The impact of commodity market volatility on China's stock market

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Abstract. The article examines individual industry data series on the Chinese stock market and international commodity markets based on the application of the method of decomposition of generalized variance of forecast errors to build a secondary volatility index and overflow network. The DCC-GARCH model proposed by the author is used to study the effect of hedging wholesale goods on the Chinese stock market. The results show that in every industry in China, industry and consumer industry are the main risk-taking market, and the energy industry and financial industry are the main export risk market.

Keywords: International commodity price · Stock market · Spillover index · Risk hedging.

1. Introduction

Many international investors include commodities into their portfolios, so it is also very necessary for cross market investors to grasp the correlation between the commodity market and China's stock market. At present, facing a complex global economic situation, ongoing trade friction between China and the US, Brexit and COVID-19, and so on, all of these have an impact on the world economy. In this context, it will be necessary to deeply analyze the impact of international commodity price fluctuations on China's stock market, accurately measure the volatility spillover between the international commodity market (Grobys, 2015) and China's stock market, systematically study the volatility spillover mechanism between the two markets and the risk hedging effect of different commodities, which will be helpful for the formulation and implementation of China's risk control policies, investors' decision-making and the smooth operation of economy and society.

Volatility spillover is an important part of portfolio allocation, portfolio strategy and hedging strategy design between assets (Diebold and Yilmaz, 2014; Kang et al., 2016; Mensi, 2016; Syriopoulos et al., 2015). Although the dynamic conditional correlation coefficient multivariate GARCH model (dcc-garch) proposed in (Engel, 2002) overcomes the defects of more parameter estimation and the trend of asset return correlation coefficient changing with time, and can better investigate the time variability of spillover, it cannot get a good description of the spillover direction, spillover contribution and net spillover effect of a single market. Based on the VAR model (Diebold and Yilmaz, 2009) created the DY spillover index model to analyze the spillover effect between stock markets in different countries. In most of the current research on volatility spillovers, the commonly

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used method is the measurement method of overall and directional volatility spillovers under the framework of generalized vector autoregression (Diebold and Yilmaz, 2012).

After understanding the risk spillover mechanism, an important problem is how to use the information about spillover effect to improve the hedging effectiveness in portfolio management activities (Kang et al., 2019). The financialization of commodities reduces the risks of stocks, bonds and portfolios (Batten et al., 2015; Khalfaoui et al., 2015). Many scholars focus on the spillover effect between oil market and stock market. (Kang et. al, 2021) incorporated oil, gold and other uncertainties into American industry exchange traded funds (ETFs) and found that oil is the most effective hedging tool for ETFs in each industry in both short and long term (Hernandez et al., 2021). (Wen et al., 2021) found that the hedging ability of most commodities decreased significantly when the crisis occurred, and NMFI (precious metals) and CRFI (grain) still had good hedging ability (Alizadeh et al., 2002).

For that reason, this paper uses the generalized prediction error variance decomposition method, combined with the spillover index method (Diebold and Yilmaz, 2012) to measure the Risk Spillover in China's stock market and international commodity market.

2. Materials and method

2.1 Calculation of volatility spillover index

When analyzing the spillover effects of various industries in China's stock market and international commodities, this paper combines the generalized vector autoregression (GVAR) method and the spillover index method (Dielbold and Yilmaz, 2012) to obtain the variance decomposition matrix. This method realizes the calculation of total spillover index, directional spillover index and net spillover index. The specific construction process of the model is as follows:

Firstly, a vector autoregressive model VAR (P) with p-order lag is established for N variables:

$$X_{\mathrm{t}} = \sum_{\mathrm{i}=1}^{P} \Phi_i X_{t-i} + \varepsilon_t \quad \varepsilon_{\mathrm{t}} \sim N(0,\Sigma) \tag{1}$$

where, X_{t} is the N-dimensional endogenous explanatory variable vector, Φ_{i} is the N*N autoregressive coefficient matrix, ε_{t} is the disturbance vector of independent and identically distributed, and obeys the normal distribution with parameters of 0 and Σ .The moving average form corresponding to the above vector autoregressive model is:

$$X_{\mathrm{t}} = \sum_{i=0}^{\infty} \Psi_{\mathrm{i}} \varepsilon_{t-\mathrm{i}} \tag{2}$$

