to capture the ARCH effects). The usual GARCH restrictions for non-negativity and stationarity were imposed. $\mathbf{C}_t$ is the time-varying correlation matrix:

$$\mathbf{C}_t = diag\{\mathbf{Q}_t\}^{-1}\mathbf{Q}_t diag\{\mathbf{Q}_t\}^{-1} \tag{4}$$

$$\mathbf{Q}_t = \left(1 - \sum_{p=1}^{P}\alpha_p - \sum_{q=1}^{Q}\beta_q\right)\overline{\mathbf{Q}} + \sum_{p=1}^{P}\alpha_p\left(\mathbf{s}_{t-p}\mathbf{s}_{t-p}^T\right) + \sum_{q=1}^{Q}\beta_q\,\mathbf{Q}_{t-q} \tag{5}$$

$$\rho_{t,i,j} = \frac{q_{t,i,j}}{\sqrt{q_{t,i,i}\,q_{t,j,j}}},\ i,j = 1,2,\ldots,n; i \neq j \tag{6}$$

where $\mathbf{s}_t$ are standardized residuals, $\overline{\mathbf{Q}}$ is the unconditional correlation matrix in dynamic correlation structure $\mathbf{Q}_t$ and $\rho_{i,j,t}$ are the estimated dynamic conditional correlations. The DCC parameters $\alpha_p$ and $\beta_q$ are estimated via maximum likelihood, for further details see Engle and Sheppard [25] and Engle [26].

The estimation of DCC within a single large system is known to produce biased correlations. It is possible to employ the MacGyver methodology proposed by Engle [31], where $\alpha_p$ and $\beta_q$ are estimated as the medians of the corresponding coefficients obtained from bivariate DCC MV-GARCH models for all of the series. Nevertheless, the dynamics of the estimated correlations will be very similar because for all pairs of stocks, the $\alpha_p$ and $\beta_q$ will eventually be the same. We have therefore decided to undertake the entire analysis using individual bivariate DCC. Newer approaches by Hafner and Reznikova [32] and Aielli and Caporin [33] could also be considered.

After calculating all of the bivariate DCCs, correlation matrices $\mathbf{C}_t^{DCC}$ of size $N$ x $N$ are formed. These are then transformed into distance matrices $\mathbf{D}_t^{DCC}$, as in Mategna [1], which are used to construct the $\text{MST}_t$.

Rolling correlations were calculated using correlation coefficients $\rho_{t,i,j}$:

$$\rho_{t,i,j} = \frac{\sum_{t=1}^{T}\left(S_{t,i} - \overline{S}_{t,i}\right)\left(S_{t,j} - \overline{S}_{t,j}\right)}{\sqrt{\sum_{t=1}^{T}\left(S_{t,i} - \overline{S}_{t,i}\right)^2}\sqrt{\sum_{t=1}^{T}\left(S_{t,j} - \overline{S}_{t,j}\right)^2}} \tag{7}$$

These coefficients form a correlation matrix $\mathbf{C}_t^{RC}$ of size $N$ x $N$. The returns vector is then drifted by $dr$ = 1 day forward, and a new $\mathbf{C}_{t+1}^{RC}$ is calculated in the same way. The correlation matrices are then transformed into distance matrices $\mathbf{D}_t^{RC}$. Finally, MSTs are calculated using Prim's algorithm [34] (see also Kruskal [35], Papadimitrou and Steigliz [36]).

Table 1 summarizes the number of constituents for each sample. We only retained stocks where the daily closing prices were available for the entire period. Further on, we were unable to fit a suitable mean or variance equation model to some series; these series were also removed from the final samples.

**Table 1** The number of observations and stocks in the window analyzed, 04.02.2010 – 11.11.2011, with $T$ = 449, $N$ = 79 constituents. Sample designations are in brackets.

| Windows and samples | DCC | RC, $dr$ = 1 |
|---|---|---|
| $w$ = 1000 ($T'$ = 1449)<br>14.02.2006 – 11.11.2011 | [DCC-1000] | [RC-1000] |
| $w$ = 500 ($T'$ = 949)<br>11.02.2008 – 11.11.2011 | [DCC-500] | [RC-500] |