Time varying volatility indexes and their determinants: Evidence from developed and emerging stock markets

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Abstract:

This paper investigates spillovers across 16 major stock markets based on the high frequency data based Realized volatility estimator (Andersen et al, 2003) using the spillover index methodology put forward by Diebold and Yilmaz (2012). These are compared with spillovers based on the Garman and Klass (1980) and the univariate GARCH estimators (Bollerslev, 1986) used in many previous studies. We find that the time series of total spillovers is similar regardless of the volatility proxy used and spillovers increased dramatically during the 2008 global financial crisis and the European sovereign debt crisis that followed. More differences arise when comparing directional spillovers for individual stock markets, particularly using GARCH based estimations. We find that the larger stock markets from the advanced western economies, particularly the US, dominate volatility transmission to other markets. Emerging markets such as China, India and Brazil are still relatively isolated, though their contribution to global volatility spillovers has increased considerably after 2006. We also investigate potential determinants of net spillovers between markets and find that the level of volatility in one market relative to that in other markets is the most important factor in increasing spillovers transmitted.

Keywords: Stock market spillovers, Realized Volatility, Spillover index, VAR, Volatility transmission

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1. Introduction

The analysis of interdependence in capital markets, and more specifically returns and volatility spillovers, has been the subject of a considerable volume of research. The impact of the global financial crisis (GFC) and the European sovereign debt crisis that followed has continued to increase interest in the topic. One of the key features of the GFC was not just the severity of its impact, but also how widespread its effects were, both globally and across asset classes. In part, this also reflects the general trend documented in past academic studies of increasing integration in stock markets around the world, particularly during crisis periods (for example, Forbes and Rigobon, 2002 and Yu et al., 2010). Nevertheless, the GFC has changed the way in which financial market linkages are viewed by market participants, academic researchers, the media and the general public as a whole.

The literature has investigated volatility spillovers using univariate GARCH methods (Engle et al., 1990, Hamao et al., 1990, Susmel and Engle, 1994, and Lin et al., 1994, *inter alia*), multivariate GARCH methods (see Soriano and Climent (2006) for a survey), and multivariate GARCH methods combined with regime switching (Edwards and Susmel, 2001, 2003, and Baele, 2005). In a recent paper, Diebold and Yilmaz (2012) extend their original spillover index methodology (Diebold and Yilmaz, 2009) which enables the estimation of volatility spillovers between various markets and assets classes that are insensitive to the ordering of variables. The major advantage of this methodology is that it allows the clear decomposition of total shocks to a given stock market into domestic market generated and international spillover components. Secondly, it enables the researcher to study spillovers in both crisis and non-crisis periods and chart their trends and cycles[1].

In this paper, we utilise Diebold and Yilmaz's (2012) approach and use intraday trade data in 16 stock markets, from advanced and emerging economies, to investigate both total spillovers and directional spillovers (that is, spillovers to/from each market in our sample) from 2000 to 2014. We use the high frequency data-based realized volatility estimator, which when used appropriately (to avoid the impact of microstructure noise) is recognized as being the closest estimate of the true latent

[1] There are a number of other advantages to the methodology. See Diebold and Yilmaz (2009, 2012) and Yilmaz (2010).

integrated volatility (Andersen et al., 2005). We believe this is the first study to use a spillover index based on realized volatility to study a broad sample of developed and emerging equity markets[2] and also examine how spillover analysis is impacted by the choice of the volatility measure, thereby bridging a gap in the existing literature, which has utilized a wide array of different volatility proxies[3]. For comparison, we also examine the spillovers generated from the Garman and Klass (1980)[4] and the univariate GARCH (Bollerslev, 1986) estimator. In addition, we investigate how various financial market variables in the stock, bond and FX markets as well as macroeconomic news impact on net directional spillovers during both crisis and non-crisis periods.

We summarize our main findings as follows. First, we find that the large developed capital markets (in particular the United States) dominated spillovers to other markets. Other significant contributors of volatility spillovers were France, Australia and the UK. The major emerging markets of Brazil, China, and India were initially quite isolated in comparison, though from 2006 onwards they contributed significantly to global stock market volatility during various periods. Second, whilst total spillovers are largely insensitive to how volatility is defined, directional spillovers are impacted (often to a significant extent) in terms of the timing and magnitude of spillover trends and cycles. GARCH-based estimations in particular differ significantly from Realized Volatility and the Garman Klass estimator, which provide more comparable results, though there are also substantial disparities at times. Third, we find that the most important determinant of net directional spillovers is relative stock market volatilities (the ratio of domestic to foreign - all other markets in the sample - volatility). Other important determinants during various periods include the relative change in bond yields, relative FX volatility, and domestic macroeconomic news. Fourth, we report that the treatment of non-synchronous

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[2] Within the Diebold and Yilmaz (2009, 2012) VAR methodologies, McMillan and Speight (2010) use realized volatility to investigate total spillovers in three Euro FX pairs. Zhou et al (2012) share some similarities with our paper in that they do investigate both total and directional spillovers in equity markets but use the daily Parkinson High Low Estimator (1980) and do so from a Chinese stock market perspective. Barunìk et al (2014) use realized volatility in their analysis of spillovers in various sectors within the US market. In the broader literature on spillovers, studies using realized volatility have examined a much smaller sample of equity markets (for example Jung and Maderitsch, 2014).

[3] We use the terms estimators, proxy, specification and measures interchangeably.

[4] Although not shown, we also investigated the Parkinson (1980) High Low estimator used in recent spillover studies such as Diebold and Yilmaz (2009, 2012), Zhou et al (2012) and Engle et al (2012). Our results were largely similar to those obtained with the Garman and Klass estimator both in terms of underlying volatility estimations and spillover results.

trading (due to non-overlapping trading hours, for example between the American and Asian markets) has little impact on total spillovers. However, it has a major impact on directional spillovers between markets. We investigate possible reasons for this gross disparity in results, and believe that this remains a very important issue for future studies of this nature.

We proceed as follows. Section 2 details the methodological approach to develop the total and directional spillover indices and defines the various volatility measures. Section 3 describes our data and presents descriptive statistics and the graphical time series analysis of volatility using the various estimators. Section 4 details the results of the VARs to create summary spillover tables and a time series of total spillovers. Section 5 examines directional spillovers for each market in our sample while Section 6 investigates the potential determinants of these spillovers. Section 7 examines the sensitivity of our results to various methodological and data specifications with particular focus on the issue of non-synchronous trading. Section 8 concludes the paper.

2. Methodology

As a starting point, a covariance stationary VAR model of order (p) and N variables, $x_t = \sum_{i=0}^{\infty} \Phi_i x_{t-1} + \varepsilon_i$ has the moving average (MA) representation $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$, where $\varepsilon \sim (0,\sum)$ is a vector of independent and identically distributed (IID) disturbances, x_t is expressed as the sum of past and present error or innovation vectors ε_t, and the $M \times M$ coefficient matrix A_i is obtained by the recursive substitution, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \phi_3 A_{i-3} + \cdots + \phi_p A_{i-p}$, with $A_0 = I_m$, which is an identity matrix of order *m*, and $A_i = 0$ for $i < 0$. The MA can then be used to forecast the future H-steps ahead. Using variance decompositions, we can determine the fraction of the H-step-ahead error variance in forecasting x_i that are due to shocks to x_i (or own system shocks) and the fraction that is due to shocks to x_j, $\forall_j \neq i$, for each *i* (or spillovers).

For financial variables, there is likely to be contemporaneous correlation, which means the covariance matrix of innovations is not diagonal. To correctly identify the distinct impulse response function (IRF) patterns or variance decompositions (VD), the error term is transformed, usually using the Cholesky decomposition which orthogonalizes the innovations, and assumes that a shock in the first market in a given order has an immediate impact on all others, the second has an impact on all other markets except the first and so on. This renders the VD highly sensitive to the ordering of variables and can lead to erroneous and unrealistic results (see Dekker et al, 2001)[5]. To overcome this problem, we use the KPPS (Koop et al., 1996; Pesaran and Shin, 1998) generalized forecast error variance decompositions (GFEVD) to develop spillover indexes, in the same manner as Diebold and Yilmaz (2012), that are insensitive to the ordering of variables. The generalized decomposition allows for correlated shocks between variables without the need to orthogonalise them, but accounts for them appropriately using the historically observed distribution of errors (Pesaran and Shin, 1998). Because the shocks are not orthogonalized, the sum of the contributions to the variance of the forecast error (the row sums of the elements in the variance decomposition table) do not necessarily sum to 1 (Diebold and Yilmaz, 2012).

2.1 Variance shares

Diebold and Yilmaz (2012) define "own variance shares" as the fractions of the H-step-ahead error variances in forecasting x_i due to shocks to x_i, for $i = 1,2,3....N,$ and "cross variance shares", or spillovers, as the fraction of the H-step-ahead error variances in forecasting x_i due to shocks to x_j, for i,j = 1,2,3, … ,N such that $i \neq j$. The KPPS GFEVD is then given by:

$$\theta_{ij}\,(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (\acute{e}_\iota A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (\acute{e}_\iota A_h \sum A'_h e_i)} \tag{1}$$

where Σ is the variance matrix of the error vector, σ_{ii} is the standard deviation of the error term for the ith equation, and e_i is the selection vector with 1 as the ith element, and 0 otherwise. As explained above, it is not necessary that the sum of all elements in each row will equal to 1 i.e. $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Each entry in the variance decomposition matrix is normalized by the row sum as follows[6]:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{2}$$

[5] In preliminary testing, our spillover results were highly sensitive to variable ordering when using the Cholesky decompositions. This is particularly critical when studying directional spillovers.

[6] Normalisation can also be done by column sum which as Zhou et al (2012) show are quite similar to those obtained by row normalisation. We follow Diebold and Yilmaz (2012), and use row normalisation for all our results.

where $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$.

2.2 Total and directional volatility spillovers

Using Equation (2), we can construct the total volatility spillover index as defined by Diebold and Yilmaz (2012) as follows:

$$S^{g}(H) = \frac{\sum_{i,j=1,\, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \quad = \quad \frac{\sum_{i,j=1,\, i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3}$$

The total spillover index measures the contribution of spillovers across all 16 stock markets to the total forecast error variance. We measure the directional volatility spillovers received by market *i* from all other markets *j* as:

$$S_{i.}^{g}\,(H) = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 \quad = \quad \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{4}$$

Similarly, we can measure the directional volatility spillovers transmitted by market *i* to all other markets *j* as:

$$S_{.i}^{g}\,(H) = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 \quad = \quad \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{5}$$

Finally, we can obtain the *net volatility spillover* for each stock market by calculating the difference between equations (4) and (5) as:

$$S_{i}^{g}(H) = S_{.i}^{g}\,(H) - S_{i.}^{g}\,(H) \tag{6}$$

The net spillover allows us to examine the true extent to which one market influences the volatility in the other markets in the sample. Diebold and Yilmaz (2012) also measure the pairwise directional spillovers between any two markets of interest. We do not study pairwise spillovers as there was no a priori reason to study directional spillovers in any two specific stock markets, or a focus on any one market in particular (Zhou et al, 2012 focus on China, for example).

2.3 Defining volatility

Our primary estimator of volatility is *Realized Volatility* (hereafter, RV). We calculate realized variance as the sum of the squared returns over 5 minute intervals (to limit the effect possible market microstructure effects; Andersen et al, 2001) for each day using the closing prices of each interval[7]. Formally, it is defined as (Andersen et al, 2003):

$$RV_t = \sum_{n=1}^{N} r_{n,t}^2 \tag{7}$$

where RV_t stands for the realized variance on day *t*, r^2 is the n^{th} 5 minute return calculated on day *t* and N denotes the number of 5 minute intervals over day *t*. The Realized Volatility (RV) is simply the square root of the realized variance RV_t. We then calculate the annualized realized volatility (in %) as $\hat{\sigma}_{it} = 100\sqrt{365 \times RV_t}$ .We also consider a number of alternative volatility measures. The Garman and Klass (1980) estimator (hereafter, GK) which Yilmaz (2010) and Diebold and Yilmaz (2010) utilise is defined as follows:

$$\tilde{\sigma}_{it}^2 = 0.511\,(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \tag{8}$$

where $\tilde{\sigma}_{it}^2$ is an estimator of the daily variance, *H, L, C* and *O* are the daily High, Low, Close and Open index prices. Our final volatility estimator is the original GARCH (1, 1) estimator (Bollerslev, 1986) of the conditional variance. We use the Student's T-distribution for the distribution of the error term. The daily variance estimated using GK and GARCH is annualized in the same manner as RV.

