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Big in Japan: Global Volatility Transmission between Assets and Trading Places

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Abstract

This paper proposes a new framework to model distinct channels of volatility transmission between assets and trading places. The model is estimated using a data set comprising of three stock indices traded at three major trading places: the Nikkei at the Tokyo Stock Exchange, the FTSE at the London Stock Exchange and the S&P500 at the New York Stock Exchange. Strong volatility transmission effects can be observed between London and New York, whereas current volatility in Tokyo mostly depends on past volatility in Tokyo. For the assets in consideration, spillovers are strong across trading zones, but weak across assets, suggesting a close connection between market places but only a loose volatility link between assets.

Volatility impulse response functions indicate a long lasting and comparably large response of volatility to shocks in Tokyo, whereas they suggest a quicker volatility decay in London and New York.

1 Introduction

Interest in volatility spillovers between different market places first aroused at the late 80's and early 90's of the past century. Beginning with the seminal work of Engle et al. (1990), channels of volatility spillovers for different markets and different assets have been detected. Engle et al. (1990) use a multivariate GARCH approach modeling a single asset that is traded in three different trading zones constructed without overlaps over a 24 hour period. They distinguish between volatility transmitted from the own trading zone (heat wave) and transmitted from foreign trading zones (meteor shower). Building on this work Hogan and Melvin (1994) investigate heat wave effects in the foreign exchange market by dividing the trading day into four non overlapping trading zones and using data on the yen/dollar exchange rate, whereas Fleming and Lopez (1999) examine heat wave and meteor shower effects for the US treasury market. In their 1990 paper, Hamao et al. (1990) model correlations between volatilities of three Assets (Nikkei, FTSE and S&P500) across three different markets (Tokyo, London and New York) by using a set of $MA(1) - GARCH(1,1)$ models, independently. They allow for volatility transmission from the preceding trading zones to the current one, but use assets and trading zones equivalently, i.e. they assume the Nikkei is only traded in Tokyo, the FTSE is only traded in London and the S&P500 is only traded in New York.

Another approach is the one of Booth et al. (1997), who investigate volatility spillovers for scandinavian stock markets. They use a multivariate GARCH model to describe transmission between Denmark, Finland, Sweden and Norway, i.e. trading zones that are almost completely overlapping. Hence, they also don't distinguish between trading zones and assets.

In a more recent approach Karunanayake et al. (2009) use a multivariate GARCH framework in a four trading zone setting to model spillovers, but by using weekly data, they exclude any intra day effects between different trading zones. Recently, Clements et al. (2015) re-investigate the results of Engle et al. (1990) and additionally estimate a set of different model specifications using realized volatility, decompositions into good and bad news as well separating realized volatility into a continuous component and a jump component. On the downside Clements et al. (2015) neither give insights to their methodology nor question the artificial construction of a non overlapping trading day. Additionally, only normally distributed innovations are used although financial returns usually exhibit fat tails (see e.g. Richard J. Rogalski and Joseph D. Vinso (1978) or Boothe and Glassman (1987) who both find that either t distributions with

slightly less than 4 degrees of freedom or stable distributions with stability parameter $\alpha < 2$ fit best to daily foreign exchange rates). Hence, a multivariate copula GARCH (CMGARCH) model based on the work of Lee and Long (2009) that can incorporate both, multiple assets in multiple (and overlapping) trading zones as well as non normal error terms is proposed.
The remainder of this paper organizes as follows: section 2 proposes the volatility transmission GARCH model and discusses its basic statistical properties. In the third section an estimation approach, based on the Differential Evolution Metropolis Hastings algorithm is developed and the fourth section applies the model to a setting of three trading zones and three assets, with each asset being traded in each trading zone. The fifth section summarizes.

2 Modeling Volatility transmissions

Modeling multiple assets that are traded in different trading places enables to distinguish between characteristics of the assets and characteristics of the trading zones. To highlight this, one asset is chosen for each trading zone that is traded at this zone, very frequently and hence, subsumes a large share of the total news belonging to this zone. This allows to investigate how market participants react to the magnitude of news regarding their *home asset* depending on how volatile trading in other trading zones, days or other assets has been. To identify transmission effects between both, assets and between trading places a model is necessary that can capture both kinds of effects, jointly. The general idea of this model is based on the seminal work of Engle et al. (1990) and Clements et al. (2015) and extends it in two directions: first, allowing for overlapping trading hours in different trading places and second, allowing for multiple assets. The first extension has already been discussed in a previous working paper, hence this paper focuses on extending the model to allow multiple assets. Consider a situation in which $k = 1, \ldots, K$ assets are traded in $i = 1, \ldots, I$ trading places. Then, the return of asset k in trading place i is denoted by $r_{k,i}$. Following previous work, the conditional covariance matrix is described using a GARCH model embedded in the copula GARCH framework of Lee and Long (2009):

