Risk Transmission Mechanism across Industries in China based on VAR-Lasso

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Abstract

It is crucial to learn how the risk has been transmitted between industries in China before and after some big events. To conduct the empirical research on risk transmission mechanism in China based on daily data of the SWS secondary industry index, I utilize the LASSO algorithm to compress, select and estimate variables and build a high dimensional VAR model to calculate the pairwise risk connectedness between different industries. With the help of network analysis, I visualize the outcome of the VAR-Lasso model. Then, both full sample estimation and rolling window estimation are applied to make a static and dynamic study of the risk transmission network. As is revealed in dynamic analysis, clustering characteristics can be easily seen in risk transmission in the market, especially between elements in the same industrial chain or between industries that are closely connected. Particularly, Oil exploitation, Insurance, Banking, and Railway Transportation are functioning as the efficient intermediary node in the whole transmission process. As for dynamic analysis, the overall risk connectedness reaches the summit of the great stock damage in 2015 and the shock of Covid-19. Comparisons are made on the risk transmission network before and after those big events.

Data

I obtain the data of 104 industries from the SWS secondary industry index, from October 12, 2010 to May 23, 2020. The data is in classical OHLC format, which contains high price, low price, open price and close price during the day. However, I find that 8 industries in the data contain missing values and most of them are 100% missing. Thus, I delete them from the raw data and the number of industries becomes 96. Before constructing the model, I must transform the OHLC data to another format. The equation to calculate the return is:

$$\widetilde{\theta}_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2$$

The example of processed data is:

Time	Agriculture	Forest	Oil
2010-01-01	0.003452	0.009871	0.004811
2010-01-03	0.004811	0.010892	0.003452
2010-01-04	0.003901	0.008912	0.004222
2010-01-05	0.004212	0.005292	0.004213
2010-01-06	0.004392	0.007291	0.003901

Methods

Vector Autoregression & Variance Decomposition

I conduct the variance decomposition on the VAR model. VAR model allows us to study the relationship between multiple variables, which are different industries in this paper. Risk connectedness measures between industries based on variance decompositions are practical and simple. First, they are directly linked to network model, and they are also related to systemic risk. Secondly, different connectedness at different horizons is allowed, leading to selection of a preferred horizon and the examination of a variety of horizons if desired. Finally, they make obvious intuitive sense, answering a key question, which at the most granular pairwise level is "How much of entity i's future uncertainty (at horizon H) is due to shocks arising not with entity i, but rather with entity j?".

Risk Connectedness Measures

We can use the result of variance decomposition to further calculate risk connectedness and the main equation is:

$$C^H = \frac{\sum_{i,j=1, j\neq i}^{N} \widetilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ji}^g(H)} = \frac{\sum_{i,j=1, j\neq i}^{N} \widetilde{\theta}_{ji}^g(H)}{N}$$

Volatility Connectedness Estimation with Lasso

I conduct the connectedness assessment on an estimated VAR approximating model. Due to the high-dimension property of the data, I need the VAR to be estimable in high dimensions, somehow recovering degrees of freedom. People can do so by pure shrinkage (as with ridge regression) or pure selection (as with traditional criteria like AIC, BIC or SC). However, combining shrinkage and selection with variants of the LASSO is particularly crucial.

$$\widetilde{\beta} = \arg\min_{\beta}\left[\sum_{t=1}^{T}\left(y_t - \sum_{i}\beta_i x_{it}\right)^2 + \lambda\sum_{i=1}^{K}|\beta_i|^q\right]$$