3. Data and descriptive statistics

We examine the daily volatilities in 16 stock market indices from 6 January 2000 to 13 June 2014 for a total of 3,767 days per index. The selection of the countries in the sample was dictated by the availability of high frequency tick data to calculate RV and the end of day data for the calculation of the other volatility measures. We obtain our data from the Thomson Reuters Tick History database via SIRCA. The stock market indices and their trading hours are detailed in Table 1. The trading hours for the various stock markets overlap to varying degrees. The European markets trade over the same hours and thus are totally overlapping, whist they partially overlap with the American markets. The Asia-Pacific markets differ in their trading hours, with some totally overlapping, for example Japan and

[7] Our results using the Open to Close returns for each interval were also very similar.

Korea. Others partially overlap, though this overlap is over the major portion of their trading hours. To address the non-synchronous trading issue, we lag the daily volatilities (for all estimators) of the American and European markets in the VAR estimations by one day relative to the Asian Pacific markets as in Cai et al (2009) and Zhou et al (2012).

Table 2 provides descriptive statistics for all three volatility estimators. In general, the average and median volatilities are similar across the RV and GK estimators. The maximum daily volatility recorded is much higher using RV in some cases (e.g. Brazil and the UK), whilst in others it is higher using GK volatility (e.g. Canada and Japan). The volatility estimates using the GARCH are higher on average across all markets. In contrast, the maximum volatility recorded is far lower. The large emerging markets of Brazil, China, and India are among the most volatile stock markets. The markets at the core of the European debt crisis, namely France, Germany and Spain are also highly volatile. The US, despite being at the center of various crisis periods exhibits relatively lower volatility on average. Australia exhibits the lowest average volatility in the sample.

Figure 1 shows the time series for each market using RV and provides a much more detailed insight into the volatility trends over time. In general, the GFC is by far the most volatile period. Markets also experienced very high volatility during the Euro sovereign debt crisis that followed. The aftermath of the September 2001 terrorist attacks, and the subsequent 2002 crash in markets was also extremely volatile for Australia, Germany, France, Switzerland, Brazil, and Mexico. The bursting of the tech bubble in the US in March and April 2000 similarly shows a spike in volatility in some markets (the US, Australia, Canada, and Mexico). Volatility spikes attributable to idiosyncratic factors can also be identified; Japan experienced a brief but amplified tsunami-related spike in volatility in early 2011. Emerging markets including India and Brazil also exhibit huge but brief spikes in volatility prior to the GFC which exceed their peak volatility during the GFC.

Figure 2 shows the time series graphs for 4 stock markets chosen to highlight the similarities and differences using different estimators. Overall, the trends are quite similar. The GK series exhibit denser clustering and there are differences in the magnitude of large spikes in volatility. Brazil experiences three major spikes in volatility under RV before 2003, which are very subdued under GK and not clearly discernable. The UK's largest spike in the midst of the GFC is much more amplified under RV. In contrast, the spike in Japanese volatility following the tsunami in 2011 is much greater in magnitude under GK. For the US, there are no major disparities of note. The GARCH series displays a much smoother pattern as expected, though it broadly captures the same volatility dynamics. The peak periods of sustained volatility (primarily the GFC) are much shallower in magnitude and the early 2000s crash and the Euro crisis are muted. Compared to the other estimators, the GARCH model does not capture sudden short term spikes in volatility.

4. Empirical results: Aggregate spillover analyses

4.1 Analysis of spillovers under different volatility measures

Table 3 presents the full sample volatility spillovers using RV. The spillover transmitted by market *i* to market *j* is represented by the numbers down the column for that market, excluding the number on the diagonal, which represents own market shocks. The numbers for a market *i* going across a particular row in the table excluding the figure on the diagonal represent spillovers received, or shocks resulting from innovations to market *j*. These are the directional spillovers from market *i* to *j* and vice versa. The off diagonal column sums labeled as “Transmitted” and the row sums labeled as “Received” represent the total spillovers contributed to and received from other markets. The net spillover row is equal to spillovers transmitted less spillovers received for each market in aggregate. Due to row normalization as per Equation (2), the row sums (including own market shocks) equal 100%, while the column sums do not. The bottom right corner of the table represents the Total Spillover Index figure, and summarizes the degree to which shocks are attributable to spillovers for the entire sample expressed as a percentage. It represents the row sum (or alternatively the column sum, as total spillover received = total spillover contributed) of all the off diagonal variances divided by the total row sum, which in this case is 1600% (16 markets x 100%).

Table 3 shows that approximately 68.1% (1090/1600) of shocks were due to spillovers with the balance (32.9%) being own market shocks. The biggest transmitters of volatility to other markets are the US (138), Canada (105), Germany (88), Hong Kong (83) and Switzerland (81) while the biggest receivers are all European markets, namely the UK (86), Germany (84), France (82), Switzerland (81). For all markets, the largest individual shocks are from their own market. Consistent with Zhou et al (2012), China, despite the rapidly increasing size of its economy and stock market, is quite isolated recording the lowest spillovers transmitted (17) and received (23). This is likely due to the lack of openness and transparency as well as limitations on foreign investment. India is also relatively isolated though less so than China. The US (60) is by far the biggest net transmitter of volatility as expected, followed by Canada (29) and Hong Kong (15). Brazil (-35), Spain (-22), Mexico (-20) and Taiwan (-13) are the biggest net receivers. Table 3 also allows us to look closely at spillovers between individual markets, for example between France and Germany or the US and Canada.

Given our focus on the aggregate directional spillovers and the total spillover index, we have structured Table 4 accordingly. The total spillover is slightly lower under GK at 63.5% (compared to 68.1% under RV), but the directional spillovers are quite similar. The US is again the strongest net transmitter, followed by Canada and Australia, while Spain, Mexico, Brazil, and Taiwan are major net receivers. China remains by far the most isolated market. The total spillover figure using GARCH is comparable in magnitude to RV at 67.4%. However, the directional spillovers are substantially different. The major net transmitters are the European markets of France and Switzerland, and the UK. Although not shown in Table 4, a major component of the volatility transmitted by these markets is again regional (as is the case in Table 3). Australia is also a significant net transmitter. Interestingly, the US is a net receiver of volatility, in stark contrast to RV and GK. This is surprising given the US is the world's largest capital market and economy, and the driver of a number of crisis periods in our study. Other differences include Canada becoming a net receiver and Japan a strong net receiver. We discuss these differences in directional spillovers in more detail in Section 5.

4.2 Dynamic rolling sample Total Spillover Analysis

Tables 3 and 4 provided a rough snapshot of the volatility spillovers for the whole sample period. However, this by itself is insufficient to analyze the time varying nature of spillovers. We now generate both the total and directional spillovers time series using a VAR (2) model with a 25 day forecast horizon and a 200 day rolling sample. The resulting spillover time series shown in Figure 3[8] begins on 11 October 2000, after accounting for the first 200 daily observations, and ends on 13 June 2014. Although there is a general trend that is common in all volatility measures, there are also some notable differences. The RV series shows a very large sudden spike in volatility when the September 2001 terrorist attacks occurred. This is not as pronounced in the other volatility measures. The GK series shows a major spike on 17 May 2004, when the Indian stock market fell by almost 12% and recorded its most volatile day under RV and GK. The trend in the GARCH series is broadly similar to the other measures, albeit with less pronounced cycles. Again, this is unsurprising; from Figure 2, the peak volatility periods for all stock markets was more muted using GARCH when compared to the other volatility measures, and large sudden spikes in volatility were not captured.

We now focus on the RV graph to analyze the various cycles in total spillovers across our measurement period. As the general pattern is very similar, the interpretation can be equally applied to all other volatility estimators as well. The first cycle of elevated spillovers begins with the September 2001 terrorist attacks, and continues on until the end of 2002. The spillover index increases rapidly from around 50% to close to 70%, with the one large spike just after attacks rising to around 85% (as mentioned above this spike is more exaggerated under RV). The S&P500 dropped 34.1% over the period from September 10, 2011 to October 9, 2002, which marked the low point for most markets in the cycle. The downturn was global with only India, Mexico and Taiwan falling less than 10%. In contrast, Germany and France recorded a fall of around 59% and 50% respectively.

After this period of turmoil, markets returned to a period of relative calm. The level of total spillovers also declines to a range between 50% and 60% before falling below 50% for the majority of 2005. The next major cycle begins in May 2006 when the spillover index crosses 70% and marks the

[8] The 200 day sample is consistent with Diebold and Yilmaz (2012). However, we selected the window after much trial and error. Longer windows such as 500 days result in a time series graph that is too smooth to spot spillover cycles clearly and it was much harder to trace the key inflection points. A shorter window such as 50 or 100 days was too short for any sort of trend to develop at all, and thus the resulting time series is not useful either in pinpointing inflection points across time.

beginning an extended period of high volatility and elevated spillovers which ends after 6 years around August 2012. Diebold and Yilmaz (2009, 2012) and Yilmaz (2010) identify the US Federal Reserve's (hereafter, FED) decision to tighten monetary policy in May 2006 as the starting point for a dramatic jump in spillovers as it led to a reversal of capital flows away from emerging markets. The decline in the Brazilian and Indian markets (around 24% and 33%, respectively) within that one month supports this explanation. The drop was in excess of 10% for all the other Asian markets except China as well as almost all the European markets in our sample. The sudden and dramatic sell-off in February 2007 in the Chinese market also worried investors and resulted in an increase in spillovers.

The index climbs further in August 2007, when it touches 80% as the subprime mortgage crisis began to hit full swing with the declaration of bankruptcy by two Bears Stearns hedge funds. In January 2008, a huge drop in new home sales in the US led to a correction across most markets in our sample of over 10% at the low point (22 January), with Australia and Hong Kong falling over 20%. This led to the spillover index reaching a high of 82%. Total spillovers remain over 80% with the takeover of Bear Stearns in March 2008. The Index reaches its zenith and crosses 85% in October 2008 after the crash of Lehman Brothers in the preceding month, signaling the peak for the GFC. Total spillovers remain near 80% till June 2009, when the combination of massive stimulus packages and dramatic coordinated easing by central banks around the world, lead to a thawing of the crisis and a dramatic fall in the level of spillovers to below 65%. The period of relative calm ends with the onset of the European debt crisis as Greek sovereign bonds were downgraded to Junk status and the subsequent bailout of Greece in May 2010. The Flash crash in the Dow Jones Index also added to general sense of fear amongst investors. After the bailout of Ireland in November 2010, the spillover index temporarily declines as volatility across global markets falls.

The final leg of extreme spillovers begins in August 2011, as the US lost its AAA rating and concerns over Italy and Spain threatened to possibly lead to a breakup of the Eurozone. The level of spillovers is sustained for nearly 8 months at 80% and ends in April 2012. By September 2012 the index falls to below 55% with the creation of the Euro Financial Stability Facility (EFSF) and the

ECB's pledge to buy unlimited amounts of sovereign distressed bonds. Towards the end of 2012, the index rises back up towards 65% in view of the then impending "Fiscal Cliff" in the US, but falls as US senators strike a deal. It rises again over 60% in 2013, as investors confronted the possibility of the FED winding back its quantitative easing and a possible slowdown in China. However, this fear recedes as volatility across almost all markets in our sample declined in 2014 and a number of markets reach new highs, notably the US as its economic outlook improved, while geopolitical tensions such as Russian intervention in Ukraine also fail to have any major impact on global market volatility.

To summarize, it is clear that the level of total spillovers very closely tracks the level of underlying volatility, with high volatility periods leading to dramatic increases in spillovers. Spillover cycles are persistent, and high total spillover periods tend to continue months or even years after a sudden shock to markets. This suggests that in highly volatile periods, diversification may not to be found in other international stock markets and investors may have to look to other asset classes.