$$
\begin{aligned}
r_t &= \boldsymbol{H}_t^{\frac{1}{2}} \epsilon_t && (1)\\
\boldsymbol{H}_t &= diag(h_t)^{\frac{1}{2}} \boldsymbol{M}_t diag(h_t)^{\frac{1}{2}} && (2)\\
h_t &= \kappa + A h_{t-1} + \tilde{A} h_t + G r_{t-1}^2 + B r_t^2 && (3)\\
\epsilon_t &= \Sigma_t^{-\frac{1}{2}} \eta_t && (4)\\
\eta_t &\sim \mathcal{F}(\eta_1, \ldots, \eta_{K \cdot I}) && (5)\\
diag(\boldsymbol{M}_t) &= \mathbf{1}_{K \cdot I} && (6)
\end{aligned}
$$

In this setup, the matrices A and G display effects of previous trading days (referred to as heat wave in Engle et al. (1990)) whereas the matrices $\tilde{A}$ and B account for effects of preceding trading places (referred to as meteor shower). In both cases, only transmission effects from within the same trading place (A and G) and the immediately preceding trading place ($\tilde{A}$ and B) are taken into account. Consequently, the following matrices are used if three trading zones were considered:

$$
A = \begin{bmatrix} A_{11} & 0 & \tilde{A}_{13} \\ 0 & A_{22} & 0 \\ 0 & 0 & A_{33} \end{bmatrix} \; B = \begin{bmatrix} 0 & 0 & 0 \\ B_{21} & 0 & 0 \\ 0 & B_{32} & 0 \end{bmatrix}
$$
$$
G = \begin{bmatrix} G_{11} & 0 & B_{13} \\ 0 & G_{22} & 0 \\ 0 & 0 & G_{33} \end{bmatrix} \; \tilde{A} = \begin{bmatrix} 0 & 0 & 0 \\ \tilde{A}_{21} & 0 & 0 \\ 0 & \tilde{A}_{32} & 0 \end{bmatrix} \qquad (7)
$$

Note that all submatrices of A, $\tilde{A}$, B and G are full matrices of dimension $K \times K$. Also note that however stored in A and G, $\tilde{A}_{13}$ and B_{13} account for effects of the immediately preceding trading place and hence, describe meteor shower patterns. Equation (6) is necessary in order to identify the model. $\boldsymbol{M}_t$ is combined from the cross sectional correlations between the different assets and the correlation between the trading places due to their overlapping trading hours:

$$
\boldsymbol{M}_t = \rho_Z \otimes \rho_{A,t}, \qquad (8)
$$

where ρ_Z is the correlation matrix resulting from overlaps and $\rho_{A,t}$ is the cross sectional correlation matrix of the assets in consideration[1]. The latter could

[1] If both, $\rho_{A,t}$ and ρ_Z are positive definite, then $\boldsymbol{M}_t$ is positive definite as well and thus, $\boldsymbol{M}_t$ is a correlation matrix once $\rho_{A,t}$ and ρ_Z are correlation matrices, too.

be modeled time variant which is not pursued in the remainder to keep the number of parameters feasible. If trading places in countries that make use of daylight savings time are chosen, it can be reasonable to use a regime switching approach on ρ_Z in order to account for potentially changing overlaps.

The log-likelihood with respect to r_t for the above model is given by the sum of the log-densities of the marginal distributions and the log-copula-density plus the sum of the Jacobian of the transformation (see Lee and Long (2009)) from innovations η_t to returns r_t, i.e. the sum of $ln\left(\left|\Sigma^{0.5}(\boldsymbol{\theta})H_t^{-0.5}(\boldsymbol{\alpha})\right|\right)$ for all observations $t = 1, \dots, T$ with $\boldsymbol{\alpha}$ denoting all GARCH parameters and $\boldsymbol{\theta}$ denoting the parameters of the marginal distributions and the copula of the error terms. Then,

$$
\begin{aligned}
ln(\mathcal{L}) = &\sum_{t=1}^{T} ln\big(f_1(\eta_{1,t})\big) + ... + ln\big(f_m(\eta_{m,t})\big) + ln\big(c(F_1(\eta_{1,t}), ..., c(F_m(\eta_{m,t}))\big) + \\
&+ \sum_{t=1}^{T} ln\left(\left|\Sigma^{0.5}(\boldsymbol{\theta})H_t^{-0.5}(\boldsymbol{\alpha})\right|\right).
\end{aligned}
$$

is the log-likelihood.

