Paper ID APEN-MIT-2022_2639
Applied Energy Symposium: MIT A+B
July 5-8, 2022 • Cambridge, USA

Early warning of critical transition in energy and stock market

Sufang An
School of Economics and Management
China University of Geosciences
Beijing, China
bjxsky@126.com

Haizhong An
School of Economics and Management
China University of Geosciences
Beijing, China
ahz369@163.com

Xiangyun Gao *
School of Economics and Management
China University of Geosciences
Beijing, China
gxy5669777@126.com

** First corresponding author(Xiangyun Gao)*
Tel.: +86 01082321403
Fax: +86 01082321783

Feng An *
School of Economics and Management
University of Science and Technology Beijing
Beijing, China
af15910602135@126.com

** Second corresponding author(Feng An)*
Tel.: +86 13021161300

***Abstract*—**Early warning is an important and challenging issue in governmental policy-making. This study proposes a skillful spillover network-based machine learning model to provide early warnings of critical transition in energy and stock markets. First, the critical transition of stock and energy time series can be detected using a hidden Markov model. Second, a dynamic spillover network is established, which can help to understand the characteristics of return volatility from the perspective of the time-varying structure of spillover relationships. A machine learning algorithm is employed to model the early warning of critical transition based on the topological structures of the network. The results demonstrated that the proposed model can identify the early warning of critical transition with the warning day, e.g., one day or thirty days, with a high generalization ability. Our study enriches critical transition research and can offer important warning signals for policy-makers and market investors.

Keywords—Machine learning, Spillover network, Critical transition, Energy and stock markets

I. INTRODUCTION

This paper investigates an important issue addressed in time series which is the detection of critical transitions, where the system shifts from one regime to another due to exogenous variables [1-3]. There are often system market crashes when critical transition occurs [2]. Numerous researchers and scholars have proposed various types of 'critical transition' named regime switching methods in nonlinear time series analysis [4-7] and other general models for critical transitions in various natural and social systems[2, 8, 9]. This theory extracts the fluctuation feature of time series to consider critical transition and rarely investigates the changeable structure of the relationships in time series. The time-varying structure of relationships across different series or sub time series can provide a large amount of important hidden time series information, which may provide early warning information for policy-makers and market investors to avoid financial crises.

This paper proposes a skillful spillover network-based machine learning model named the SN-ML model to provide early warnings of critical transition in energy and stock markets, where the combination of complex networks and machine learning algorithms has become a new and hot method in data mining [10, 11]. There are two contributions of our research as follows: (1) We use a model for the detection of critical transition in financial time series based on an HMM [3, 7] (2) We establish a dynamic spillover network model to investigate the time-varying structure of the spillover across markets. Then, we study the nonlinear relationship between spillovers and critical transition using a machine learning tool. Our approach builds a platform for econometric models, complex networks and machine learning, which can provide early warnings of critical transition in financial markets. The model can help policy-makers and investors minimize market losses appropriately.

II. METHOD

In this section, we propose an early warning model named the SN-ML model, as shown in Fig. 1.

First, we introduce the sliding time window method to transform the entire energy and stock time series into a high-dimensional system that can describe the dynamic process of series. We use the sliding time windows to divide the whole time series from left to right with step.

Second, we detect the critical transition of the high dimension data using an HMM model and entropy theory. We first measure the data heterogeneity from the role of space based on the spatial entropy [12]

Third, thousands of spillover networks are established to characterize the time-varying structure of spillovers across markets based on GARCH-BEKK model [13]. Network indicators such as the network diameter, average path length (APL), network density, average out-strength (AOS), average normalized betweenness centrality (ABC) and average closeness centrality (ACC) are measure the topological structures.

Fourth, several machine learning algorithms such as support vector machine (SVM), gradient boosted decision tree (GBDT), artificial neural network (ANN) and deep neural network (DNN) [14]are established to predict and provide early warnings of critical transition.