5. Empirical results: Directional spillover analyses

5.1 Description of changes in directional spillovers by market

We now focus on directional spillovers for each market. Figure 4 shows the directional spillovers for Japan, the UK and the US as examples. Our primary focus is on the RV net spillovers for each market displayed in Figure 5. It is apparent that all the markets act as both net transmitter and receiver during various periods. Periods of positive net spillovers equate to a particular market being a net transmitter and vice versa. We now analyze the net spillovers for each market.

5.1.1 Asia-Pacific markets

Australia is on average the third largest net transmitter in our sample. The first cycle as a net transmitter was from June 2005 to July 2006, when the Australian market was amongst the best performers with a booming commodities industry driven by the rapid growth of China and India. Australia became a net receiver during the GFC before reverting back to transmitting volatility from January to August 2009 as it outperformed most markets. Australia's most significant transmission cycle is from May 2010 to May 2012, peaking at over 7% in August 2011 when its volatility approached levels similar to the GFC as European debt crisis gained momentum and a slowdown in China threatened its commodities industry. Australia also exhibits one small and brief transmission cycle from May to December 2013, with the magnitude of transmissions for the most part being below 2%.

Hong Kong largely acts as a net receiver peaking during the GFC like many other markets, which is in contrast to Table 3, where it was a strong net transmitter. This illustrates that the whole sample spillover tables provide only a rough picture, and the dynamic rolling windows demonstrate that the time series of spillovers may paint a different story. China and Taiwan are also net receivers for a majority of their time series, though both markets have two cycles as a net transmitter. China transmitted very strongly (peaking at 9%) from May 2006 to July 2007 when it was by far the most volatile market as it tripled in value in that time. This cycle also incorporated the sudden flash crash in its stock market on 27 February 2007, when the SSEC fell over 9% in a single day before bouncing back by 4% the following day. China then transmits from July 2009 to February 2011, when it was again the most volatile and also the worst-performing market. The amplitude of this cycle was much shallower and not sustained continuously, with downside volatility mainly in effect. China then becomes a net receiver for the rest of the study period. Taiwan's first cycle as a net transmitter between October 2007 and October 2008 overlaps with Japan and Korea and was relatively shallow, although it did exceed 6% at its peak. In contrast to Japan, the Taiwanese market was actually one of the better performing in our sample, falling by a little over 6%. Its second cycle as a transmitter overlaps with China's, and is likely driven by the volatility in the Chinese market given its proximity to China.

Japan's first notable transmission cycle begins in January 2008 and its stock market acts as a very strong net transmitter through the GFC before ending in October 2009. The Japanese market was hit particularly hard and fell more than all other markets (-26.1%), with the exception of China during this period. Given the size of its economy and stock market, it is not surprising that Japan was a net transmitter during the GFC along with the US. During the Euro crisis however, Japan acted as a net receiver, apart from a brief period in March 2011 when it becomes a transmitter, due to the Japanese tsunami disaster. It remains a net receiver after this brief reversion for the rest of the study period.

India acted as a net receiver for the majority of our sample period. The first cycle as a net transmitter coincided with China's, from November 2005 to April 2007, when the Indian market performed outstandingly (returning over 55%) and was also highly volatile. India also acted as a net transmitter from February 2008 to July 2009, with the exception of a few days in October 2008 when global market volatility peaked. Over this period India was amongst the most volatile markets, along with China and Brazil. It then switches to a net receiver, peaking at around -4% during the European debt crisis. India has one very brief transmission cycle from July to September 2013, peaking at over 4% when it was highly volatile with a number of days where returns exceeded plus or minus 2%.

Korea experienced two major cycles as a net transmitter. The first occurred between March 2004 and May 2006. During this period of relative calm, the Korean market was amongst the most volatile in our sample. Its second cycle from August 2007 to May 2009 is not very dense, although it has a peak of around 5% and covers the core crisis period of the GFC. Korea acts as a transmitter for the bulk of this period, like a number of other emerging markets such as India and Brazil. There are also has two small cycles as a transmitter, in 2011, and from May 2012 to June 2013 respectively.

5.1.2 The Americas

Like the other emerging markets, Brazil and Mexico are also net receivers for the majority of our study period. Brazil has two cycles as a net transmitter. The first comes in the midst of the GFC in October 2008 and ends in November 2009, during which the Brazilian market was the most volatile in our sample, and its transmission peaked at over 8%. Mexico also has significant overlap in its first cycle as a transmitter on the back of its rapidly worsening economic prospects. However, the cycle is much shallower in magnitude and length and ends in May 2009. Brazil's second transmission cycle occurs during the Euro crisis, and the drivers for Brazil's net spillover appear to be common with Australia and Mexico, based around diminished growth opportunities, although Brazil's cycle is relatively muted compared to Australia's and Mexico's (which peaks at over 9%)[9] .

The US is by far the largest net transmitter of volatility, and transmits for the vast majority of the time period we study, closely tracking the time series of total spillovers. Interestingly, the US acts as a net receiver beginning in September 2001 (after the terrorist attacks), which seems a rather counterintuitive result. The US market was closed for a number of days after the attack, and reopened on 17 September, when it experienced a brief spike as a net receiver of over -5%. By this time, markets around the world and in particular Europe (where markets became very strong transmitters) had already reacted to the news of the attacks days before, and this flowed into the US stock market. The US switched back to being strong net transmitter in July 2002 (rising to over 7%), which was the peak period in the 2002 crash. In the tranquil period from March 2004 to April 2006, the US continued acting as a small (in magnitude) net transmitter. From March 2007 to November 2012, the US switched to its major cycle as a transmitter, covering the GFC, the Euro crisis, and its credit rating downgrade in August 2011. After a brief period as a net receiver, the US resumes transmitting volatility from September 2013 onwards, as concerns over the FED's pulling back on its quantitative easing concern global markets, even as the S&P 500 approached all-time highs by the end of our study period.

Canada, like Hong Kong also functioned as a net receiver for the majority of our study period unlike the result in Table 3. Canada's first cycle as a net transmitter occurred at the start of the time series leading up to the September 2001 attack, when it became a net receiver like the US (the Canadian market was also closed on the day after the attack). The proximity to the US (Canada's volatility is overall most highly correlated with the US at 0.84) is likely the reason its spillover pattern mirrored that of the US during this period and its two stronger cycles as a net transmitter from January 2007 to March 2008, and from October 2008 to July 2009 when its correlation with the US reached 0.91.

[9] The transmission cycles for Brazil and Mexico at least in part reflect a dramatic jump in correlation with the US after the downgrade in its credit rating on 5 August 2011. In the days after the downgrade, the rolling 200 day correlation for both markets jumped by over 25%, and peaked at over 90% in October 2011. For Australia, there was a jump of over 20%. The downgrade serves as a catalyst for all 3 markets to increase spillover transmission dramatically. Thus, they likely reflect volatility from the US to other markets in our sample to some extent.

5.1.3 European markets

The spillover series for Germany and France together are quite similar which is unsurprising given their underlying volatilities are very highly correlated at 0.93. France is on average the second strongest net transmitter after the US. France acted as a strong transmitter until March 2003, peaking on the day of the September 2001 attacks and covering the 2002 global market downturn, when European markets as a whole were extremely volatile and significantly underperformed. Germany also acted as a net transmitter during this period, although the magnitude of spillovers transmitted is far smaller. France's next cycle as a net transmitter occurred between December 2003 and February 2007, largely overlapping with Germany's second cycle when both markets outperformed substantially and were among the most volatile developed markets during this period in our sample. The upside volatility was channeled particularly to the other markets in the same region, such as Switzerland and Spain. Both markets act as strong net receivers during the GFC. Interestingly, neither market acted as large net transmitters for the majority of the Euro crisis. France experienced a minor transmission cycle between January 2010 and March 2011, but became a net receiver for much of 2011. Both markets became net transmitters in July 2012 as the crisis abated and continued to transmit almost continuously until the end of the study period. During this last cycle, again both markets outperformed significantly, whilst also being the most volatile developed markets in the sample.

Switzerland and Spain too share a reasonably similar pattern. Switzerland had one major period as a net transmitter during the early 2000s overlapping with France, Germany and the UK. Switzerland was then mostly a net receiver of volatility. In June 2013, Switzerland began a second cycle as a net transmitter again overlapping with France, Germany and the UK. Spain also experienced one minor cycle as a net transmitter in the early 2000s, as with the other European markets. For majority of our sample period, Spain is also a net receiver, but like the other European markets, it too acted a net transmitter from between 2012 and 2014 during various times, though the cycles are much weaker.

The UK, like the other European markets, was a strong net transmitter (peaking at over 9% in July 2002) for most of the period until April 2004, before switching to being a small net receiver. The UK experienced a smaller second cycle as a net transmitter in the tranquil period from May 2006 to February 2007, overlapping with both France and Germany. The UK acted as a net receiver through both the GFC and the majority of the Euro crisis. From May 2012 when the crisis began to abate, the UK functioned as net transmitter again until the end of our sample period, although reverting back to being a net receiver for a few months from June to September 2013 as with France and Germany. None of the European markets acted as transmitters in the later high volatility periods (as they do in the early 2000s crisis), but are strong net transmitters in periods of relative calm.

We now summarize our findings. Our first observation is that the financial market linkages analyzed through the VAR methodology occasionally work in a counterintuitive manner. For example, while the European markets strongly transmitted volatility after the 2001 terrorist attacks, during the recent Euro crisis, they were net receivers for a significant portion of the crisis timeline. Rather, the US, as well as a number of emerging markets, and Australia, became net transmitters as they acted as proxies for a slowdown in the global economy.

Our second finding is that exceptional volatility (both upside and downside), often associated with significant over/under performance in terms of relative returns, consistently led to a particular market becoming a net transmitter. For example, China transmitted strongly pre-GFC due to its volatility being the highest in our sample on the back of an enormous surge in its stock market, whilst India and Brazil were strong transmitters during the GFC due to their exceptional volatility. In a similar vein, during the period covering the 2002 downturn the European markets transmitted more strongly than the US due to their much higher levels of volatility and the more dramatic declines in their markets.

Our third finding is that while the major emerging markets such as Brazil, China, India, and Mexico are still net receivers for the majority of their time series, they have also been very strong transmitters from 2006 onwards at various times. This likely reflects the rapidly increasing size of both the stock markets and economies in these countries and thus their increasing importance to market participants globally. It also reflects the increasing integration of these markets with the rest of the world over time. Our fourth observation is that there is a very high degree of integration in the European markets. This is evidenced by the similarities in their time series in Figure 5, and also if we look back at Table 3, a majority of spillovers in these markets was regional.

Finally, the US is by far the largest net transmitter overall, in keeping with its status as the world's largest stock market and economy and the source of both the early 2000's crash and the GFC. The US was also a major source of volatility during the European debt crisis. Unsurprisingly, the US net spillover series has largely tracked the total spillover series and major events that caused downturns over the last 14 years. Markets that are highly correlated with the US such as Canada (Brazil, Mexico and Australia during the EU crisis) also exhibited cycles as a strong net transmitter.

5.2 Comparing Directional spillovers across Volatility Estimators

Figure 6 shows the net spillovers for a sample of 4 selected stock markets which we (for brevity) use to compare net spillovers using the various volatility estimators. Australia is one of the strongest net transmitters across all measures of volatility. The GK spillovers bear more resemblance to RV, though significant disparities also exist. For example, Australia's cycle as a net transmitter, which started in 2009, is much stronger and sustained under GK, while it is comparatively shallower and also far less dense under RV. The reverse is true for the major cycle beginning in May 2010. Under GK, Australia acts as a strong transmitter till the end of 2003, which is much more extended the other two estimators (it is a strong net receiver under RV from January 2002). The GARCH estimator generates more disparities, for example from July 2009 to April 2011, when Australia transmitted very little volatility or acts as a receiver, while under the other two measures it is a strong transmitter. The magnitude of transmission cycles under GARCH is much higher and approaches 15% at its peak.