2.1 Stationarity

For the non overlapping specification with $\tilde{\boldsymbol{A}} = \mathbf{0}$, $\boldsymbol{A}$ being diagonal and only a single asset in consideration, stationarity conditions can be found in Engle et al. (1990). The stationarity conditions for the above specification will now be evaluated. The one step ahead forecast of h_t is given by $E\left[h_t|\mathcal{F}_{t-1}\right]$ where $\mathcal{F}_{t-1}$ denotes all information up to $t-1$, i.e $\mathcal{F}_{t-1} = \{r_0, \dots, r_{t-1}, h_0, \dots, h_{t-1}\}$. Starting at equation (7) and taking expectations yields:

$$
E\left[h_t|\mathcal{F}_{t-1}\right] = E\left[\boldsymbol{k} + \boldsymbol{A}h_{t-1} + \tilde{\boldsymbol{A}}h_t + \boldsymbol{B}r_t^2 + \boldsymbol{G}r_{t-1}^2|\mathcal{F}_{t-1}\right],
$$

and applying iterated expectations to $E\left[r_t^2|\mathcal{F}_{t-1}\right]$ results in

$$
E\left[h_t|\mathcal{F}_{t-1}\right] = \boldsymbol{k} + \boldsymbol{A}h_{t-1} + \tilde{\boldsymbol{A}}E\left[h_t|\mathcal{F}_{t-1}\right] + \boldsymbol{B}E\left[h_t|\mathcal{F}_{t-1}\right] + \boldsymbol{G}r_{t-1}^2,
$$

since $diag(\boldsymbol{H}_t) = h_t$ and hence

$$
E\left[h_t|\mathcal{F}_{t-1}\right] = (\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}(\boldsymbol{k} + \boldsymbol{A}h_{t-1} + \boldsymbol{G}r_{t-1}^2). \tag{9}
$$

Accordingly, the $n \geq 1$ step ahead forecast is given by

$$E\left[h_t|\mathcal{F}_{t-n}\right] = (\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}\Big(\boldsymbol{k} + (\boldsymbol{A} + \boldsymbol{G})E\left[h_{t-1}|\mathcal{F}_{t-n}\right]\Big), \tag{10}$$

applying iterated expectations on $E\left[r_t^2|\mathcal{F}_{t-n}\right]$ and $E\left[r_{t-1}^2|\mathcal{F}_{t-n}\right]$.
Evaluating $E\left[h_{t-1}|\mathcal{F}_{t-n}\right]$ in (10) recursively for $n \to \infty$ reveals that stationarity requires all eigenvalues of $(\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}(\boldsymbol{A} + \boldsymbol{G})$ to lie inside the unit circle. If the process is stationary, the unconditional variance is given by

$$\boldsymbol{h} = \lim_{n\to\infty} E\left[h_t|\mathcal{F}_{t-n}\right] = (\boldsymbol{I} - \boldsymbol{A} - \tilde{\boldsymbol{A}} - \boldsymbol{B} - \boldsymbol{G})^{-1}\boldsymbol{k}. \tag{11}$$

Equation (11) allows to control a given parametrization for non-negativity of the unconditional variance $\boldsymbol{h}$.

3 Estimation

3.1 Randomized Blocking Differential Evolution Metropolis Hastings Algorithm

The proposed model in a setting of three trading places and three assets requires the estimation of in total 123 parameters. Thus, a Differential Evolution Metropolis Hastings algorithm (DE-MH) -a combination of the Differential Evolution optimizer and a Metropolis-Hastings sampler- augmented by the use of randomized blocking (see Chib and Ramamurthy (2010)) is used for estimation. DE-MH offers two major advantages over the ordinary Metropolis-Hastings algorithm: first, DE-MH does not rely on a precise specification of the proposal distribution and thus can handle large parameter spaces easily and second, DE-MH profits from running a large number of Markov Chains in parallel and thus, is perfectly suited to be used on a large scale cluster computer.
The general idea of the DE-MCMC is rather simple[2]: N Markov chains are run in parallel with $\theta_{i,j}$ denoting the parameter vector of chain j in iteration i. Then a value for $\theta_{i+1,j}$ is proposed by

$$\theta_{p,j} = \theta_{ij} + \gamma(\theta_{i,a} - \theta_{i,b}) + \epsilon \tag{12}$$

where a and b are two different randomly drawn elements from $\{1, ...N\}\backslash j$ and ϵ is drawn from a symmetric distribution with unbounded support to

