Ripples on Financial Networks

Abstract

The study addresses the topic of determining how shocks originating in one asset have spillover or ripple effects in other assets. This is accomplished by establishing a network of the estimated conditional volatility series from asset returns and estimating a multidimensional VAR model with unique identification criteria based on the network topology.

Keywords

1) **Volatility Shock** - A volatility shock refers to a sudden and significant increase in the volatility of financial markets or a specific asset. These can be triggered by unexpected data

releases, geopolitical events etc. and can lead to rapid and large price movements over short durations.

2) **Network Centrality** - Refers to the measure of a node's importance or influence within a network. It quantifies the position of a node based on its connections to other nodes.

3) **VAR (Variable Autoregressive) models** - They are used to capture the relationship between multiple variables over time by just considering their correlation, the previous values of variables and an error term.

4) **GARCH model** - It stands for Generalised Autoregressive Conditional Heteroskedasticity. Unlike the VAR model which focuses on the mean and average behaviour of the series, GARCH models basically focuses on the volatility and variance of the series.

Mathematical Formulation

- Firstly, we start with 100 stocks listed on the NYSE with a period over 16 years (2002-2017). We divide the series in 4 time periods T1, T2, T3, T4 of 4-year periods each.
- Calculate daily returns on closing prices of each stock as

$$r_{it} = \log(p_{it}) - \log(p_{i,t-1})$$

- Now we construct a conditional volatility series using GARCH(p,q) modelling from each of the return series {r(i,t)}. So,

$$r_{it} = \mu_i + \sigma_{it}\epsilon_{it}$$

$$\sigma_{it}^2 = c_i + \sum_{l=1}^{p} \alpha_{il} r_{i,t-l}^2 + \sum_{j=1}^{q} \beta_{ij} \sigma_{i,t-j}^2.$$

where the conditional volatility of i-th stock is [σ(i,t)]^3

- Now, we construct a cross-correlation matrix using {r(i,t)} and {σ(i,t)} series by using pairwise correlation coefficients

$$\gamma_{ij}^x = \frac{E\left((x_{it} - \bar{x}_i)(x_{jt} - \bar{x}_j)\right)}{\sigma_i^x . \sigma_j^x}$$

- To quantify the spillover effects, we proceed with *Katz-Bonacich centrality* measures based on the absolve cross corr matrix.

$$c^{KB}(\alpha) = \left((I - \alpha A^T)^{-1} - I\right)\mathbf{I},$$

with ɑ → 1/max(λ) where max(λ) is the maximum eigenvalue obtained. So this c(KB)(ɑ) converges to the eigenvector centrality.

- We calculate VAR model with p-lags as

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t$$

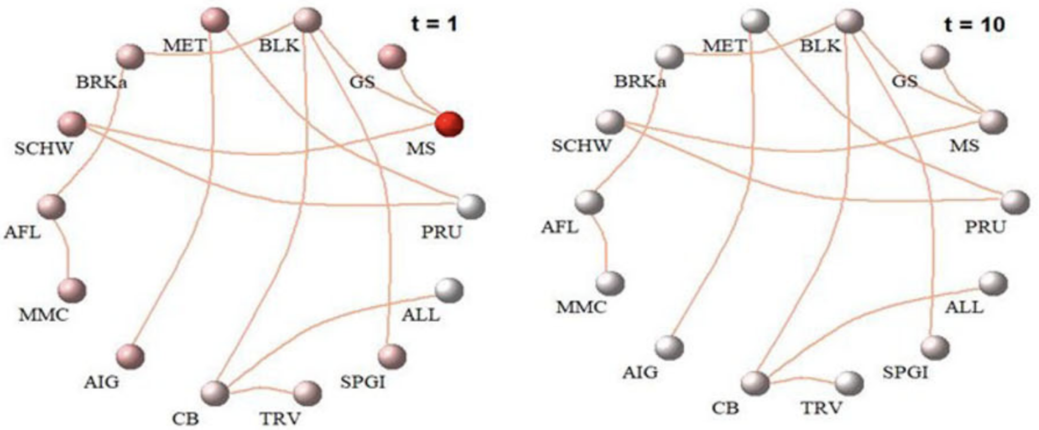
- Finally to get positive distances in MST, we use distances as

$$d_{ij} = \sqrt{2(1 - \gamma_{ij})}.$$

Visualisation

For visualisation of shock propagation, we construct a network based on the correlation structure of the stocks and extract the minimum spanning tree. We plot the impulse responses across the network emanating from chosen epicentres. Also, the magnitude of impact was captured through intensity of colour.