For China, the time series for all three estimators is similar in terms of the timing of cycles. Under GK, the magnitude of both transmission cycles is much more subdued relative to RV and GARCH. The second transmission cycle is also more extended under RV than the other two estimators. Like Australia, the magnitude of the transmission cycles under GARCH for China is exceptional, with peaks at almost 30% during the 2006-07 cycle.

We use the UK as our representative market for Europe. The GK spillovers have some differences with RV, particularly the UK's cycle as a net transmitter from May 2012 which is barely noticeable under GK. Under GK, the UK acts as a receiver from early 2007 onwards, which is months earlier than under RV. The GARCH results are comparable, though the cycles as a net receiver are much shallower and short-lived (for example during the GFC). As is the case with the other 3 markets, the absolute magnitude of the transmission cycles is much higher.

Our last market for comparison is the US. Comparing the RV and GK graphs, the strength of the transmission overall is considerably weaker under GK, and a major difference arises during the GFC and especially the post GFC period where the US transmits very little till August 2011 (and also to a lesser extent in 2005-2006 and 2013-2014). The GARCH series is vastly different to both RV and GK, with the US being a net receiver for a majority of its time series, including the midst of the GFC in 2008, during the European debt crisis and the market crash in the early 2000s.

To summarize, the RV and GK spillovers share similarities, though there were also significant differences on a number of occasions. Further differences arose under the GARCH not just in the timing of various cycles but also in terms of magnitude with peaks exceeding 15% or more in transmission cycles. The GARCH results for the US (and to a lesser extent Australia) in particular were vastly different. Thus, in contrast to total spillovers, when analysing directional spillovers in individual markets, the choice of volatility specification can have a very significant bearing.

6. Empirical results: Determinants of net spillovers

We now directly investigate potential determinants of net spillovers. We do not use the net spillover time series as our dependent variable, as the 200 day rolling window introduces significant positive autocorrelations. Instead, we generate our dependent variable as follows[10]:

$$\Delta Spillover = Net\ Spillover\ (200) - Net\ Spillover\ (199) \quad (9)$$

where 200 and 199 refer to the size of the rolling window. Figure 7 presents the $\Delta Spillover$ time series graphs for a sample of four markets. The time series closely resembles the return series for a stock

[10] We do not use the first difference of net spillovers as this effectively deletes the first observation at the start of each window and thus would not correctly show the exact impact on day T of our regressors. This is because the results would be also impacted by the deletion of any information on day T – 199.

market, with most observations hovering near 0 and a few observations which are quite extreme. Our dataset is from 11 October 2000, the starting date for the net spillover series in Section 5. The major spikes in Figure 7 correspond with the inflection points in Figure 5, denoting the peaks in various cycles, or when a market started or ended a cycle as a transmitter and became a receiver or vice versa.

The regressors are defined in Table 5. Theoretically, if one market transmits volatility to others, our hypothesis is that this may be due to something exceptional about that market, for example its size or its volatility relative to the other markets. In Section 5, we explored the events that occurred during various spillover cycles, and found that in the majority of these cases the market transmitting was exceptionally volatile, and this was often associated with exceptional positive or negative returns. Here we explicitly test the validity of this explanation, and whether a number of other determinants from the Stock, Bond and FX markets, and scheduled macroeconomic news announcements impacted on net spillovers.

Data for the first two variables (Relative Stock Market Return and Volatility respectively) are based on the data from Thomson Reuters Tick History used to generate our estimations and results in the previous sections. Bloomberg provided the underlying data for the rest of the variables. For three variables we have data limitations and hence are only able to test from 30 April 2003 onwards. Consistent with Section 3, we lag all the variables in Table 5 for the American and European markets to deal with the non-synchronous trading problem. A brief explanation on the calculation of some of the variables is necessary. We could not use Bond Yields in levels as the series were non stationary (based on ADF tests). Hence we calculate the Bond Yield Return as the logarithmic change in bond yields to provide comparable results for each market[11]. We then use a 1 month (21 trading days) rolling window to calculate the monthly RV using the sum of squared returns over each window[12] and annualise as before but now using 12 months (as it is monthly RV). We use the same approach with

[11] To use first differences in raw form would not be appropriate given bond yields differ greatly across markets. There is thus a scaling issue. Using the logarithmic change gives us the log return which is perfectly comparable across markets.
[12] An alternative approach to calculate Yield Volatility is to use the standard deviation of the daily logarithmic yield return over the 1 month window and annualise (see Fabozzi, 2009). The results using this approach are almost identical for both the Bond market and the FX market.

FX returns to generate the rolling 1 month RV and annualise.

Our Local News index is based on a selection of major news announcements for each market. We examined the unexpected component of each news variable, since it is only this component that should theoretically have an impact on capital markets. We use a simple dummy variable approach where we assign the value of 1 if an announcement differs from the analyst forecast obtained from Bloomberg, and 0 if the actual and forecast are the same, or if there was no announcement on a particular day. Our News Index is then defined as the sum of all news surprises on Day T for each market[13].

To analyze how the determinant variables impact spillovers, we utilize Panel regressions. We use a Cross Section Fixed Effects model as the Hausman test rejected the null of a Random Effects model at the 5% significance level or better (for all samples in Table 6 below). Our panel regression model is defined below. We include the first lag of the dependent variable, as for the majority of markets it is highly significant.

$$\begin{aligned} \Delta Spillover_{it} = {} & \alpha + \beta_1 RelStockRet_{i,t} + \beta_2 RelStockVol_{i,t} + \beta_3 RelTurn_{i,t} \\ & + \beta_4 RelBondYieldRet_{i,t} + \beta_5 BondYieldVol_{i,t} + \beta_6 RelFXRet_{i,t} \\ & + \beta_7 RelFXVol_{i,t} + \beta_8 News_{i,t} + \beta_9 \Delta Spillover_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{10}$$

We test our Panel regression model across 6 samples (Table 6) to understand how the determinant variables effected net spillovers across various high and low volatility/spillover regimes. We choose our regimes exogenously, based both on the history of key events that affected financial markets in our study period and on the time series of market volatility and total spillovers in Figures 1 and 3 respectively.

Our first sample, Full Sample 1, is for the entire period for which we have spillover data. Crisis Sample 1 covers the 2001 terrorist attacks and the global downturn in 2002-03. We choose 30 April 2003 as the end date based on Figure 3, when total spillovers fell back to around 50%. For both samples, we use a truncated version of Equation (10), omitting the variables for which we do not have data

[13] For example if there are 3 announcements on Day T but only 2 announcements differed from forecasts then a value of 2 would be assigned. Days with no news announcements are assigned a value of 0.

availability from 11 October 2000. In Full Sample 2, and we run Equation (10) in full to test the impact of all the determinants. We use the Pre-GFC sample to test the significance of the determinants and contrast with our second Crisis sample which covers both the GFC and the subsequent European debt crisis. We choose 26 July 2007 as the start point when total spillovers rapidly increased towards 80% (Figure 3). September 2012 is chosen as the endpoint, when total spillovers fell dramatically towards 55%. The Post-Crisis sample commences from 1 October 2012 to the end of our study period, when total spillovers remained under 70% throughout and underlying market volatility remained largely subdued across all the markets in our sample (similar to our Pre crisis sample).

Table 7 presents the results of our panel regressions. It is clear that the first lag of the dependent variable is highly significant and negative across all samples. From our determinant variables, Relative Volatility is by far the most important. The coefficient is always positive across all 6 samples implying that higher relative domestic volatility is channeled to other markets, leading to a significant increase in net spillover transmission. Relative Volatility is highly significant at the 1% level in five samples, with the exception being the Post Crisis sample, where it is insignificant. The result substantiates our analysis in Section 5 above.

Relative Stock market return is marginally significant in three samples (Full Sample 2, Pre GFC and Crisis 2). Interestingly, the coefficient is negative which suggests that higher (lower) relative market returns lead to decreases (increases) in net spillovers. From Table 7, the strongest result is in the Crisis 2 sample, where the P-value is close to the 5% level. During the GFC and the European debt crisis, there were a large number of trading days with extreme negative returns (far outnumbering such positive days), which supports our interpretation that higher negative relative returns led to increased spillover transmission to other markets. It also suggests that market participants pay more attention to declines in stock markets as opposed to increases.[14]

Relative Turnover is positive and highly significant at 1% in the Crisis 2 sample implying that

[14] There is a large body of research which deals with the asymmetric response in volatility to good news (positive returns) and bad news (negative returns). See Bekaert and Wu (2000).

higher relative turnover during the GFC and the EU crisis was a strong driver of increased volatility transmission to other markets. The frequency of trading days with extreme returns and volatility is by far the highest in the Crisis 2 sample period, and stock market turnover was also much higher relative to other trading days. The higher turnover during such days in one market (for example the US) likely acted as a signal that something serious was occurring (combined with extreme returns and volatility), impacting on volatility in other markets as market participants acted on this information.

The Relative Bond market Yield Return is insignificant in the Pre GFC period and marginally significant in Full Sample 2, but is significant at the 5% level in the Crisis 2 sample, and the 1% level in the Post Crisis sample. The coefficient is always positive indicating that a larger positive change in bond market yields is associated with higher spillover transmission. As bond yields and prices have an inverse relationship, this implies that net spillovers were impacted by a decline in bond prices. The GFC appears to have changed the way stock market participants view changes in bond yields with the dramatic shift of capital back towards bond markets as investors panicked. Changes in yield were likely even more important during the European debt crisis which directly affected global bond markets. In both these periods, bond yields rose for markets considered risky, for example Brazil and Mexico during the GFC, and Spain during the Euro crisis. Thus large increases in bond yields appear to hold important information during these crisis periods and further increased stock market volatility. The result is even stronger in the Post crisis sample. As the level of quantitative easing began to reduce in the US, bond yields rose significantly in both the developed markets such as the US, Germany and Australia as well as the major emerging markets of Brazil, China, India and Mexico. Stock markets around the world were similarly concerned by this and likely reacted to the increase in bond yields.

Relative Bond Yield volatility is only marginally significant and negative in the Post Crisis sample. This is a counterintuitive result, especially given that the Relative Yield return has the opposite sign. At face value, this suggests that higher bond market volatility is negatively associated with net spillovers in the stock markets. This may be because in the Post crisis sample, the very high bond market volatility across many markets did not translate to their stock markets. We do note that the variable is only marginally significant and has no explanatory power in any of the other samples. Hence it is difficult to gather too much insight from this result.

Relative FX return is insignificant across all six samples. Relative FX volatility is significant in both the Pre-GFC and Post-Crisis samples, but not during either Crisis sample 1 or 2. The coefficient is negative, implying that higher relative FX volatility is negatively associated with net spillovers. This suggests that higher FX volatility during relatively tranquil periods perhaps led to withdrawals of capital away from some markets (or were a symptom of that withdrawal), and thus led to them (particularly emerging markets) becoming more isolated and contributing less to spillovers. Spillovers during crisis periods such as the GFC directly reflected the underlying stock market volatility and thus the second order effects from FX volatility would have been minimal (Bond market volatility was also insignificant in the Crisis 2 sample). However, during the Pre-GFC and Post-Crisis periods, when stock market volatility was low, exceptional Relative FX volatility did have an impact on spillovers.

Domestic macroeconomic news is significant in the Pre-GFC sample and the Post-Crisis sample but insignificant in either Crisis sample, as other unexpected and unforeseen events likely took precedence, for example the September 2001 attacks or the collapse of Lehman Brothers. Interestingly, the coefficient for News has opposite signs during the two samples where it is significant. In the Pre-GFC sample, macro news lead to an increase in net spillovers. In contrast, in the post crisis period, the effect is the opposite suggesting that once the actual announcement is made, volatility declines perhaps because the level of information uncertainty declines (see Jiang et Al, 2012, Beber and Brandt, 2009). Our results show that the effect of News on spillovers is time varying. Although the coefficients are insignificant, if we look at the signs in the first 4 samples, it is positive. It is negative in the Crisis 2 and Post Crisis samples. Thus it appears the nature in which unexpected (different from forecast in this context) but scheduled news is absorbed by markets has changed with the advent of the GFC and the European debt crisis, from creating potential uncertainty to reducing uncertainty in more recent times as news serves to provide more indicators on the condition of the economy.