[2]For a textbook like treatment of the algorithm, see the paper of Braak, Cajo J. F. Ter (2006), that also contains some pseudo code for a basic DE-MCMC sampler.

ensure irreducibility of the chains. In other words, DE-MH randomly chooses two different chains at each step, computes the difference of the parameter vector of those chains, scales this difference with a factor γ, adds some random noise ϵ and finally adds everything to the parameter vector of the current chain. Then, the proposed new parameter vector is accepted with probability $\alpha = min\left\{1, \frac{p(\theta_{p,j}|\boldsymbol{y})}{p(\theta_{i-1,j}|\boldsymbol{y})}\right\}$[3] with $p(\cdot|\boldsymbol{y})$ being the posterior distribution of the parameter vector θ given the data $\boldsymbol{y}$.

For a large number of chains N and a small variance of the noise ϵ, the proposal asymptotically (in this context, asymptotically refers to the number of chains and not to sample size) looks like $\theta_{p,j} = \theta_{ij} + \gamma\varepsilon$ as $N \to \infty$ with $E(\varepsilon) = \mathbf{0}$ and $Cov(\varepsilon) \to 2\Omega$, the covariance matrix of the posterior distribution (see Braak, Cajo J. F. Ter (2006)). Additionally to the DE proposal, the parameters are randomly blocked according to Chib and Ramamurthy (2010), in order to speed up convergence. At each iteration, the parameter space is split up into a random number of blocks uniformly distributed between $max\left(\underline{n/5} - 10, 5\right)$ and $min\left(\underline{n/5} + 10, 40\right)$[4], then the parameters are randomly assigned to the blocks. As they're of no interest in terms of volatility transmission, the constants κ in the GARCH specification (7) are fitted every time new parameters are proposed according to the moment conditions in equation (11). This ensures that small increments close to the stationarity boundary don't result in large changes of the unconditional variance of the model and hence, prevent large jumps of the likelihood. This approach might lead to a asymmetric proposal for k which is not accounted for, here, as it is not the focus of this paper to correctly estimate the level of unconditional volatility. The prior distributions of all parameters are set to uniform distributions with boundaries applied, where necessary.

The given scheme results[5] in N Markov chains with unique stationary distribution that has density $p(\cdot|\boldsymbol{y})^N$. Thus, once all chains converged, all draws can be used as posterior samples leading to a large reduction in computation time. In a simulation study on a 100-dimensional normal distribution, Braak shows that convergence speed strongly depends on the number of parallel Markov chains and can be substantially increased by choosing a high number of chains. This underlines that DE-MCMC is perfectly tailored for cluster computers with the

[3] The acceptance probability is just the ratio of the posterior distributions as the DE-MH algorithm is used with a random walk proposal and thus just behaves like a random walk Metropolis-Hastings algorithm. For a textbook treatment see Greenberg (2008).

[4] This rule is completely arbitrary, but worked rather well.

[5] For a proof, see Braak, Cajo J. F. Ter (2006).

ability of evaluating many chains in parallel. This argument gets even stronger the more complex and time consuming the evaluation of the likelihood is as the fraction of overhead reduces, the longer each individual processor needs for computation.

4 Three Markets with three Assets

This section conducts analyzes a setting consisting of three market places with three assets being traded. The market places are Tokyo, London and New York and the respective *home assets* are the Nikkei225, FTSE100 and SP500[6] indices. The trading hours of the market places are Tokyo:10pm-10am CET, London: 8am-4pm CET and New York: 12pm-9pm CET and hence, two overlaps (Tokyo and London share two hours and New York and London share four hours of common trading time) are included. The conditional volatility of each asset will be modeled separately for each trading place. This constellation leads to 123 parameters, 114 of which will be estimated by the above mentioned sampler. The remaining nine parameters (the intercepts in each of the GARCH equations (7)) are computed using the moment conditions in equation (11) by equating the theoretical unconditional volatility and the volatility of the data set and solving the equations for the intercept terms, each time new parameters a proposed. For the sake of reducing computation time and complexity, the model is estimated under the assumption of multivariate normal innovations.
The dataset that is used in this paper is taken from Dukascopy (2019) Historic Data feed. It's built from hourly price data and consists of 1,227 observations ranging from January 3rd, 2014 to December 14th, 2018. The above described RBDEMH algorithm has been used on a single node of PALMA II using 72 cores to draw 500 parallel Markov Chains. Point estimates (posterior means) for all parameters can be found in the appendix of this paper. To visualize how shocks influence conditional volatility, volatility impulse response functions (VIRF) are computed. According to Hafner and Herwartz (2006), the VIRF is given by

$$V_t(\eta_0) = E(vech(H_t)|\eta_0, \mathcal{F}_{t-1}) - E(vech(H_t)|\mathcal{F}_{t-1}), \tag{13}$$