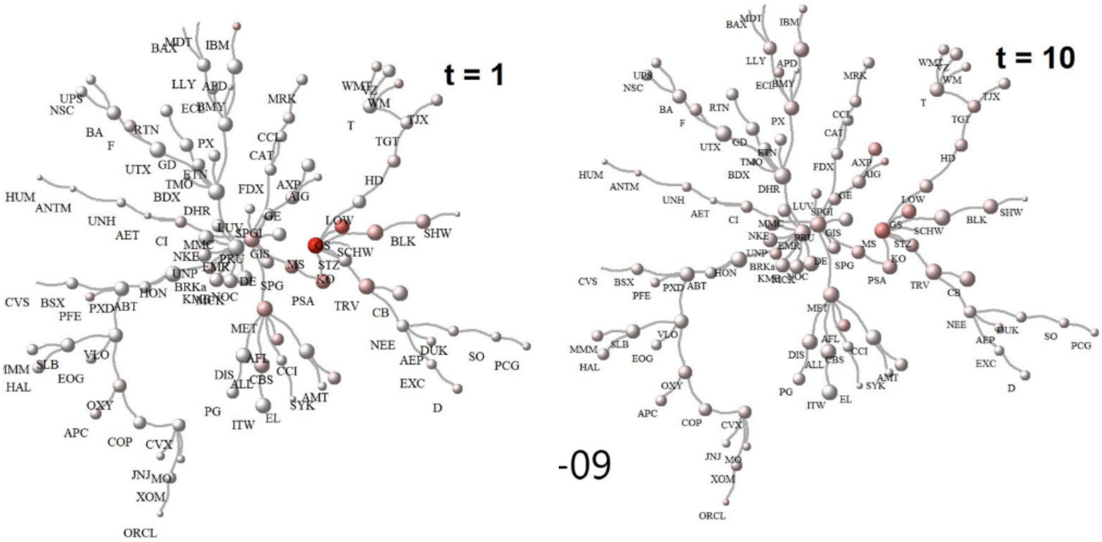
For example, then positive shock was given to Morgan Stanley(MS),



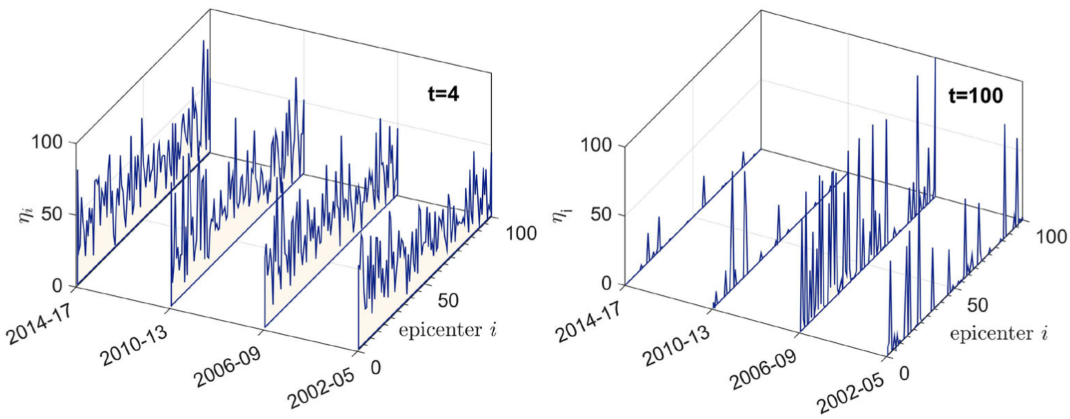
We see that Charles Scwab Corp. (SCHW), Berkshire Hathaway Inc. (BRKA), MetLife Inc. (MET), BlackRock Inc. (BLK) and Goldman Sachs Group Inc. (GS) were immediately affected. But after 10 periods, most of them have recovered with some residual impacts on BLK and GS.

Interpretations from Graphs

Similar idea but with more stocks gives a easily understandable graph like, again with positive shock given to MS,



This, although understandable, can be condensed into much useful form by representing it in the following way. On the *x*-axis, we show four periods 2002–05, 2006–09, 2010–13 and 2014–17. On the *y*-axis, we show the stock identities in terms of numbers (arranged in terms of centralities) which act as the epicentres of the ripple effects. We give unit shocks to all the stocks treating them as epicentres and trace the ripples emanating from them spreading throughout the network.



It can be noticed that first, there is a sharp decline in the number of stocks showing responses for all epicentres. Second, a large number of stocks in the period 2006–09 still shows comparatively high response indicating that during the time of financial crisis, the effects of the shock remained more persistent than during the other periods.

Conclusion

The study introduces a novel method for analysing financial networks by estimating a VAR model on stocks' latent volatility processes. They use centrality measures based on the dominant eigenvector of return correlation matrices for identification, offering insights into network structure and core-periphery dynamics. The study can help in choosing other stocks in case of heavy volatility in a particular stock or prevent investing in some. This relative movement of stocks can be helpful in devising an effective strategy to hedge the risks and make optimum profits.