We summarize our results by stating that it is clear the relative level of volatility has a direct and highly significant impact on volatility transmission to other markets. The relative magnitude of bond yield changes has also become a significant driver of increased spillover transmission to other markets from the GFC onwards and this has continued till date. Relative FX volatility in contrast had the opposite effect, though it is insignificant in either Crisis sample, when stock market volatility was at its highest. Finally macroeconomic news was significant during relatively tranquil periods, but it appears that after the GFC and the Euro crisis, the way market participants perceive and act on scheduled news announcements has changed. The results from our other determinant variables were either marginally significant or completely insignificant in the case of Relative FX return.

7. Sensitivity and Robustness Testing

We consider the sensitivity of our results above to a number of possible changes in specifications[15]. Perhaps the biggest impact on the nature of the results generated is the non-synchronous trading problem on directional spillovers. In Figure 8 we compare our original Total spillover series with another specification where the volatilities in the European and American markets are not lagged by a day with respect to the Asian Pacific markets. We can see that total spillovers are insensitive to either specification. The real impact is on the directional spillovers. We can compare the net spillovers in Figure 9 with those in Figure 6. We now have a rather extreme result where Australia acts as a net receiver for virtually the entire time under the No Lag specification, while the US net spillover transmission is amplified even further. A similar result occurs for all other Asian markets with China being the only relative exception though it too is impacted to a large extent. In contrast the European and other American markets act as much stronger transmitters in the same vein as the US.

Our first observation is that the results above are quite extreme and may be erroneous. Lagging volatilities essentially accounts for the fact that Asian markets are likely to take their lead from what happened overnight in the European and American markets (particularly the US). In general, they do

[15] We also considered the robustness of our results to changes in the number of lags used in the VAR as well as changes in forecast horizon. The general trend is identical, though as we increase the number of lags, the absolute magnitude of spillovers increases. Similarly, the only impact is that longer horizons lead to slightly higher absolute levels of spillovers. This is expected based on our impulse response analysis. Increasing the forecast horizon beyond 25 days leads to very marginal if any increases in the level of spillovers and thus serves as the optimal forecast horizon for our study.

appear to behave in this manner. Under the No lag specification, the situation is reversed with the American and European markets trading on the same calendar date and looking to take their lead from what happened in the Asian markets a few hours before. However, this does not appear to be the case at all, with the result of virtually zero net spillovers transmitted from most Asian markets for the vast majority of the time period tested. An alternative explanation then is that Asian markets under the Lagged specification are not actually transmitting volatility spillovers on their own, but rather channeling volatility from the previous day's trading in the US (and other American markets) and European sessions to the following day's trading in these markets.

We run an additional test using RV to substantiate the validity of our observations. From Table 8, we can see that within the Asian Pacific region, the level of total spillovers for the full sample at 40.7% is much less than the overall sample at 68.1% (Table 3). Thus, a reasonable argument could be made that if Asian markets do not play a large role in influencing each other's volatilities, they are much less likely to be transmitting volatility to markets in other regions and time zones. Australia is particularly interesting given it was a strong net transmitter of volatility in the lagged specification. In Table 8, it is a major net receiver and thus not a major influence on any of the Asian markets. This provides further support that at least some Asian pacific markets are largely reflecting what occurred overnight in the European and American markets. In sharp contrast, total spillovers in the American and European markets in Table 9 is 75.8%, much higher than the overall sample. The US is by far the strongest contributor as expected. Thus given that these markets strongly react to each other and still dominate global capital market flows, there is some support to the validity of the results in Figure 9.

8. Conclusion

In this paper we used generalized variance decompositions within the VAR framework established by Diebold and Yilmaz (2012) to create total and directional volatility spillover indices for a sample of 16 major stock markets. This framework is insensitive to variable ordering, thus allowing us to examine directional spillovers apart from total spillovers which have been the focus of a number of previous studies. Using Realized Volatility based on 5 minute intervals as our primary measure of volatility, we found that the level of total spillovers increased dramatically during high volatility periods, particularly the GFC and the subsequent European debt crisis.

Our results show that the US is the largest contributor of volatility spillovers to other markets, which is expected given the size and importance of the US economy and its capital markets. We also find that the large emerging markets of India, China, Brazil and Mexico are relatively isolated and act as volatility receivers for a majority of the study period. However they also have acted as strong volatility transmitters to other markets at various times after 2006, including during the GFC. Our analysis on the time series of net spillovers and our panel regressions found that relative volatility is the major driver of increased volatility spillovers to other markets. A number of other determinant variables were also significant in various samples, notably the relative bond yield return, the relative stock market turnover, the relative FX market volatility and the macroeconomic news index.

We investigated the impact of using different volatility estimators and found that although the time series of total spillovers was largely similar, more differences arise when analyzing directional spillovers. We showed that while the GK net spillovers are comparable to RV, there are also substantial variations that occur in a number of markets, which could lead to different analysis and interpretations of spillovers over a given time period. We also concluded that the GARCH estimator led to very disparate and sometimes extreme results for some markets such as the US, and thus it may not model spillover dynamics as well as the other volatility estimators used.

Finally, we also tested the impact of the non-synchronous trading problem on our results. While all our main results are generated by lagging the volatilities of the American and European markets, removing the lag resulted in vastly different results in terms of directional spillovers for the Asian Pacific markets. We investigated some of the possible explanations and conclude that it is plausible that the result with no lags may hold some validity given that the Asian markets do not influence volatility dynamics in each other to any significant extent. In contrast, spillovers dominate the volatilities of the European and American markets rather than own market shocks, providing support to the idea that they could also be the major source of volatility spillovers to the Asian markets.

The spillover methodology established by Diebold and Yilmaz (2012) serves as a very interesting addition to the large array of methodologies already in existence in the investigation of volatility and return spillovers and correlations. It would be interesting for future work to use the same methodology to test other markets and asset classes on a much larger scale than Diebold and Yilmaz (2012). Further, the impact of different volatility specifications on spillovers in other asset classes using this framework would also be a topic of interest.

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Figure 1 - Time Series of Realized volatilities

The graphs below show realized volatilities for the all 16 stock markets we consider in this paper.

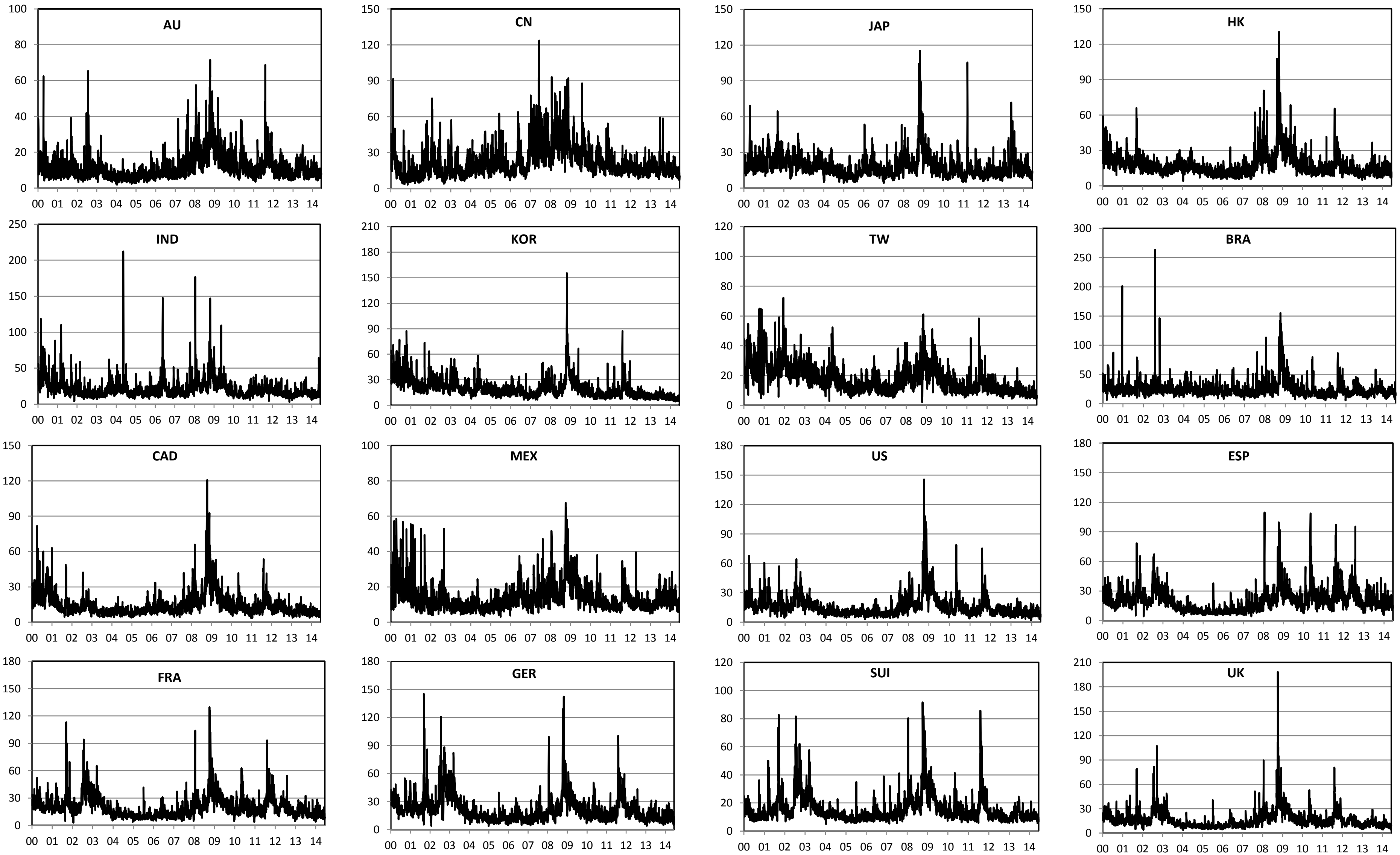

Figure 2 – RV, GK and GARCH Time Series (Select Countries)

Figure 2 shows the volatility time series using the RV, GK and GARCH (1,1) estimators for 4 stock markets chosen to highlight their similarities and differences.

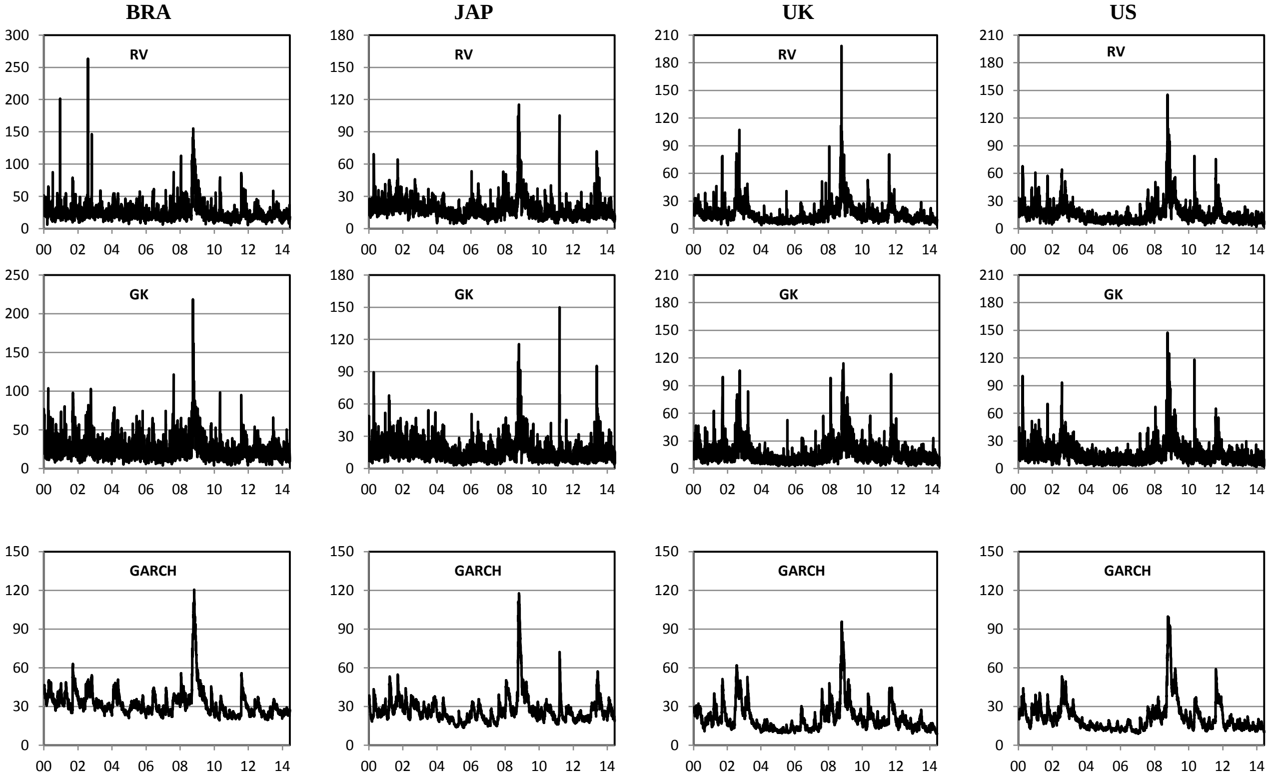

Figure 3 – Total Volatility Spillovers Time Series

Figure 3 shows the time series of total spillovers using a VAR (2) model with a 25 day forecast horizon and a 200 day rolling sample for the RV, GK and GARCH estimators.