In the above formula, Ψ_{i} is a matrix of N*N units. When i<0, Ψ_{i} =0 ; i>0, $\Psi_{\mathrm{i}} = \Phi_1 \Psi_{\mathrm{t}-1} + \Phi_2 \Psi_{\mathrm{t}-2} + \ldots + \Phi_{\mathrm{p}} \Psi_{i-\mathrm{p}}$. Then, the variance decomposition of generalized prediction error is carried out. Under the framework of GVAR model, the variance of H-Step prediction error of variable pair X_{j} to X_{i} is:

$$\omega_{\mathrm{ij}}^{H}=\frac{\sigma_{\mathrm{jj}}^{-1}\sum_{\mathrm{h}=0}^{H-1}\left(e_i^{'}\Psi_h\sum_{\varepsilon}e_j\right)^2}{\sum_{h=0}^{H-1}\left(e^{'}\Psi_h\sum_{\varepsilon}\Psi_h^{'}e_i\right)}, \quad i,j=1,2......N \tag{3}$$

where, $\sum_{\varepsilon}$ represents the variance matrix of the error term ε_{t}, σ_{jj} is the standard deviation of the prediction error of the j-th variable, e_i, e_j is the selection vector, indicating that the i (j) element is 1, and the other elements are column vectors of 0.

In the generalized VAR model, volatility shocks are not necessarily orthogonal, so the sum of each row element in the variance decomposition table is not equal to 1. In order to facilitate analysis, each element of ω_{ij}^{H} will be standardized according to the sum of each line, and the spillover effect of X_j to X_i after standardized treatment is:

$$\widetilde{\omega}_{ij}^{H}=\frac{\omega_{ij}^{H}}{\sum_{j=1}^{N}\omega_{ij}^{H}} \tag{4}$$

In the above formula, $\sum_{j=1}^{N}\widetilde{\omega}_{ij}^{H}=1$, $\sum_{i,j=1}^{N}\widetilde{\omega}_{ij}^{H}=N$ 。

Formula can construct total spillover index S^H,directional spillover index $S_{N,i\to\bullet}^{H}$ and $S_{N,i\leftarrow\bullet}^{H}$,net spillover index $S_{N,i}^{H}$ and net spillover index between the two markets S_{ij}^{H} .

$$S^H=\frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\widetilde{\omega}_{ij}^{H}}{N}*100 \tag{5}$$

$$S_{N,i\to\bullet}^{H}=\frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\widetilde{\omega}_{ij}^{H}}{N}*100 \tag{6}$$

$$S_{N,i\leftarrow\bullet}^{H}=\frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\widetilde{\omega}_{ij}^{H}}{N}*100 \tag{7}$$

$$S_{N,i}^{H}=S_{N,i\to\bullet}^{H}-S_{N,i\leftarrow\bullet}^{H} \tag{8}$$

$$S_{ij}^{H}=\left(\frac{\widetilde{\omega}_{ij}^{H}}{\sum_{n=1}^{N}\widetilde{\omega}_{in}^{H}}-\frac{\widetilde{\omega}_{ji}^{H}}{\sum_{n=1}^{N}\widetilde{\omega}_{jn}^{H}}\right)*100 \tag{9}$$

Net spillover index $S_{N,i}^{H}$ is the net directional volatility spillover from market i to all other markets. If the net spillover index of a market is positive, it indicates that the market is the net spillover of risk.

On the contrary, the market is the net input of risk, which is more vulnerable to the influence of other markets and more sensitive to information. The spillover index S_{ij}^{H} between two markets represents the net spillover between different markets i and j, which is defined as the difference between the directional spillover effect of market j to market i and the directional spillover effect of market i to market j; If the net spillover value is positive, it means that the Risk Spillover intensity of market j to market i is greater; otherwise, it means that the Risk Spillover intensity of market i to market j is greater.

