

Table 3: Estimation Results for Testing Changes in United States Pairwise Spillovers

	Subprime Financial Crisis	
i	ω_{ij}	α_{ij}
Australia	1.975	1.155
	(0.01)	(0.034)
Canada	0.07	0.015
	(0.002)	(0.007)
China	1.353	0.604
	(0.007)	(0.025)
Germany	0.166	0.254
	(0.003)	(0.01)
Japan	1.843	1.677
	(0.014)	(0.049)
United Kingdom	0.134	0.255
	(0.003)	(0.009)

Standardized errors follow the methodology of Newey and West [1987] for calculating a covariance matrix corrected by heteroscedasticity and autocorrelation. $j =$ United States.

Our hypothesis is that spillovers from the United States to the other countries increased significantly during the recent crisis, as the dynamic of capital flows changed dramatically, responding to changes in risk aversion of international investors. Table 3 shows regression results. All constants (ω_{ij}) are positive and statistically significant at conventional levels, indicating that volatility in these countries is increased by stock market shocks coming from the US during the sample period. These linkages are larger for Australia, China, and Japan. Furthermore, the coefficient associated to the dummy variable corresponding to the subprime financial crisis, DM_t, is positive and statistically different from zero in all cases, confirming our hypothesis that spillovers increased significantly during this crisis episode. The coefficients of this dummy variable corresponding to the regressions for Australia and Japan were considerably higher than for the rest of the countries. This result suggests that these two countries were more affected by US volatility spillovers than other developed countries during the crisis. In contrast, the value of the coefficient for Canada was substantially lower.

5 Conclusion

In this study we construct volatility spillover indexes for some of the major stock markets indexes in the world, using a DCC-GARCH framework for modeling the multivariate relationships of volatility among markets. We extend the framework of Diebold and Yilmaz [2012], following Gamba-Santamaria et al. [2016], and compute spillover indexes directly from the series of returns considering the time-variant structure of their covariance matrices. Our spillover indexes use daily stock market data of Australia, Canada, China, Germany, Japan, the United Kingdom, and the United States, for the period between January 2001 and August 2016.

We obtain several relevant results. First, total spillovers present substantial variation over time, being considerably higher in moments of market turbulence. The total spillover shows an increasing pattern from mid-2007 to 2009, and remains in high levels up to the end of 2011. During that period of time, corresponding to the international financial crisis, the total spillover reaches levels above 67%, substantially higher than the average before the crisis (around 40%). From 2011 on it reduces, but remains in higher levels than those that prevailed before the US subprime financial crisis. This indicates that the intensity of spillovers has increased recently, even during non-crisis periods.

Second, the net position of each country does not change during the sample period. The United States, the United Kingdom, Canada, and Germany, are always net transmitters, while Canada, China, and Japan are net receivers. However, as it is also the case when the total spillover is considered, their intensities exhibit important time-variation. The highest spillovers are observed around the Lehman Brothers' event in September 2008, and around the European sovereign bond crisis of late 2011.

Transmission originates in the most developed markets, as expected. And the intensity of transmission within this set of countries is lower than others. Of special relevance, even though the Chinese stock market has grown importantly over time, it is still a net receiver of volatility spillovers.

To test whether spillovers among this set of countries were significantly higher during the subprime financial crisis, we regress pairwise spillovers on a constant term and a dummy variable, taking the value of one during the period of the financial crisis. We find that all constants are positive and statistically significant. This result implies that volatility in countries different from the United States is increased by stock market shocks coming from the United States during the sample period. These linkages are larger for Australia, China, and Japan. Additionally, we find evidence that spillovers increased significantly during this crisis episode. The coefficients of this dummy variable corresponding to the regressions for Australia and Japan were considerably higher than for the rest of the countries, while the value of the coefficient for Canada was substantially lower.