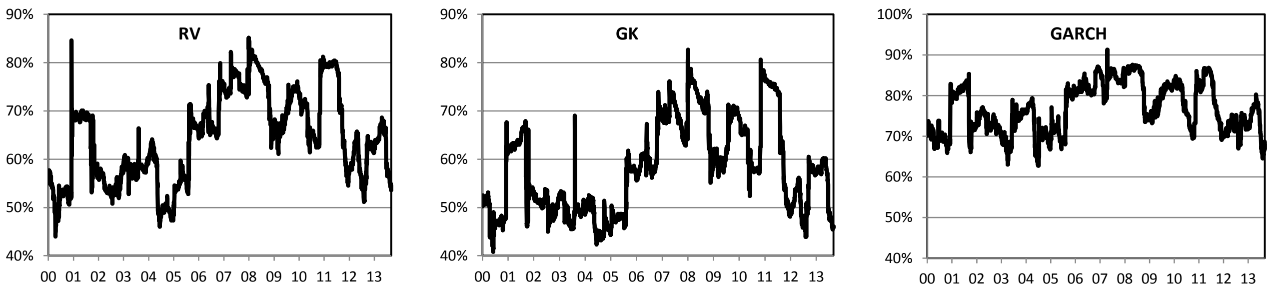

Figure 4 – RV Directional Spillovers

The graphs below shows the directional spillovers for Japan, the UK and the US.

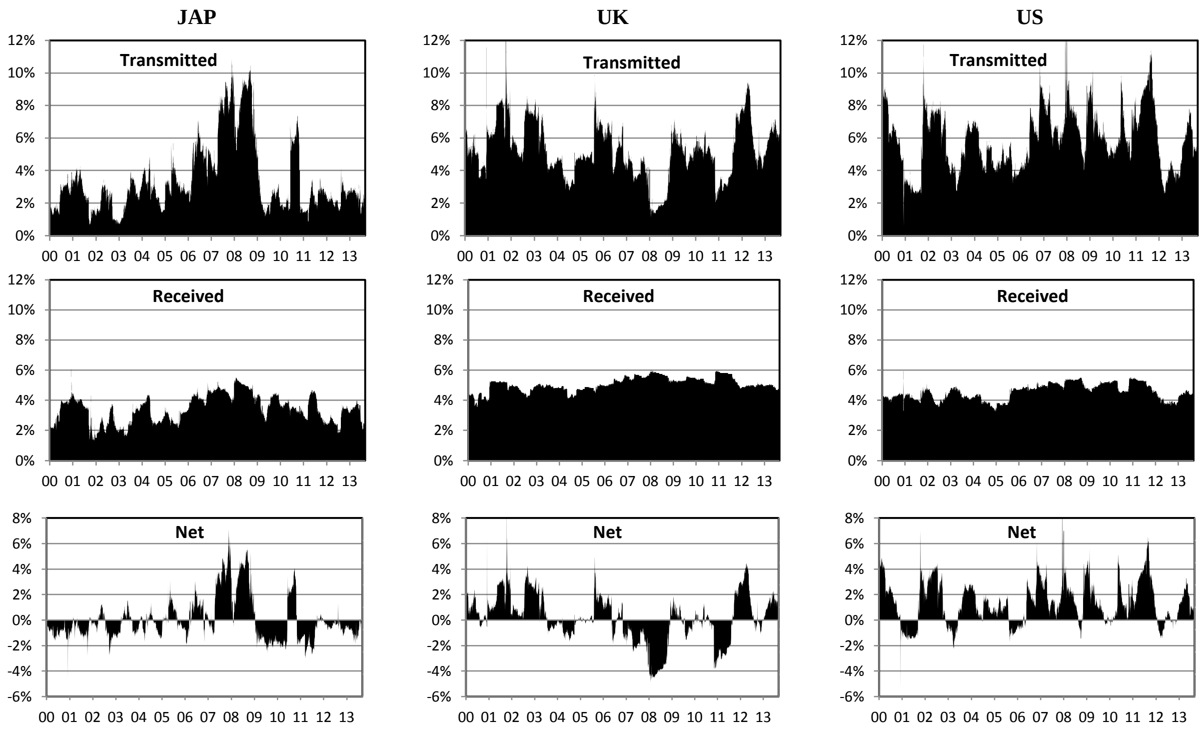

Figure 5 – RV Net Spillovers

The graphs below show net directional spillovers for the all 16 stock markets we consider in this paper.

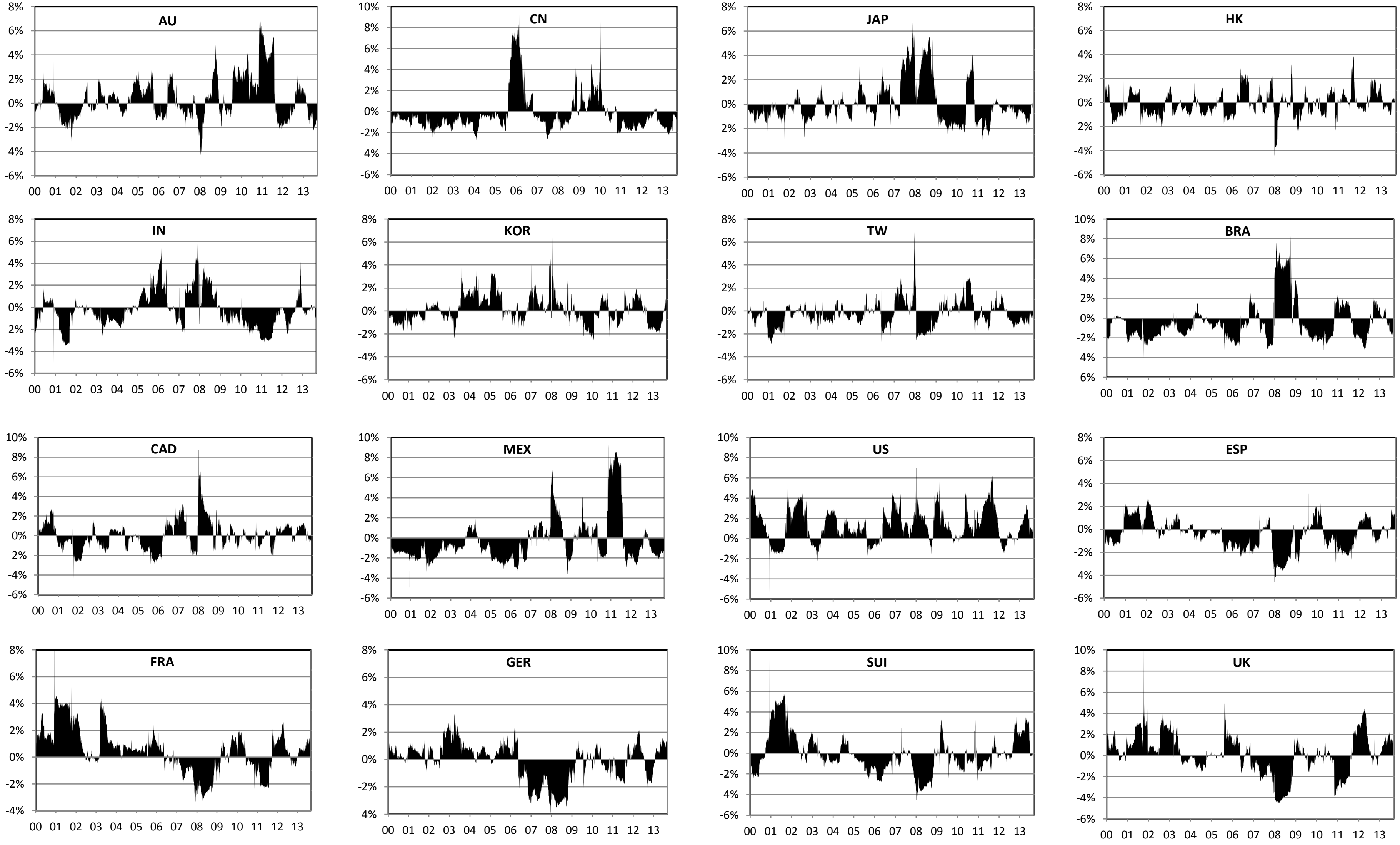

Figure 6 – Comparing Net spillovers across Volatility Specifications

Figure 6 compares net spillovers using the RV, GK and GARCH (1,1) estimators.

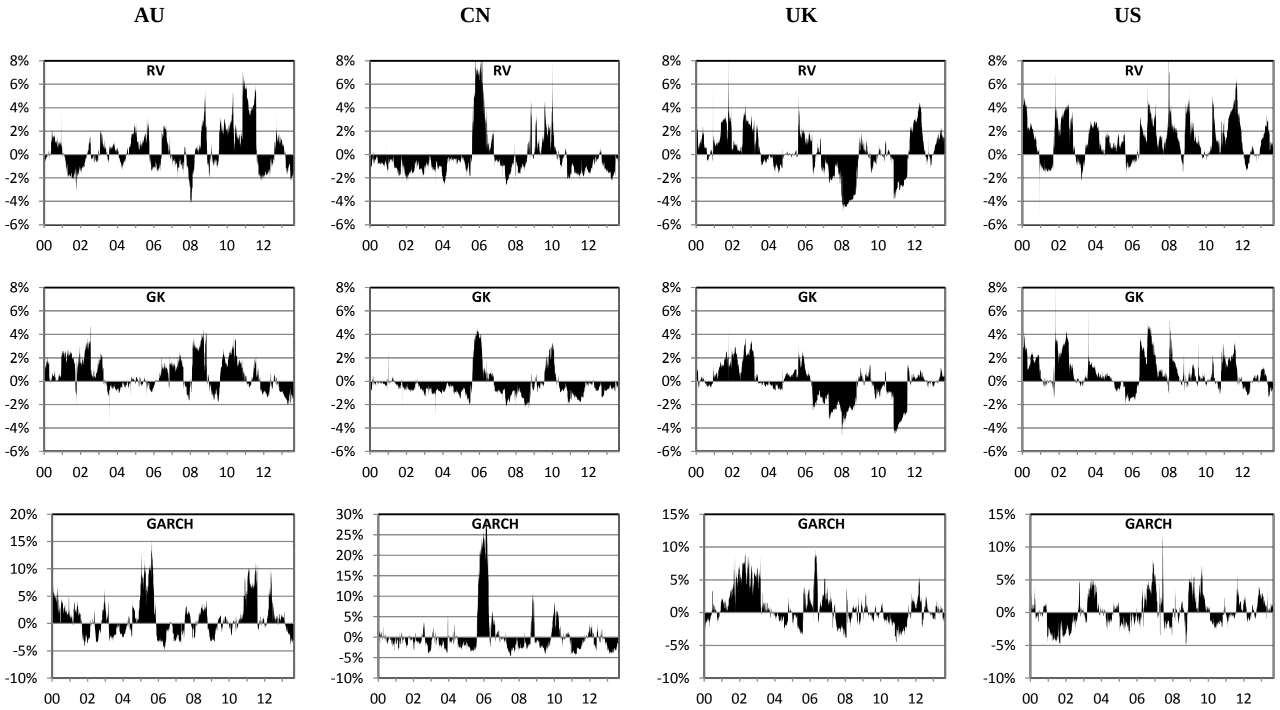

Figure 7 – ΔSpillover Time Series

Figure 7 displays the ΔSpillover time series for 4 stock markets.