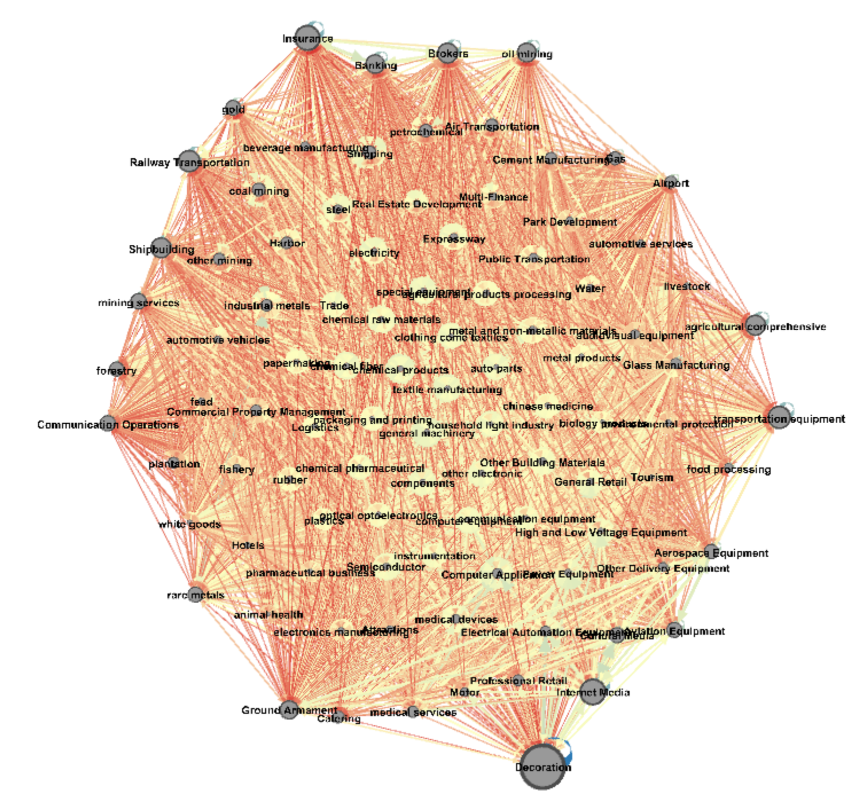
Network Model

The issue of how to display results takes on great importance in high-dimensional network analysis. In our subsequent work, I will construct a network connectedness model with 97 nodes, but presenting and examining 97 × 97 = 9409 estimated pairwise variance decompositions would be thoroughly uninformative. Therefore, I characterize the estimated network graphically using five instruments: side color, node size, node color, node location and link arrow sizes.

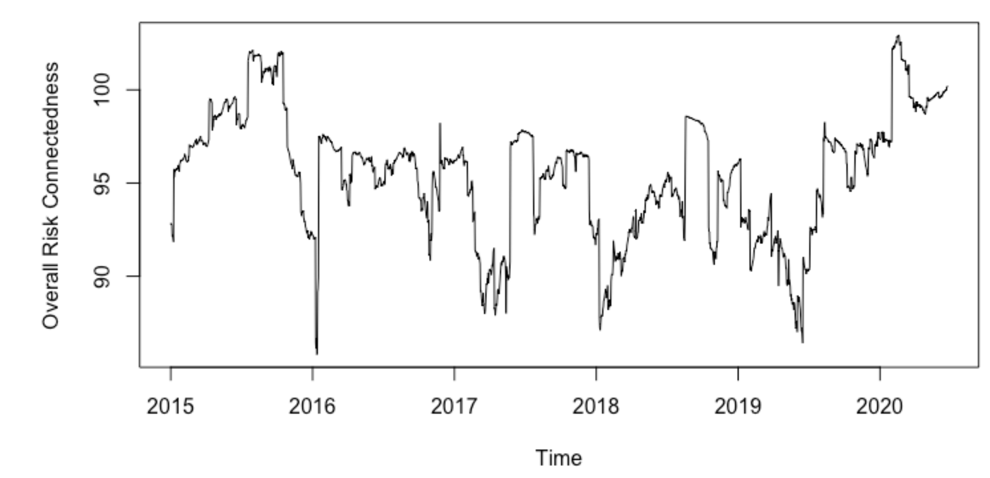
Results

Static Analysis

The clustering feature can help us explore the potential transmission chains between industries. Generally, the clustering feature will become more obvious as the relationship among industries becomes closer, thus leading to stronger risk transmission. The result shows that the clustering characteristics of many industries in similar business areas and close correlation are obvious.



Dynamic Analysis



I estimate the overall risk connectedness through *equation 6*, which is also called the systematic risk. To calculate the systematic risk, I choose 60 days as the rolling sample period and get the total volatility connectedness, which continuously changes with time. Then, I show the time series plot and decompose it to get the tendency.

Two peaks are obvious, in August, 2015 and February, 2020, which correspond to the stock disaster in China and the outbreak of Covid-19. I can conclude that the emergence of crisis boosts the risk connectedness effects.

Conclusions

We have used LASSO methods to shrink, select, and estimate the high-dimensional network linking the SWS secondary industry index, 2010–2020. We characterized static network connectedness using full-sample estimation and dynamic network connectedness using rolling-window estimation. Statically, we found that industries in the same industry chain and industries which have close relationship with each other have shown remarkable clustering features. In addition, oil exploitation, finance, insurance, brokerage and railway transportation exert the most significant influence on others. Dynamically, we found that risk connectedness increases during crises, with clear peaks during the Vovid-2019 and the stock crash in China.

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