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A Specification Tests

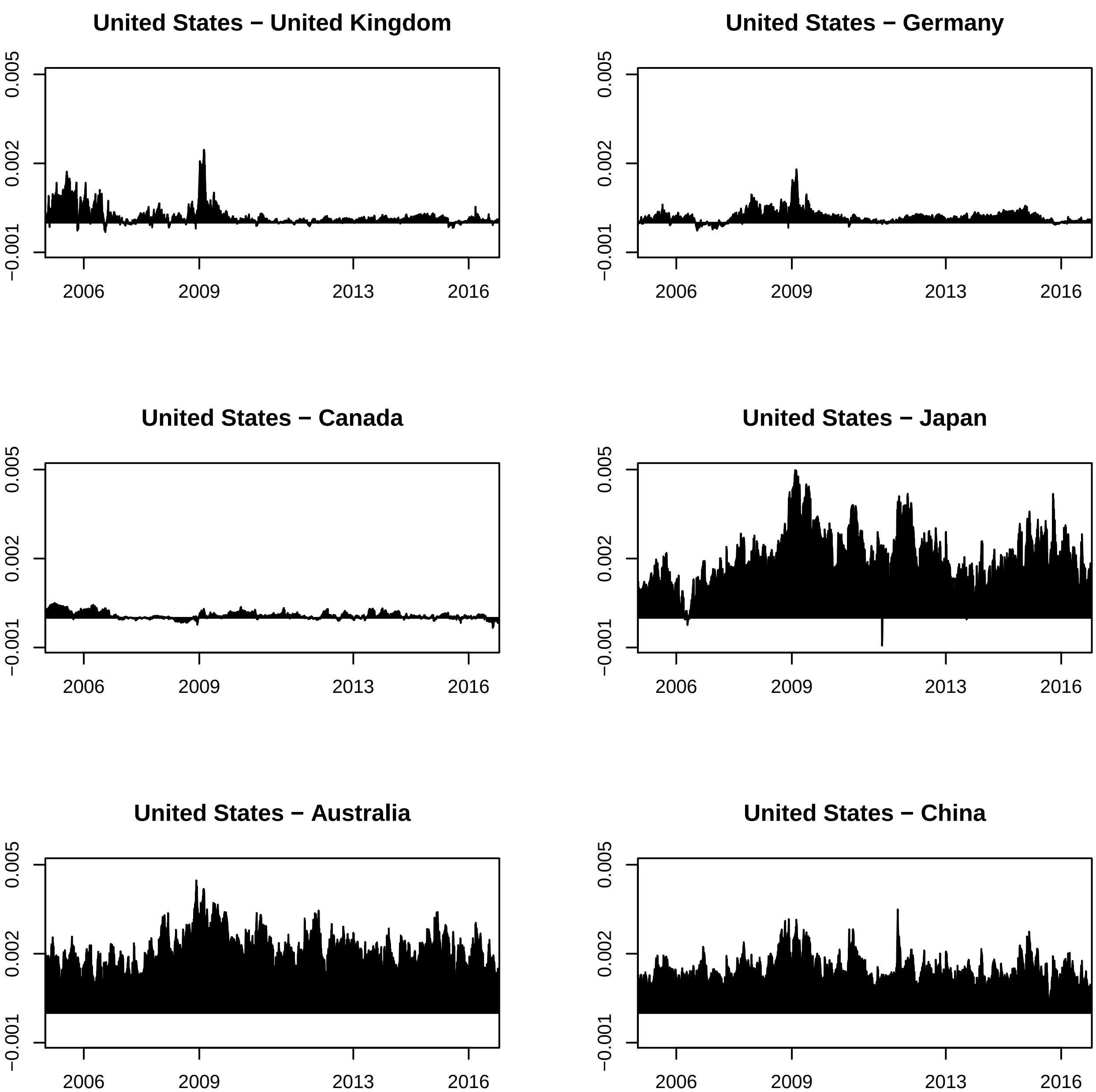
Table 4: Ljung-Box Tests on the DCC-GARCH Errors (p-values)

Lag	United States	United Kingdom	Germany	Canada	Japan	Australia	China	Multivariate Test
Standardized Errors								
5	0.63672	0.88778	0.99330	0.99671	0.98671	0.99742	0.99218	1
10	0.96725	0.99381	0.99936	0.94679	0.99980	0.99923	0.99976	1
15	0.99583	0.99938	0.99998	0.99271	0.99998	0.99989	0.99990	1
20	0.99959	0.99995	1	0.99940	1	0.99999	1	1
25	0.99976	0.99996	1	0.99991	1	1	1	1
30	0.99983	0.99999	1	0.99997	1	1	1	1
Squared Standardized Errors								
5	0.84340	0.50107	0.92291	0.25931	0.91552	0.25784	0.42763	0.00136
10	0.95945	0.43106	0.87792	0.32221	0.9885	0.57483	0.33365	0.08784
15	0.98451	0.07030	0.98321	0.28853	0.70054	0.79674	0.24976	0.04034
20	0.90312	0.08191	0.98174	0.53407	0.68882	0.69145	0.46239	0.15756
25	0.83126	0.12238	0.99662	0.75596	0.87524	0.86827	0.59717	0.34470
30	0.68505	0.18569	0.99733	0.80166	0.92926	0.83530	0.78907	0.39983

None of the null hypothesis is rejected for each market at a 1% level of significance.