3.2. Hedging and optimization of portfolio

In practice, it is necessary to make a preliminary and accurate estimation of the time covariance matrix to formulate the optimal portfolio according to the risk management and portfolio allocation decision criteria. In this paper, DCC-GARCH model is used to study the dynamic correlation between various industries in the stock market and commodities, so investors can make the best portfolio decision by constructing a dynamic risk minimization hedge ratio. Based on this, this paper quantifies the optimal portfolio weight and hedging ratio to design the optimal hedging strategy.

Firstly, assuming that investors hold short futures of Q_{ES} long positions in spot and Q_F short positions, the returns of spot and futures are expressed as R_t^{ES} and R_t^{F} respectively at time t, and the hedging ratio β_t represents the ratio of the position of hedged assets to the position of hedged assets. Then the return R_t^{H} of holding the portfolio of spot (ES) and Futures (F) positions can be expressed as:

$$R_t^H = \frac{Q_{ES} S_t \times R_t^{ES} - Q_F S_t \times R_t^F}{Q_{ES} S_t} = R_t^{ES} - \beta_t R_t^F \tag{10}$$

When T-1, the variance of the yield of the portfolio held by investors is:

$$Var\left(R_t^H I_{t-1}\right) = Var\left(R_t^{ES} I_{t-1}\right) - 2\beta_t \operatorname{cov}\left(R_t^F R_t^{ES} I_{t-1}\right) + \beta_t^2 Var\left(R_t^F I_{t-1}\right) \tag{11}$$

Based on this, the hedging ratio with the minimum variance is taken as the optimal hedging ratio. The smaller the variance of the portfolio, the more effective the hedging strategy is. Then the derivation result β_t of the above formula is as follows:

$$\beta_t^* I_{t-1} = \frac{\operatorname{cov}\left(R_t^{ES} R_t^F | I_{t-1}\right)}{Var\left(R_t^F | I_{t-1}\right)} \tag{12}$$

According to the method of Kroner and Sultan (1993) to quantify the hedging ratio, the conditional volatility obtained by GARCH model can be used to construct the hedging ratio. Measure the hedging degree of long position (buy) of 1 unit by short position (sell) of the β_t unit in the futures market; namely:

$$\beta_t^* = \frac{h_t^{F,ES}}{h_t^F} \tag{13}$$

β_t^* is the optimal hedging ratio, which is defined as that when holding a long spot position of a unit, it should hold a short futures position of the unit β_t^* at the same time to hedge the risk. If investors hold spot investment positions and try to hedge their adverse effects with commodity futures (F), follow Kroner and Ng (1998) to define the portfolio weight of spot (ES) in the investor's portfolio as:

$$w^{ES} = \frac{h_t^F - h_t^{F,ES}}{h_t^F - 2h_t^{F,ES} + h_t^{ES}}, w_t^{ES} = \begin{cases} 0, w_t^{ES} < 1 \\ w_t^{ES}, 0 \le w_t^{ES} \le 1 \\ 1, w_t^{ES} > 1 \end{cases} \tag{14}$$

In the above formula, h_t^F, h_t^{ES} and $h_t^{F,ES}$ are the conditional volatility of the futures investment market at time t, the conditional volatility of the spot market and the conditional covariance between the futures market and the spot market respectively, and all the information required for calculating the weight can be obtained from the DCC-GARCH model. By comparing the realized hedging errors, the hedging effectiveness of the constructed portfolio can be evaluated, which is defined as:

$$HE = 1 - \frac{Var_{hedged}}{Var_{unhedged}} \tag{15}$$

Among them, the variance Var_{hedged} of the hedged portfolio is the variance of the return of the weighted portfolio holding both spot (ES) and Futures (F), while the variance of the sum of the unhedged portfolio represents the variance Var_{hedged} of the return of the benchmark portfolio. A higher HE ratio means that adopting this kind of portfolio will reduce the variance of the portfolio and improve the hedging efficiency. Therefore, it means that the corresponding portfolio strategy is a superior hedging strategy.