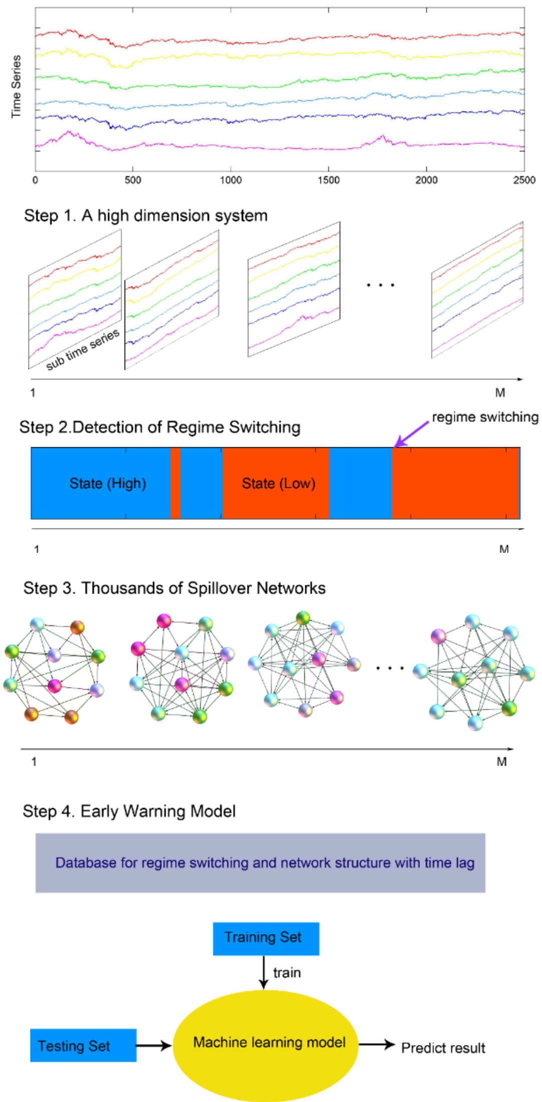

Fig. 1. The process of the SN-ML model

III. RESULTS

A. Data and preprocess

The data in this paper are taken at daily frequencies from January 2007 to April 2020. Brent and WTI crude oil future prices and natural gas future prices. The seven main stock market indices chosen are the Shanghai Stock Exchange illustrates the dynamic network indicator of the stock and energy markets. For example, the dynamic average out-strength of the stock and energy time series is presented in 错误!未找到引用源。 (d). The results show that the average importance of the financial market transmitting spillovers to other markets changes with time. During the global finance crisis, the average importance jumps from high to low and (SSE), FTSE 100, DAX, Nikkei 225, S&P/asx200 Index (SP Index), Singapore Straits Times Index (STI), and S&P 500. We select paper selects 220 days as the window width since the economic cycle is approximately one year to obtain a high-dimensional system consisting of thousands of sub time series.

B. Detection of critical transition

Fig. 2 shows that the entropy of thousands of sub time series is time-varying. The results show that the heterogeneity of financial markets jumps from high to low during the global financial crisis (2007–2009) and European debit crisis I (2009–2010). During European debit crisis II (2011–2012), the heterogeneity begins with a lower value and then increases sharply. The global economy recovered between 2013 and 2014. From 2014 to 2016, more related oil and natural gas events occurred, oil prices collapsed, and the heterogeneity of financial markets fluctuated from lower value to higher value. During the China-US trade frictions and COVID-19, the heterogeneity fluctuates with a lower value. This suggests that the structure of financial markets as a whole becomes less complex and uncertain. This finding complements those of [13] who reported that the structure of financial markets as a whole is time-varying before 2017.

Fig. 2. (a) Entropy of the high-dimensional system. (b) The state of the high-dimensional system. The white parts reflect the low states, and the purple parts reflect the high states.

C. Dynamic structure of spillover networks

Fig. 3illustrates the dynamic network indicator of the stock and energy markets. For example, the dynamic average out-strength of the stock and energy time series is presented in Fig. 3 (d). The results show that the average importance of the financial market transmitting spillovers to other markets changes with time. During the global finance crisis, the average importance jumps from high to low and then fluctuates at a higher value. From 2014 to 2016, the average importance begins with a lower value and then increases sharply, indicating that the importance of the financial market transmitting spillovers to others increases. The average importance fluctuates with a lower value during China-U.S. trade frictions and COVID-19.