[6]The Nikkei index comprises of 225 large companies and is the stock market index for the Tokyo Stock Exchange, the FTSE contains 100 UK listed companies and the S&P500 covers 500 large companies, listed in New York.

i.e. the impact of a shock in $t = 0$ on volatility, given some initial state of volatility h_0. Using equation (9), the VIRF can be computed as

$$\begin{aligned} V_1(\eta_0) =& vech\Bigg[diag\Bigg(\big((\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}(\boldsymbol{k} + \boldsymbol{A}h_0 + \boldsymbol{G}r_0^2)\big)^{\frac{1}{2}} \Bigg) \\ & \boldsymbol{M}\ diag\Bigg(\big((\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}(\boldsymbol{k} + \boldsymbol{A}h_0 + \boldsymbol{G}r_0^2)\big)^{\frac{1}{2}} \Bigg) \\ & - diag\Bigg(\big((\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}(\boldsymbol{k} + \boldsymbol{A}h_0)\big)^{\frac{1}{2}} \Bigg) \boldsymbol{M} \\ & diag\Bigg(\big((\boldsymbol{I} - \tilde{\boldsymbol{A}} - \boldsymbol{B})^{-1}(\boldsymbol{k} + \boldsymbol{A}h_0)\big)^{\frac{1}{2}} \Bigg) \Bigg], \end{aligned} \tag{14}$$

where $\boldsymbol{I}$ is a $(K \cdot I) \times (K \cdot I)$ identity matrix and $diag(\boldsymbol{x})$ creates a diagonal matrix with the elements of $\boldsymbol{x}$ on its main diagonal. $V_t(\eta_0)$ for $t \geq 2$ can be computed using the recursion in equation (10), straightforwardly. Figure 1 shows the VIRFs of the conditional volatilities of all assets for a shock in their respective home trading zone[7] for three initial levels of volatilities (solid: $h_0 = h$, dashed: $h_0 = 0.5h$, dotted: $h_0 = 2h$, where h denotes the unconditional volatility deduced from equation 11). Each plot contains the responses in all three trading zones (Tokyo: black, London: red, New York: blue). The plots reveal persistent shocks in Tokyo, no matter which asset or trading zone initiated the shock. As can be expected, responses are very pronounced in situations of increased initial volatility compared to situations with low initial volatility, but their decay is similar to regimes with low initial volatility. The fastest decay can be observed in New York putting London between New York and Tokyo. In general, responses are larger the closer the responding trading zone is to one originating the shock. Following the idea of Engle et al. (1990) to distinguish between heat waves and meteor shower effects, one can summarize all transmission parameters that belong to either effect in order to obtain the total heat wave and total meteor shower effect of the underlying combination of assets and trading places. The median total heat wave effect is 0.3065 (2.5% and 97.5% quantiles: 0.1619 and 0.4801) and in contrast, the median total meteor shower effect is 0.8381 (2.5% and 97.5% quantiles: 0.6352 and 1.0334). These strong volatility transmissions across trading zones can be seen as an indicator of strong global financial interconnectednes. Besides the classification into *heat waves* and *meteor showers*, the entire set of volatility transmission effects can be aggregated into four groups: on the one hand, local transmission effects from the own trading place

[7]If there is a shock in any other than the last trading zone, the initial conditional volatility of all subsequent zones needs to be matched accordingly, because the shock already took place.

against transmission effects from foreign trading zones and on the other hand, transmission through the past of the asset in consideration against transmissions from other assets. The joint effect of each group[8] is defined as the sum of all parameters that belong to the group divided by the number of assets or trading zones that are affected.

Table 1 shows all aggregated effects: it's clearly visible that both, spillovers from other assets and transmissions originating in foreign trading zones, are present in the data. Aggregating transmission effects reveals an astounding heterogeneity between trading zones: when being traded in London and New York, an assets volatility depends to a large share on the previous volatility in preceding trading zones whereas in Tokyo the volatility primarily depends on the volatility of the previous trading day in Tokyo. Similar results are obtained, if effects are grouped by asset: when an asset is traded in Tokyo, then the current conditional volatility is almost not affected by volatility of other assets, whereas there is a fairly strong dependency on the volatility of other assets whilst trading takes place in either London or New York.