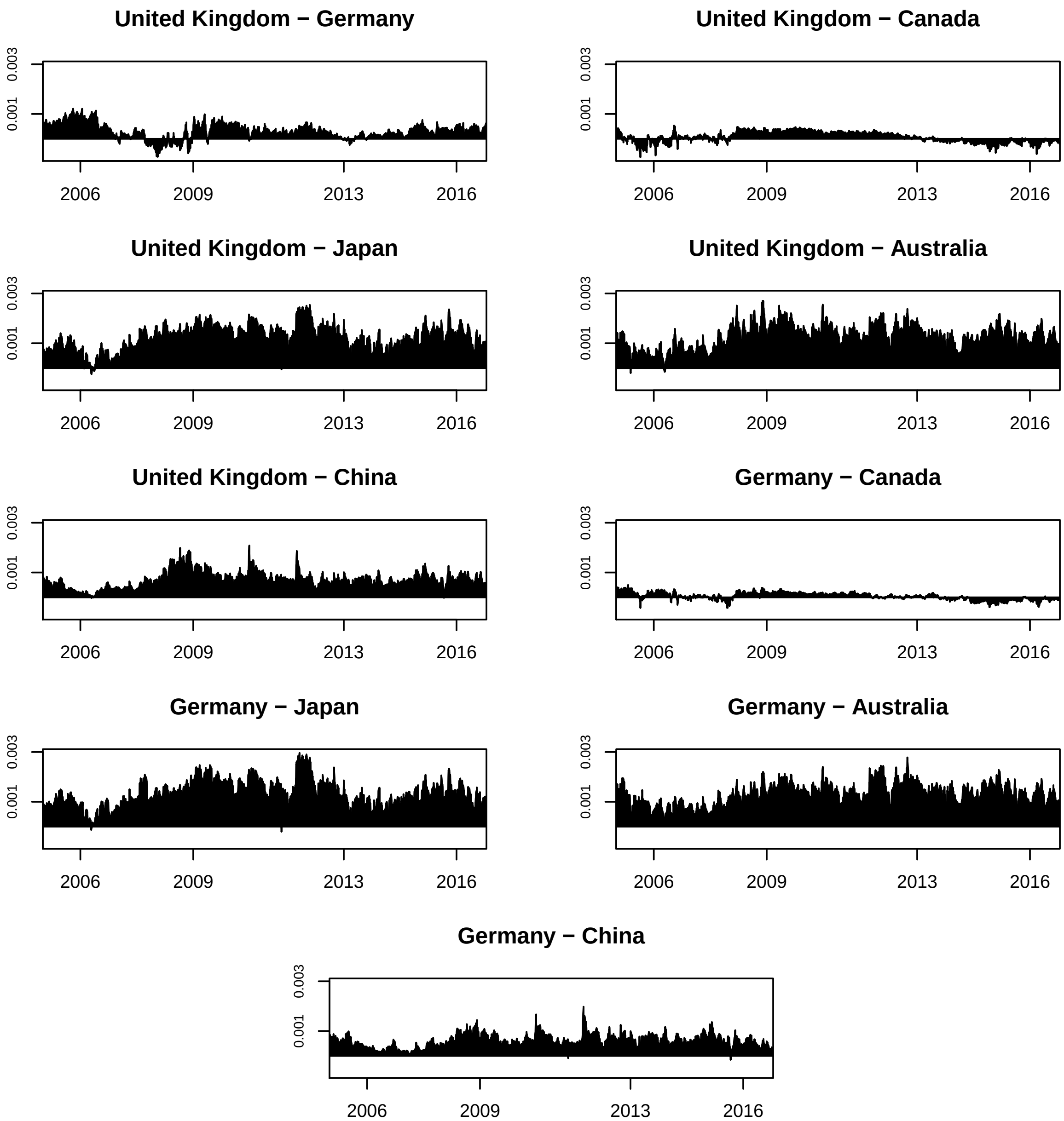
B Pairwise Spillover indexes

Figure 4: Pairwise Spillover Index between United States and the rest of the system