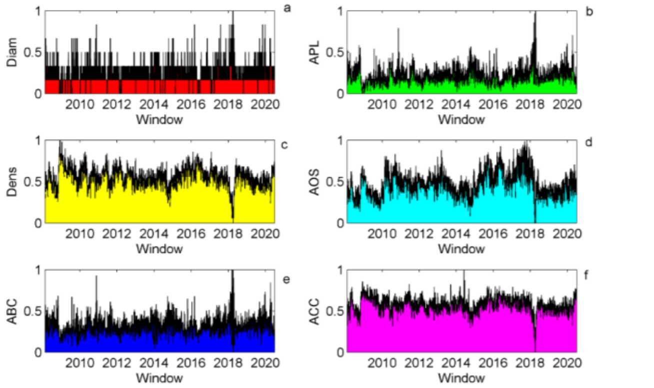

Fig. 3. (a) Dynamic diagram of the spillover network, (b) dynamic APL of the spillover network, (c) dynamic density of the spillover network, (d) dynamic AOS of the spillover network, (e) dynamic ABC of the spillover network, and (f) dynamic ACC of the spillover network. Note: The results are normalized network indicators, and the window is the last day of the sub time series in hing-dimensional system

D. Early warning of the critical transition

Step four of our study investigates the early warning of critical transition. First, we use the efficient information extracted from the spillover network structures with the time lag as the input variable and critical transition with the time lag as the output variable. Second, we build a dataset based on the input and output variables and then randomly select 80% (20%) of the dataset as the training (testing) set. Third, we construct machine learning algorithms, such as the SVM, GBDT, ANN and DNN, to train the model and predict the data. Fourth, we calculate indicators such as the prediction accuracy, recall accuracy and F1-score to measure the generalization abilities of the proposed model. In addition, the generalization ability depends not only on the reliability of the dataset with the time lag but also on the selected machine learning algorithms.

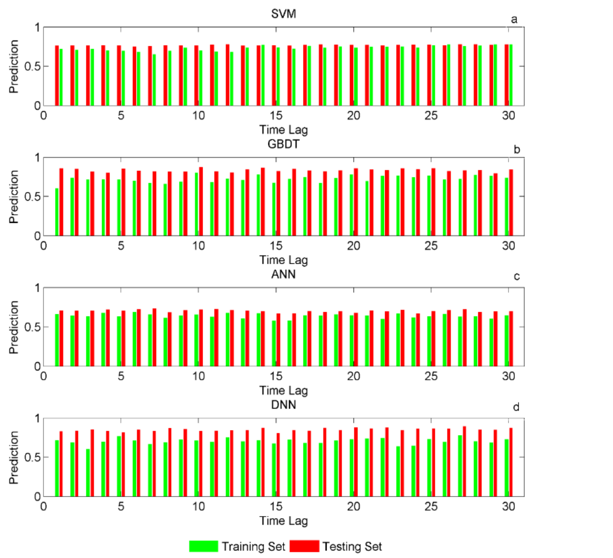

Fig. 4 (a) Prediction accuracies of the SVM on the training and testing sets, (b) prediction accuracies of the GBDT on the training and testing sets, (c) prediction accuracies of the ANN on the training and testing sets, and (d) prediction accuracies of the DNN on the training and testing sets.

Fig. 4 presents the prediction accuracies of the four algorithms with different time lags. These results show that the prediction accuracies of the training and testing sets with the warning day in an algorithm are time-varying. For example, Fig.(a) illustrates the dynamic prediction accuracies of the SVM on the training and testing sets. The dynamic prediction accuracy of the SVM on the training set ranges from 0.7512 to 0.7813, and the prediction accuracy of the SVM on the testing set is between 0.6553 and 0.7814. As the time lag increases, the prediction accuracies of an algorithm fluctuate. The users can set the time lag according to the economic cycle and the actual situation. In addition, comparing the ranges of the prediction accuracies and their means for the four algorithms, our findings indicate that the GBDT and DNN have higher prediction accuracies than the others.