Looking into the assets in consideration, it is visible that the volatility of all assets is mostly driven by the the own past volatility (median values Nikkei: 0.8411, FTSE: 0.7636 and S&P500: 1.2513) but also by the volatility of foreign trading zones (median values Nikkei: 0.7145, FTSE: 0.8688 and S&P500: 0.9321). If all spillover effects are separated into spillovers from the same asset versus spillovers from other assets, it's apparent that spillovers between assets (median: 0.1961, 2.5% quantile: 0.02790, 97.5% quantile: 0.3722) are much less pronounced than spillovers within the same asset (median: 0.9512, 2.5% quantile: 0.8304, 97.5% quantile: 1.0619).

[8] An overview over the group assignments can be found in table 2 in the appendix.

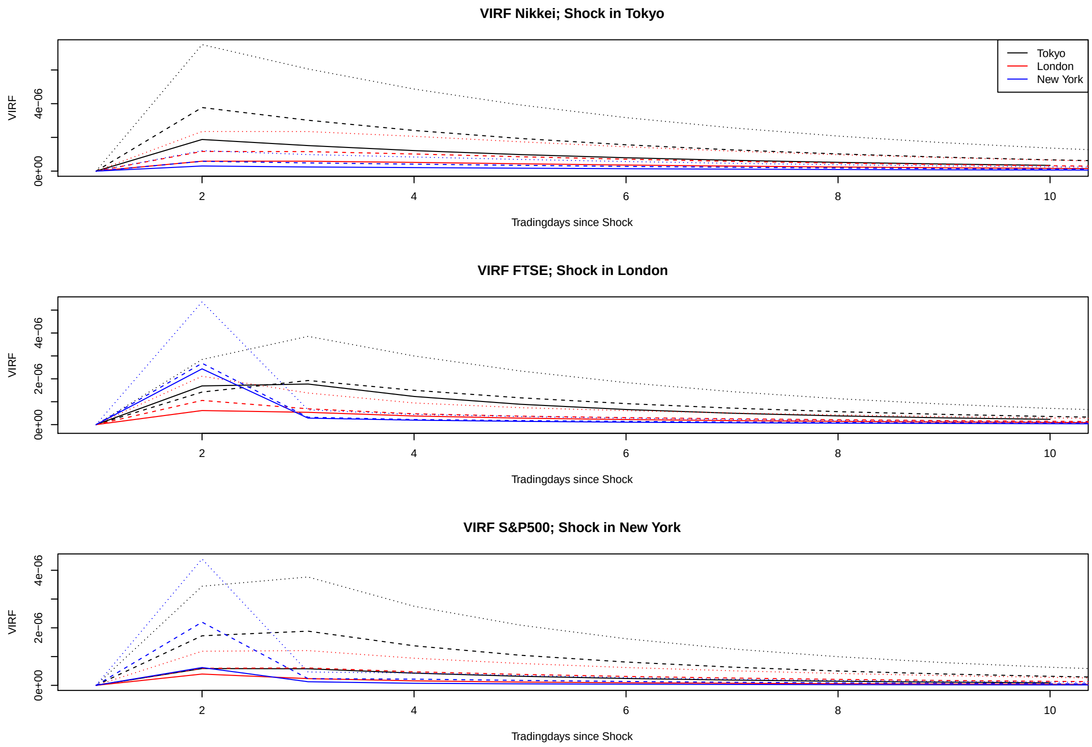

Figure 1: *VIRFs of Nikkei, FTSE and S&P500. Shocks happen in the respective home trading zones and have a magnitude of one standard deviation.*

Nikkei:

Asset/Zone	local	foreign	**total**
own	0.0960 0.3264 0.5099	0.3504 0.5128 0.7099	0.6931 0.8411 0.9604
other	-0.3547 0.0046 0.4510	-0.2812 0.2064 0.6119	0.0056 0.2102 0.4710
total	0.0177 0.3303 0.6829	0.3723 0.7145 1.0685	

Tokyo:

Asset/Zone	local	foreign	**total**
own	0.4903 0.7118 0.8035	0.1197 0.2396 0.4106	0.7309 0.9527 1.0689
other	-0.1974 0.0667 0.5210	-0.1617 0.0116 0.1519	-0.1404 0.0827 0.4487
total	0.4943 0.7769 1.1601	0.1350 0.2491 0.3795	

FTSE:

Asset/Zone	local	foreign	**total**
own	0.0226 0.2347 0.3870	0.2725 0.5261 0.8359	0.5115 0.7636 0.9803
other	-0.1935 0.0864 0.4471	-0.2086 0.3314 0.8779	-0.0023 0.4161 0.8797
total	0.0940 0.3184 0.5777	0.4839 0.8688 1.2806	

London:

Asset/Zone	local	foreign	**total**
own	-0.1488 0.1066 0.3748	0.4062 0.8819 1.3313	0.6680 0.9652 1.3261
other	-0.4773 -0.1351 0.2223	-0.4089 0.3344 0.9892	-0.2934 0.2188 0.6146
total	-0.2999 -0.0307 0.2398	0.6578 1.2000 1.7212	

S&P500:

Asset/Zone	local	foreign	**total**
own	0.1290 0.3318 0.6075	0.4913 0.9233 1.2576	1.0191 1.2513 1.5011
other	-0.2475 -0.0702 0.1063	-0.1581 0.0100 0.2159	-0.1852 -0.0548 0.0981
total	0.1329 0.2722 0.4166	0.6619 0.9321 1.1905	

New York:

Asset/Zone	local	foreign	**total**
own	-0.0786 0.0782 0.2726	0.5991 0.8526 1.1117	0.7663 0.9339 1.1103
other	-0.0774 -0.0938 0.2370	-0.0594 0.2027 0.4426	0.0519 0.2921 0.5235
total	0.0431 0.1739 0.3046	0.8197 1.0494 1.3050	

Table 1: *Total effects grouped into trading zones and assets. The values are computed by the sum of all corresponding parameters divided by the number of assets/trading zones that are considered. In each cell,* 2.5% *quantile, median and* 97.5% *quantile are reported, based on* 250,000 *posterior observations.*

5 Conclusion

This paper shed light on the extent of which volatility is transmitted both, geographically between trading zones and between different assets. To that end, a new copula GARCH framework that builds onto the work of Engle et al. (1990) and Clements et al. (2015) was proposed and estimated using a novel combination of the Differential Evolution Metropolis Hastings sampler augmented by randomized blocking of the parameter space. The application in a setting of three assets that are traded at three major trading places Tokyo, London and New York reveals new insights: A strong persistence of Japanese volatility can be observed, which, to a large extent, depends on past Japanese volatility and is almost independent of the volatility of other trading zones. This is very much in contrast to London an New York where volatility strongly depends on the volatility of foreign trading zones. This can be interpreted as a stronger interconnectedness in Europe and the US compared to Japan.

When looking at the aggregated effects concerning the assets in consideration it is apparent that in general, spillovers are stronger between trading zones than within a trading zone (median total effects 0.8382 and 0.3065) and stronger within a single asset than between assets (median total effects: 0.9512 and 0.1961). Consequently, volatility is immediately transmitted across boarders but there is only a weak link between the volatility of different assets. The same structure is also apparent if spillover effects are broken down into the distinct assets.

The presence of both types of effects, those associated to trading zones and those associated to the assets in consideration necessitates to distinguish between assets and trading places in a thorough analysis of volatility spillovers.

6 Appendix

6.1 Parameters and group assignment

Parameter indices and group assignment:
$\kappa = (1, 2, 3, 4, 5, 6, 7, 8, 9)'$

$$\boldsymbol{A} = \begin{bmatrix} 10 & 13 & 16 & & & & 37 & 40 & 43 \\ 11 & 14 & 17 & & & & 38 & 41 & 44 \\ 12 & 15 & 18 & & & & 39 & 42 & 45 \\ & & & 19 & 22 & 25 & & & \\ & & & 20 & 23 & 26 & & & \\ & & & 21 & 24 & 27 & & & \\ & & & & & & 28 & 31 & 34 \\ & & & & & & 29 & 32 & 35 \\ & & & & & & 30 & 33 & 36 \end{bmatrix} \boldsymbol{B} = \begin{bmatrix} & & & & & & & & \\ & & & & & & & & \\ & & & & & & & & \\ 46 & 49 & 52 & & & & & & \\ 47 & 50 & 53 & & & & & & \\ 48 & 51 & 54 & & & & & & \\ & & & 55 & 58 & 61 & & & \\ & & & 56 & 59 & 62 & & & \\ & & & 57 & 60 & 63 & & & \end{bmatrix}$$

$$\boldsymbol{G} = \begin{bmatrix} 64 & 67 & 70 & & & & 91 & 94 & 97 \\ 65 & 68 & 71 & & & & 92 & 95 & 98 \\ 66 & 69 & 72 & & & & 93 & 96 & 99 \\ & & & 73 & 76 & 79 & & & \\ & & & 74 & 77 & 80 & & & \\ & & & 75 & 78 & 81 & & & \\ & & & & & & 82 & 85 & 88 \\ & & & & & & 83 & 86 & 89 \\ & & & & & & 84 & 87 & 90 \end{bmatrix} \tilde{\boldsymbol{A}} = \begin{bmatrix} & & & & & & & & \\ & & & & & & & & \\ & & & & & & & & \\ 100 & 103 & 106 & & & & & & \\ 101 & 104 & 107 & & & & & & \\ 102 & 105 & 108 & & & & & & \\ & & & 109 & 112 & 115 & & & \\ & & & 110 & 113 & 116 & & & \\ & & & 111 & 114 & 117 & & & \end{bmatrix}$$

