A VaR and CoVaR connectedness method measuring financial contagion: the case of oil and G20 stock markets

Bing-Yue Liu [1], Ying Fan [1,*], Qiang Ji [2]

[1] School of Economics & Management, Beihang University, Beijing 100191, China
[2] Center for Energy and Environmental Policy Research, Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China

[*] Corresponding author, Email: yfan1123@buaa.edu.cn

Abstract

Overview

With the development of financial integration, the relationships between financial markets become increasingly closer, and the stability of a financial system decreases dramatically. Modern communication technologies also create favorable conditions for financial risk contagion. The extreme risks of one financial market or institution can spread to other markets or institutions via the open financial market system, causing risk spillovers and even financial contagion. The 2008 global financial crisis and the 2010 European debt crisis both bear witness to this phenomenon. The crucial commodity of crude oil especially plays a pivotal role in economic activities and has a great effect on stock markets (Jones and Kaul, 1996; Kilian and Park, 2009; Mensi et al., 2017). Thus, this paper tries to model the financial contagion and explore the risk spillovers from oil market to the stock market system, which can offer some theoretical and practical insights for investors and financial regulators to handle oil shocks, monitor oil risk spillovers, and even prevent systemic risks caused by extreme oil risks.

Adrian and Brunnermeier (2016) proposed conditional Value-at-Risk (CoVaR) to measure systemic risk or risk spillovers, and Brownlees and Engle (2012) showed how to measure marginal expected shortfall (MES) to further research systemic risks via a dynamic conditional correlation model. Further, Liu et al. (2017) conducted an CoVaR empirical analysis via a dynamic copulamodel, and Eckernkemper (2017) showed how to measure MES via a dynamic copula model, since the relationships between financial markets are always nonlinear, even more strikingly when extreme risk events occur.

However, CoVaR and MES may have some defects for describing the interactions of risks for every financial institution as well as the complex systemic characteristics exhibited during a period of extreme market risk. Particularly, Diebold and Yılmaz (2014) proposed to

employ the connectedness measure method to construct a financial network and explore its systemic risks or risk spillovers. Thus, this paper tries to combine the Copula-CoVaR method with the connectedness measure method to explore the relationships or network structure among the CoVaR values for all G20 countries under the condition that the oil market is in extreme distress. Furthermore, this paper tries to explore the effects of extreme oil risks on the network of global stock risks, and then analyzes the risk of spillovers from the oil market to the global stock market system. In particular, a CoVaR connectedness has the following characteristics:

1) It is a VaR network given some extreme conditions. As a VaR network may fully describe the interactions among all extreme stock market or all financial institution risks, compared with VaR model, a VaR network model is preferred to explore the financial contagion inside the whole market system, i.e. financial market system extreme risk modelling.

2) A CoVaR network can be employed to analyze the risk spillovers from the conditional variable to the whole system of a financial market or financial institutions; that is, a CoVaR network is preferred to explore financial contagion in cases where the contagion sources are outside the network.

The paper described by this abstract will be organized with an introduction, a second section on the research methodology, a third section on the empirical analysis, and a final conclusion.

Methodology

1) This paper's analytical approach combines four generalized autoregressive conditional heteroskedasticity (GARCH) models, a standard GARCH, a GJRGARCH, an APARCH, and a CSGARCH, all with six distributions, including standard normal, skewed normal, standard t, skewed t, generalized error distribution, and skewed generalized error distribution, to obtain a total of 24 ARMA-GARCH class models. Then, the optimal marginal distribution for G20 stock returns and oil returns are selected using the Bayesian information criterion (BIC).

2) The optimal copula dependence structure for G20 stock and oil returns is selected using 10 time-varying copulas, i.e. time-varying normal, t, four clayton-class copulas, and four gumbel-class copulas. Then, the CoVaR and MES values are computed and compared.

3) The connectedness measure method is employed to construct the CoVaR network for the empirical analysis.

Conclusion

This paper will propose to employ a CoVaR connectedness method to explore the risk spillovers from an exterior source to a financial network and the resulting complex interactions among the extreme risks of all components inside the financial network, i.e. modelling of financial contagion or a financial crisis phenomenon. The case study results show that extreme oil risks can affect the systemic risks of the G20 stock market system, although different countries show different reactions to extreme oil risks. The empirical conclusions can offer some theoretical and practical insights for investors and financial regulators to handle oil shocks, monitor oil risk spillovers, and even prevent systemic risks caused by extreme oil risks.

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