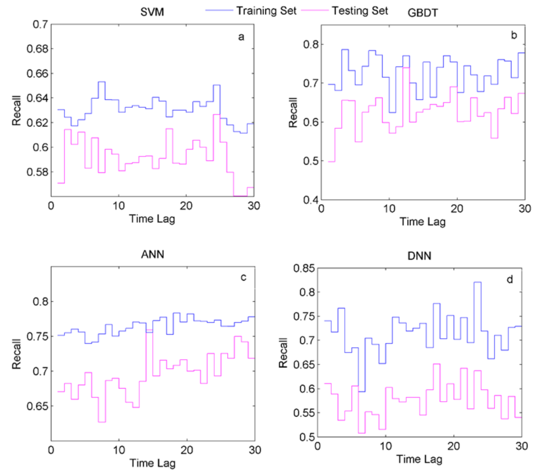

Fig. 5 (a) Recall accuracies of training and testing sets in SVM, (b) recall accuracies of training and testing sets in GBDT, (c) recall accuracies of training and testing sets in ANN, (d) recall accuracies of training and testing sets in DNN.

The recall accuracies of the four algorithms with different time lags are shown in Fig. 5. Our findings indicate that the recall accuracies of the algorithms on the training and testing sets with the warning day change with time. For example, Fig. 5 (b) presents the dynamic recall accuracies of the GBDT on the training and testing sets. The figure shows that the recall accuracies with different time lags are different, indicating that the recall accuracy on a dataset is time-varying. The dynamic recall accuracy on the training set ranges from 0.6243 to 0.7868, and the mean of these indicators is 0.7248. Comparing with the range of the recall accuracies of these four algorithms as a whole, the results show that the recall accuracies of the GBDT are better than those of the other three algorithms.

Fig.6 shows the F1-scores in four algorithms with different the time lags. These results shows that F1-scores of training and testing sets with the day of warning in an algorithm change with time. For example, Fig. 6 (a) presents the dynamic F1-scores of training and testing sets in SVM. F1-score of training set belongs to (0.6811,0.7065). With the increase of the time lag, the F1-score in an algorithm fluctuate. The users can take the time lag according to economy cycle and the actual situation. In addition, compared with the ranges of the F1-scores and their mean in four algorithms, our findings indicates that the GBDT and DNN have greater average F1-scores of training set, and

GBDT and ANN have greater average F1-scores of testing set. Above all, GBDT has greatest F1-scores of samples.

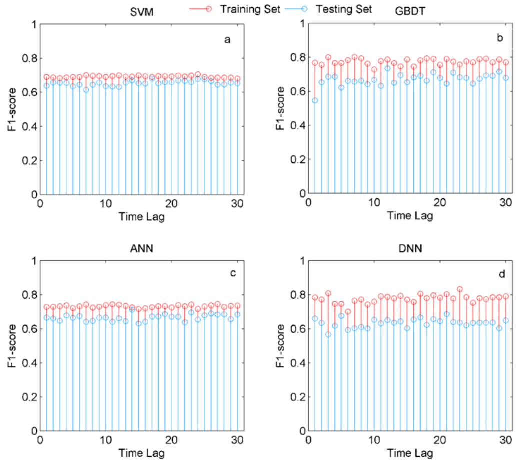

Fig. 6 (a) F1-scores of training and testing sets in SVM, (b) F1-scores of training and testing sets in GBDT, (c) F1-scores of training and testing sets in ANN, (d) F1-scores of training and testing sets in DNN

Overall, the prediction accuracies, recall accuracies and F1-scores of the training set and testing set are time-varying. First, compared with the SVM, GBDT, ANN and DNN models as a whole, the GBDT and DNN have better generalization abilities. This may be because the GBDT is a well-known two-class classifier and the DNN has a good deep learning algorithm structure. Second, due to the dynamic time lag, policy-makers and market investors choose machine learning algorithms that have a better generalization ability at that time lag to make predictions.

IV. Conclusion and Policy Implication

This paper proposes a spillover network-based machine learning model for the early warning of critical transition in energy and stockmarkets. We first establish an HMM model to identify critical transition in a high-dimensional system reconstructed from energy and stocktime series. Then, thousands of spillover networks are established to describe the dynamic process of spillovers across markets, which can help to deeply understand return volatility. Machine learning algorithms including the SVM, GBDT, ANN and DNN are employed to model the early warning of critical transition based on spillover networks. Our findings can be described as follows:

First, we can identify critical transition with two states by analyzing the time-varying heterogeneity of time series. By analyzing the time-varying structure of the spillovers across energy and stock markets, we provide new evidence for the structure of spillovers across these markets during China-US trade frictions and COVID-19. Second, our proposed SN-ML model can provide an early warning of critical transition with a warning day from one day to thirty days with a high generalization ability. Comparing with the generalization abilities of the four learning algorithms, the GBDT and DNN perform significantly better than the other machine learning models.