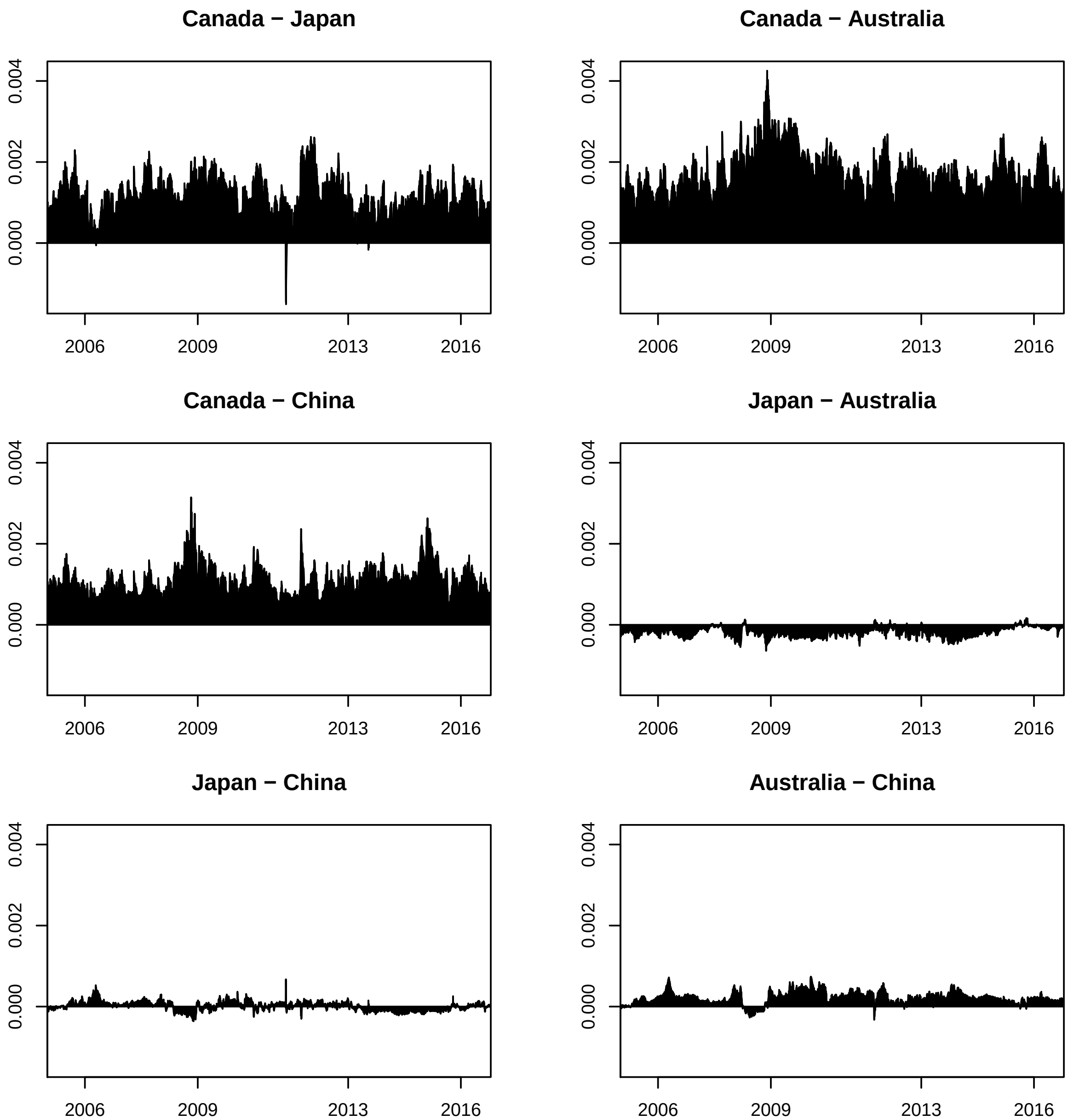
Pairwise spillover indexes are the difference between the volatility transmitted from one market to another and the volatility received by that one market from the other. Hence when the index is positive the first market transmits more volatility to the second, whereas it is negative, the second markets send more volatility to the first one.

Figure 5: Pairwise Spillover Index between United Kingdom, Germany and the rest of the system



Pairwise spillover indexes are the difference between the volatility transmitted from one market to another and the volatility received by that one market from the other. Hence when the index is positive the first market transmits more volatility to the second, whereas it is negative, the second markets send more volatility to the first one

Figure 6: Pairwise Spillover Index among the rest of the system



Pairwise spillover indexes are the difference between the volatility transmitted from one market to another and the volatility received by that one market from the other. Hence when the index is positive the first market transmits more volatility to the second, whereas it is negative, the second markets send more volatility to the first one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