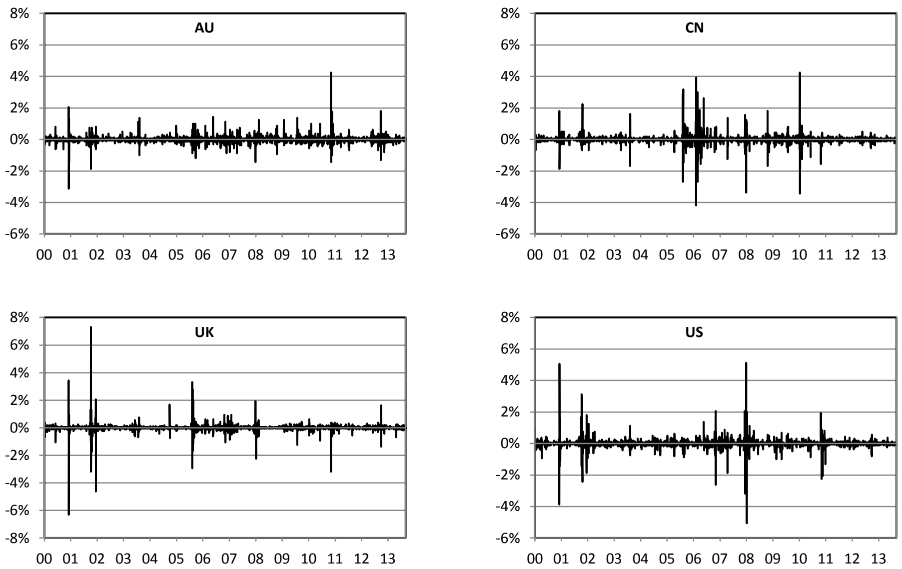

Figure 8 –RV Total Spillovers under a No Lag specification

The time series of total spillovers is compared to a specification where the volatilities in the European and American markets are not lagged by a day with respect to the Asian Pacific markets.

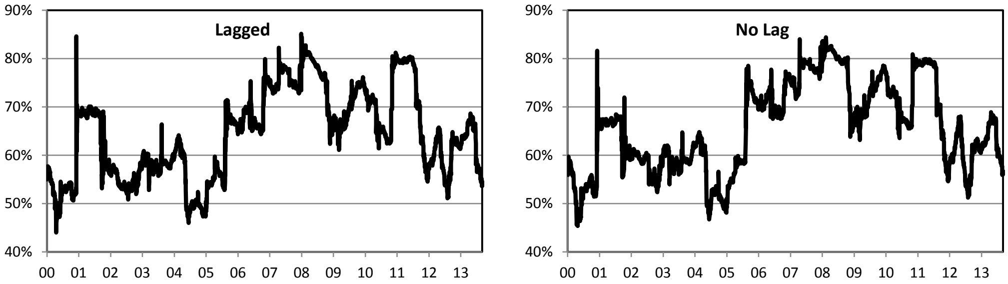

Figure 9 – Net Spillovers under a No Lag specification

Net directional spillovers using a No Lag specification are displayed to highlight the significant differences with the original lagged specification (Figure 6), particularly for the Asian Pacific markets.

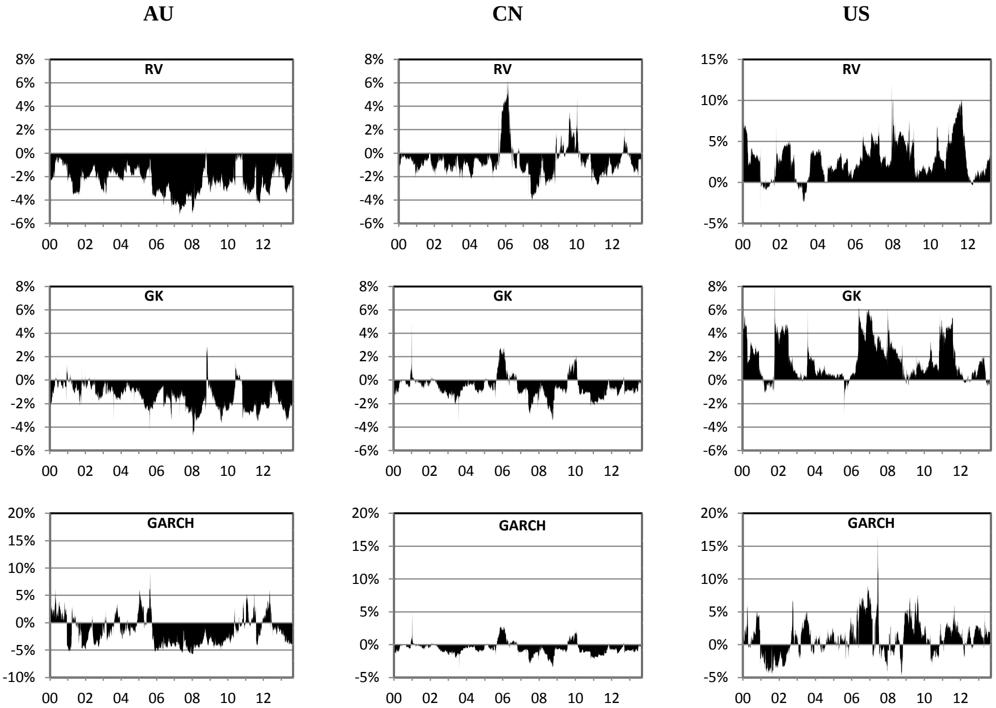

Table 1 – Stock market trading hours

The table below presents the stock index details and market trading hours of the 16 markets we consider in this paper.

Country	Code	Index	Trading Hours (GMT/Local)[16]
Asia Pacific			
Australia	AU	ASX All Ordinaries	0:00-6:00/10:00-16:00
China	CN	SSEC (Shanghai) Composite Index	01:30-07:00/09:30-15:00
Japan	JAP	Nikkei 225	0:00-6:00/9:00-15:00
Hong Kong	HK	Hang Seng Index	01:30-08:00/09:30-16:00
India	IN	Sensex 30	03:45-10:00/09:15 -15:30
Korea	KOR	Kospi Composite Index	0:00-6:00/09:00-15:00
Taiwan	TW	TSEC Taiwan Weighted Index	01:00-05:30/9:00-13:30
Americas			
Brazil	BRA	Bovespa Index	13:00-20:00/10:00 -17:00
Mexico	MEX	IPC Index	14:30-21:00/08:30-15:00
Canada	CAD	TSX60 Index	14:30-21:00/09:30-16:00
United States	US	S&P 500	14:30-21:00/09:30-16:00
Europe			
Spain	ESP	Ibex 35	08:00-16:30/09:00-17:30
France	FRA	CAC 40	08:00-16:30/09:00-17:30
Germany	GER	DAX 30	08:00-16:30/09:00-17:30
Switzerland	SUI	SSMI Swiss Market Index	08:00-16:30/09:00-17:30
United Kingdom	UK	FTSE 100	08:00-16:30/08:00-16:30

[16] Inclusive of Lunch hours for the Shanghai, Tokyo, and Hong Kong stock exchanges which are currently (at the time of writing) 11:30-13:00, 11:30-12:30 and 12:00-13:00 (local time) respectively.

Table 2 – Summary statistics of stock market volatilities[17]

The table presents summary statistics of intraday and daily volatilities of stock market returns. The volatility measures included are realized volatility calculated from tick by tick data; Garman Klass from daily high, low, open and close prices; High Low from daily high and low prices; and GARCH (1,1) from daily close prices.

	Asia Pacific							Americas				Europe				
	AU	**CN**	**JAP**	**HK**	**IN**	**KOR**	**TW**	**BRA**	**CAD**	**MEX**	**US**	**ESP**	**FRA**	**GER**	**SUI**	**UK**
RV																
Mean	11.24	21.22	18.09	17.31	21.42	19.76	17.47	24.68	14.64	13.64	15.69	20.44	21.67	20.11	15.55	16.04
Median	9.44	17.83	16.34	14.96	18.13	16.95	15.19	21.81	11.67	11.57	13.09	18.82	18.18	17.51	12.60	13.42
Min	1.82	3.21	4.46	4.33	3.23	4.63	2.22	5.44	3.47	3.07	2.13	4.34	3.93	3.14	5.22	3.92
Max	71.47	123.79	115.38	130.48	212.19	155.39	72.30	263.03	120.61	67.54	145.53	109.71	145.21	129.50	91.60	198.13
Std Dev	6.80	12.18	9.22	9.33	12.55	11.10	9.14	13.48	9.99	7.22	10.44	10.93	13.42	11.44	9.31	10.22
Skew	2.84	1.91	3.15	3.35	3.83	2.42	1.28	4.95	3.45	2.26	3.34	2.00	2.45	2.42	2.76	4.11
Kurt	12.92	5.68	19.75	21.72	31.50	12.50	2.07	49.05	19.52	8.03	19.85	8.34	10.67	11.28	11.44	39.83
GK																
Mean	11.17	20.15	16.22	16.25	20.43	19.19	15.85	25.00	16.74	16.85	15.48	20.37	20.92	18.97	15.01	16.42
Median	9.19	17.06	14.18	13.64	17.13	16.06	13.43	22.00	13.34	14.19	12.67	17.86	17.21	15.98	12.09	13.45
Min	1.65	2.54	2.97	3.10	4.66	3.20	1.98	4.07	1.47	2.68	1.83	3.11	2.49	2.84	2.76	2.80
Max	91.24	122.80	149.72	194.10	193.55	193.02	93.75	218.51	220.96	125.46	147.31	101.50	167.67	123.55	106.50	114.08
Std Dev	7.54	12.16	9.72	10.38	13.40	12.48	9.46	13.97	12.84	10.69	11.10	12.00	14.33	12.05	10.28	10.97
Skew	3.07	2.24	3.37	3.93	3.36	3.03	1.74	3.19	4.12	2.56	3.37	1.76	2.47	2.30	2.79	2.64
Kurt	16.16	8.52	24.29	36.07	22.58	19.58	4.86	22.02	33.38	11.62	20.78	5.23	10.66	8.80	11.69	12.01
GARCH (1, 1)																
Mean	16.74	29.19	27.25	26.77	27.44	28.91	26.12	32.62	20.63	24.25	21.57	26.79	26.83	26.20	20.41	20.99
Median	14.34	25.92	25.27	22.22	23.49	24.66	23.75	30.55	16.92	21.13	18.25	24.40	22.95	23.17	17.08	17.93
Min	7.14	15.29	13.71	12.02	13.01	11.44	10.13	19.51	8.73	11.14	9.09	10.49	11.40	11.67	8.91	8.88
Max	73.97	71.37	117.72	123.06	105.57	100.54	73.88	120.47	97.31	88.69	99.54	96.01	94.11	99.24	99.67	95.68
Std Dev	8.37	10.33	10.64	13.42	12.32	13.53	10.85	10.86	11.59	10.16	11.84	12.19	13.05	12.26	10.53	10.95
Skew	2.56	1.34	3.67	2.57	2.09	1.48	0.88	3.28	2.87	1.95	2.78	1.72	1.80	1.98	2.64	2.41
Kurt	9.71	1.22	21.50	9.55	5.73	2.73	0.50	17.17	11.45	5.56	11.02	4.78	3.58	5.25	9.73	8.73

[17] The null hypothesis of a unit root is rejected at the 1% level using the ADF test (including an intercept and trend) for all markets, with the exception of Canada, Taiwan and the US when using GARCH(1,1), for which the ADF test rejects at the 5% level.