Our findings provide a dynamic process orientation to explore the early warning of critical transition in energy and stocktime series for policy-makers and market investors. Therefore, policy-makers can have a deeper understanding of the dynamic process of spillovers across energy and stock markets and can use a dynamic early warning model of critical transition to foster market stability. The early warning of critical transition using dynamic graphical tools can provide a clear time-varying structure for market investors to avoid market losses.

This paper only establishes the early warning of critical transition in energy and stock time series based on a spillover network, an HMM model and four typical machine learning algorithms. Future research could investigate the other co-movement relationships across many more energy and stock markets, such as bulk mineral communities. Other econometric models and machine learning algorithms, such as convolutional neural networks, could be used to explore the early warning of critical transition in the future.

Acknowledgment

This research is supported by the National Natural Science Foundation of China (Grant Nos. 42001242, 71991485, 71991481 and 71991480) and the Fundamental Research Funds for the Central Universities (Grant No. 2652018247).

References

[1] J.D. Hamilton, "Rational-expectations econometric analysis of changes in regime : An investigation of the term structure of interest rates", Journal of Economic Dynamics and Control, vol.12, pp.385-423,1988.

[2] M. Scheffer, J. Bascompte, W.A. Brock, V. Brovkin, S.R. Carpenter, V. Dakos, H. Held, E. Nes, M. Rietkerk, and G. Sugihara, "Early-Warning Signals for Critical Transitions", Nature, vol.461,pp.53-59, 2009.

[3] Y. Huang, G. Kou, and Y. Peng, "Nonlinear manifold learning for early warnings in financial markets", European Journal of Operational Research, pp. S037722171630697X, 2016.

[4] J. Fu, J. Wei, and H. Yang, "Portfolio optimization in a regime-switching market with derivatives", European Journal of Operational Research, vol.233,pp.184-192, 2014.

[5] H. Xiong, and R. Mamon, "A higher-order Markov chain-modulated model for electricity spot-price dynamics", Applied Energy,pp. 495-515, 2019

[6] G. Gozgor, A.K. Tiwari, N. Khraief, and M. Shahbaz, "Dependence structure between business cycles and CO2 emissions in the U.S.: Evidence from the time-varying Markov-Switching Copula models", Energy, vol.188,pp. 115995, 2019.

[7] Y. Lin, Y. Xiao, and F. Li, "Forecasting crude oil price volatility via a HM-EGARCH model", Energy Economics, vol.87, pp.104693, 2020.

[8] J. Tan, and S. Cheong, "Critical slowing down associated with regime shifts in the US housing market", European Physical Journal B, vol.87,pp. 1-10, 2014.

[9] B. Goswami, N. Boers, A. Rheinwalt, N. Marwan, J. Heitzig, S. Breitenbach, and J. Kurths, "Abrupt transitions in time series with uncertainties:, Nature Communications, vol.9, pp.48, 2018.

[10] M. Zanin, D. Papo, P.A. Sousa, E. Menasalvas, A. Nicchi, E. Kubik, and S. Boccaletti, "Combining complex networks and data mining: why and how", Physics Reports, pp.1-44, 2016.

[11] Z. Yong, R.V. Donner, N. Marwan, J.F. Donges, and J. Kurths, "Complex network approaches to nonlinear time series analysis", Physics Reports, vol.787,pp. 1-97, 2019.

[12] L. Altieri, D. Cocchi, and G. Roli, "A new approach to spatial entropy measures", Environmental & Ecological Statistics, vol. 25,pp.1-16,2017

[13] S. An, X. Gao, H. An, F. An, Q. Sun, and S. Liu, "Windowed volatility spillover effects among crude oil prices", Energy, vol.200,pp. 117521,2020

[14] M.H. Farrell, T. Liang, and S. Misra, "Deep Neural Networks for Estimation and Inference", Econometrica, vol.89,pp.181-213, 2021