$\rho_A = (118, 119, 120)'$, $\rho_Z = (121, 122, 123)'$

Nikkei:

Asset/Zone	local	foreign
own	10,19,28,64,73,82	37,46,55,91,100,109
other	13,16,22,25,31,34, 67,70,76,79,85,88	40,43,49,52,58,61, 94,97,103,106,112,115

FTSE:

Asset/Zone	local	foreign
own	14,23,32,68,77,86	41,50,59,95,104,113
other	11,17,20,26,29,35, 65,71,74,80,83,89	38,44,47,53,56,62 92,98,101,107,110,116

S&P500:

Asset/Zone	local	foreign
own	18,27,36,72,81,90	45,54,63,99,108,117
other	12,15,21,24,30,33, 66,69,75,78,84,87	39,42,48,51,57,60, 9,,96,102,105,111,114

Tokyo:

Asset/Zone	local	foreign
own	10,14,18,64,68,72	37,41,45,91,95,99
other	11,12,13,15,16,17, 65,66,67,69,70,71	38,39,40,42,43,44, 92,93,94,96,97,98

London:

Asset/Zone	local	foreign
own	19,23,27,73,77,81	46,50,54,100,104,108
other	20,21,22,24,25,26, 74,75,76,78,79,80	47,48,49,51,52,53, 101,102,103,105,106,107

New York:

Asset/Zone	local	foreign
own	23,32,36,82,86,90	55,59,63,109,113,117
other	29,30,31,33,34,35, 83,84,85,87,88,89	56,57,58,60,61,62, 110,111,112,114,115,116

Table 2: *Group assignment*

6.2 Point estimates

Point estimates based on the posterior mean of 50,000 draws.

$$
\boldsymbol{A} = \begin{bmatrix}
0.721 & 0.282 & -0.434 & & & & 0.375 & 0.227 & -0.289 \\
-0.012 & 0.627 & 0.127 & & & & 0.082 & 0.138 & -0.123 \\
-0.011 & 0.050 & 0.541 & & & & 0.014 & 0.076 & 0.011 \\
& & & 0.265 & -0.062 & -0.190 & & & \\
& & & 0.057 & -0.041 & -0.025 & & & \\
& & & -0.124 & 0.007 & 0.072 & & & \\
& & & & & & -0.052 & 0.132 & 0.013 \\
& & & & & & -0.084 & 0.059 & 0.056 \\
& & & & & & -0.096 & -0.080 & 0.273
\end{bmatrix}
$$

$$
\boldsymbol{B} = \begin{bmatrix}
& & & & & \\
& & & & & \\
& & & & & \\
0.013 & 0.056 & 0.596 & & & \\
0.005 & 0.456 & 0.227 & & & \\
-0.003 & 0.031 & 0.532 & & & \\
& & & 0.277 & -0.019 & 0.187 \\
& & & 0.060 & 0.146 & 0.138 \\
& & & 0.035 & 0.043 & 0.385
\end{bmatrix}
$$

$$
\boldsymbol{G} = \begin{bmatrix}
0.037 & -0.003 & 0.112 & & & & 0.062 & -0.038 & 0.112 \\
0.004 & 0.109 & 0.044 & & & & -0.029 & 0.065 & 0.032 \\
-0.002 & -0.001 & 0.118 & & & & -0.005 & 0.009 & 0.031 \\
& & & 0.048 & 0.013 & -0.060 & & & \\
& & & 0.018 & 0.018 & -0.024 & & & \\
& & & -0.006 & -0.002 & -0.038 & & & \\
& & & & & & 0.018 & 0.051 & 0.121 \\
& & & & & & -0.011 & -0.013 & 0.086 \\
& & & & & & -0.011 & 0.008 & 0.158
\end{bmatrix}
$$

$$\tilde{\boldsymbol{A}} = \begin{bmatrix} 0.340 & -0.116 & -0.116 & & & \\ -0.041 & 0.475 & 0.505 & & & \\ 0.130 & -0.172 & 0.702 & & & \\ & & & 0.382 & -0.011 & 0.074 \\ & & & 0.085 & 0.267 & 0.114 \\ & & & -0.035 & 0.050 & 0.812 \end{bmatrix}$$

$\rho_A = (0.290, 0.413, 0.388)',\ \rho_Z = (0.122, -0.037, 0.273)'$

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