Table 3 – Full Sample Spillover Table[18]

Table 3 presents the full sample volatility spillovers using RV. The spillover transmitted by market *i* to market *j* is represented by the numbers going down the column for that market, excluding the number on the diagonal, which represents own market shocks. The numbers for a market *i* going across a particular row in the table excluding the figure on the diagonal represent spillovers received, or shocks resulting from innovations to market *j*. These are the directional spillovers from market *i* to *j* and vice versa.

	Asian Pacific Markets							**American Markets**				**EU Markets**					
	AU	**CN**	**JAP**	**HK**	**IN**	**KOR**	**TW**	**BRA**	**CAD**	**MEX**	**US**	**ESP**	**GER**	**FRA**	**SUI**	**UK**	**Received**
AU	31.9	3.4	4.8	6.3	2.3	1.8	1.4	2.6	9.1	5.2	10.3	3.3	4.4	1.9	5.7	5.5	68
CN	4.1	76.6	1	8	1.8	0.5	0.5	0.9	1	1.4	1.3	0.6	0.2	1.2	0.3	0.6	23
JAP	4.7	0.6	36.7	7.3	3.5	7.2	3.4	3.1	6.6	3.5	9.3	1.4	2.9	2.7	4	3.1	63
HK	5.5	3.3	5.9	32.3	6.4	7.7	4.2	2.5	8.6	4.5	9.1	1.1	1.9	1.1	2.4	3.5	68
IN	2.6	1.5	4.1	10.1	53	5.9	3.2	1.9	7.6	4.9	3.6	0.2	0.3	0.2	0.3	0.8	47
KOR	1.7	0.6	4.9	9.1	4.6	40.4	9	1.5	7.7	2.5	7.2	0.6	2.4	3.8	1.7	2.2	60
TW	0.8	0.3	3.4	5.8	4.1	14.7	45.3	0.6	4.7	1.6	5.6	1	3	4.5	2.3	2.2	55
BRA	5.8	1.1	4.9	4.9	2.7	3.5	2	29.1	9	4.6	11.3	2.7	4.4	3.6	5.2	5.1	71
CAD	7.7	1.4	4.2	6.9	3.9	5	3.5	3.3	24.2	7.3	15.2	2.3	4.1	2.7	2.9	5.6	76
MEX	8.1	1.8	4.1	6.4	4.1	4.3	2.2	3.2	14.2	28.3	10.1	1.9	3.2	1.9	2.4	3.9	72
US	6.5	0.9	4.7	5.1	2.1	4.5	3.1	3.8	11.6	4.7	22.5	4.4	6.8	5.8	6.8	6.7	78
ESP	5.6	0.1	2.1	2.1	0.6	1.1	1.3	2.4	4.5	2.3	9.6	22.4	15.3	10.8	10.4	9.6	78
GER	5.3	0.3	2.7	2.5	1.1	2.6	1.9	2.3	5.2	2.6	11	11.2	16.1	12.7	12.4	10.2	84
FRA	3.6	0.1	3.2	2.1	0.9	3.9	2.3	2.2	4.2	1.8	10.3	9.6	15.1	17.9	13.2	9.5	82
SUI	6.5	0.8	4.1	2.9	1.1	2.5	1.6	2.8	4.5	2.2	11.9	7.5	12.1	10.8	19	9.7	81
UK	6.7	0.9	3.7	3.9	1.7	2.7	1.8	2.8	6.9	3.3	12.5	7.8	11.4	8.9	11	14	86
Transmitted	75	17	58	83	41	68	42	36	105	52	138	56	88	73	81	78	1090
Including Own	107	94	94	116	94	108	87	65	130	81	161	78	104	91	100	92	**68.10%**
Net Spillover	7	-6	-5	15	-6	8	-13	-35	29	-20	60	-22	4	-9	0	-8	0

Table 4 – Spillover summaries – GK and GARCH

Table 4 presents the full sample volatility spillovers using GK and GARCH volatility measures

	Asian Pacific Markets							**American Markets**				**EU Markets**					
	AU	**CN**	**JPN**	**HK**	**IN**	**KOR**	**TW**	**BRA**	**CAD**	**MEX**	**US**	**ESP**	**FRA**	**GER**	**SUI**	**UK**	**Totals**
GK																	
Transmitted	87	12	47	77	43	66	32	53	85	50	113	53	73	71	70	85	1016
Received	61	21	55	62	45	57	50	64	70	67	75	73	82	78	77	80	1016
Net Spillovers	26	-9	-8	15	-2	9	-18	-11	15	-17	38	-20	-9	-7	-7	5	**63.50%**
GARCH (1,1)																	
Transmitted	87	13	42	74	26	61	35	61	61	44	71	72	105	81	124	121	1079
Received	72	15	66	73	39	67	56	74	69	75	79	76	82	80	76	81	1079
Net Spillovers	15	-2	-24	1	-13	-6	-21	-13	-8	-31	-8	-4	23	1	48	40	**67.40%**

[18] All the spillover results in this paper are based on a VAR of order 2 selected using the Bayesian Information Criterion (BIC). The BIC was used as it selected order 2 for all volatility estimators with the exception of GARCH (1,1). For GARCH, the HQC selected lag 2, while BIC selected Lag 1. A 25 day-ahead volatility forecast was used. This is longer than in previous research; however our analysis of the actual decompositions and the generalized impulses responses suggested that the shocks continue to have an effect that dies out almost completely only after 25+ days ahead. We look at the effect of various lag and horizon specifications on our results in Section 7.

Table 5 – Determinants of net spillovers

Table 5 displays the various variables we examine as potential determinants of net spillovers. These include a number of financial market variables and macroeconomic news for each market.

Variable	Definition	Data Availability
Relative Stock Market Return	Stock market Return for Market *I* / Average Stock Market Return for all other Markets J	11/10/2000 – 13/06/2014
Relative Stock Market Volatility	RV for Market *I* / Average RV for all other Markets J	11/10/2000 – 13/06/2014
Relative Stock Market Turnover	Stock market turnover in $USD for Market *I* / Average turnover in $USD for all other Markets J	30/04/2003 – 13/06/2014
Relative 10 Year Bond Yield Return	Bond Yield Return for Market *I* / Average Yield return for all other markets J	30/04/2003 – 13/06/2014
Relative Bond Market Volatility	Bond Yield Volatility for Market *I* / Average Yield volatility for all other markets J	30/04/2003 – 13/06/2014
Relative FX Return	FC Return for Market *I* / Average FX Return for all other Markets J	11/10/2000 – 13/06/2014
Relative FX Volatility	FX Volatility For Market *I* / Average FX Volatility for all other Markets J	11/10/2000 – 13/06/2014
Local News Index	Aggregated Index based on scheduled macroeconomic announcements for each market.	11/10/2000 – 13/06/2014

Table 6 – Panel Regression Samples

Sample	Period	Total Obs	Obs/Market
Full Sample 1	11/10/2000 – 13/06/2014	57072	3567
Crisis Sample 1	03/09/2001 – 30/04/2003[19]	6912	432
Full Sample 2	30/04/2003 – 13/06/2014	46432	2902
Pre GFC	30/04/2003 – 25/07/2007	17680	1105
Crisis Sample 2	26/07/2007 – 28/09/2012	21616	1351
Post Crisis	01/01/2013 – 13/06/2014	7104	444

[19] It is coincidental that 30/04/2003 is the end of this sample and also the date from which we are able to estimate Equation 10 in full.

Table 7 – Panel Estimation Results[20]

Results from our panel estimation for Equation (10). Data for some variables was unavailable for some markets until April 2003, and hence they are not tested under the first two sample periods.

Variable	Full 1	Crisis 1	Full 2	Pre GFC	Crisis 2	Post Crisis
Const	-0.2496***	-1.1442***	-0.1469**	-0.1377**	-0.3746***	0.1375**
	(0.0002)	(0.0000)	(0.0190)	(0.0388)	(0.0028)	(0.0384)
Relative Stock Market Return	-0.0068	-0.0004	-0.0117*	-0.0180*	-0.0093*	0.0613
	(0.4609)	(0.9979)	(0.0939)	(0.0585)	(0.0904)	(0.8025)
Relative Stock market volatility	0.2820***	1.0679***	0.2114***	0.1979***	0.3080***	0.1529
	(0.0000)	(0.0000)	(0.0001)	(0.0003)	(0.0018)	(0.1372)
Relative Stock market Turnover			0.0094	-0.0112	0.0832***	-0.0160
			(0.2055)	(0.1094)	(0.0001)	(0.3516)
Relative 10 YR Bond Yield Return			0.0063*	0.0012	0.1220**	0.0060***
			(0.0761)	(0.5476)	(0.0409)	(0.0023)
Relative Bond Market Volatility			-0.0226	-0.0046	0.0088	-0.0716*
			(0.2394)	(0.7864)	(0.8311)	(0.0611)
Relative FX Return	-0.0648	-0.0459	0.0000	-0.0234	0.0872	-0.0663
	(0.1403)	(0.7520)	(0.9991)	(0.6250)	(0.5290)	(0.5598)
Relative FX Volatility	-0.0391	0.0364	-0.0577*	-0.0632**	-0.0344	-0.1822**
	(0.1182)	(0.4489)	(0.0909)	(0.0232)	(0.5891)	(0.0382)
Local News Intensity Index	0.0031	0.0664	0.0012	0.0253**	-0.0034	-0.0335**
	(0.8310)	(0.3106)	(0.9417)	(0.0248)	(0.8985)	(0.0269)
$\Delta Spillover_{i,t-1}$	-0.1790***	-0.2364***	-0.1545***	-0.2753***	-0.1021***	-0.2327***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Adjusted R^2	0.0337	0.0611	0.0247	0.0767	0.0112	0.0545
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Durbin Watson	2.054231	2.154553	2.0251	2.0525	2.0173	2.0367

Numbers in parenthesis are P-values.
*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

[20] We scale the dependent variable by 1000 to make the results more presentable. Return variables are further rescaled by 1000.

Table 8 – Asian Pacific region spillovers (RV)

Full sample spillover table for the Asian pacific markets only using a no lag specification.

	AU	CN	JAP	HK	IN	KOR	TW	Received
AU	56.2	6.3	10.3	15.5	5.1	4.3	2.3	44
CN	5.3	80	1.3	10	2.6	0.4	0.4	20
JAP	7.9	1	54.2	13.3	6.1	12.2	5.4	46
HK	9.3	4.9	9.8	47.4	11	12.4	5.6	53
IN	3.9	2	5.5	13.6	63	8.1	3.5	37
KOR	2.7	0.6	7.6	13.7	6.9	55.8	12.7	44
TW	1.1	0.3	5	8.6	5.5	21.4	58.2	42
Transmitted	30	15	39	75	37	59	30	285
Net Spillovers	-14	-5	-7	22	0	15	-12	**40.70%**

Table 9 – American and European region spillovers (RV)

Full sample spillover table for the American and European markets using a no Lag specification.

	American Markets				European Markets					
	BRA	**CAD**	**MEX**	**US**	**ESP**	**FRA**	**GER**	**SUI**	**UK**	**Received**
BRA	29.8	13.7	7.2	16	4.2	7	5.8	7.9	8.2	70
CAD	5.5	30.5	11.1	22	4.2	7.3	5	5.6	9.4	69
MEX	5.2	21	31.7	16	3.5	6.1	3.7	5.1	7.6	68
US	5.6	16.2	7.2	27	6.3	9.8	8.4	9.5	9.9	73
ESP	3.3	6.4	3.4	12	23.2	16.7	12.1	12	11.2	77
FRA	3.4	7.7	4	14	12.6	17.8	14.3	14	12.1	82
GER	3.2	6.3	3	13	11	17	20	15	11.3	80
SUI	4	7.2	3.8	15	9.2	14.3	12.7	21	12.2	79
UK	4.2	10.4	5.3	16	9.5	13.7	10.8	13	16.3	84
Transmitted	34	89	45	125	60	92	73	82	82	682
Net Spillovers	-36	20	-23	52	-17	10	-7	3	-2	**75.80%**