3. Results and discussion

When studying the risk spillover mechanism of domestic financial market, the transaction date and transaction time are consistent. However, when studying the systemic risk between international financial markets, we will encounter the problems of inconsistent transaction dates in different countries and asynchronous transaction time caused by time difference, which will make the income series asynchronous. In order to solve the problem of inconsistency, this paper preprocesses the collected data and uses the weekly rate of return data instead of the daily rate of return to synchronize the income series.

According to (Alizadeh et al., 2002; Diebold and Yilmaz, 2009), it is assumed that volatility is fixed in a certain period (such as a week) and variable in different periods. Therefore, this paper uses the weekly highest price, weekly lowest price, weekly opening price and weekly closing price to calculate the weekly yield of various industries in China's stock market and international bulk commodities, and estimates the weekly yield volatility. The specific calculation method is as follows:

$$\begin{aligned} \tilde{\sigma}^2 = {} & 0.511(H_t - L_t)^2 - 0.019\left[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)\right] \\ & -0.383(C_t - O_t)^2 \end{aligned} \tag{16}$$

In the above formula, H_t is the highest price from Monday to Friday, L_t the lowest price from Monday to Friday, O_t is the opening price on Monday and C_t is the closing price on Friday. All the above are taken as natural logarithms.

An analysis on the yield series of eleven industry index materials of China's stock market and six selected international commodity indexes.

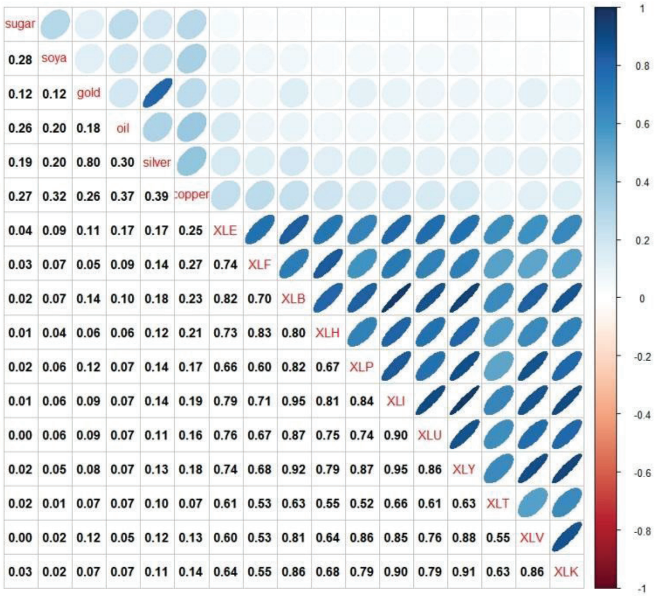

Fig. 1. thermodynamic diagram of correlation.

The results obtained are shown in Figure 1, and the correlation between the two is presented in the form of thermodynamic diagram. Eleven industries are: materials (XLB), utilities (XLU), industry (XLI), telecommunications services (XLT), energy (XLE), information technology (XLK), optional consumption (XLY), Finance (XLF), real estate (XLH), daily consumption (XLP) and health care (XLV); Six international commodity futures are: CBOT (soya), Comex (gold), Comex (silver), ICE 11 (sugar), LME (copper) and NYMEX (oil).

Figure 1 shows the visual correlation matrix between different asset return series. The color intensity of the shadow box indicates the size of the correlation. Blue is positive correlation and red is negative correlation. The results of Figure 1 show that the correlation coefficients between the return series of various industries in China's stock market selected in this paper are greater than 0 and greater than 0.5, indicating that there is a medium to strong positive correlation between various industries in China's stock market.

4. Conclusion

Based on the GVAR model, this article builds a general secondary index, a directional secondary effect index, a net secondary effect index and a net secondary effect index between two markets in accordance with the Diebold and Yilmaz secondary index method (2012) and measures the secondary risk of the Chinese stock market and the international commodity market from static and dynamic perspectives, Analyze the mechanism secondary distribution of risks; On this basis, the DCC-GARCH model and the risk hedging model are used to analyze the risk hedging of various industries in the Chinese stock market with six international commodities. The main conclusions of this document can be summarized in the following four aspects:

1) The secondary risk index of industrial and optional consumer industries in the Chinese stock market is relatively high, which is more vulnerable to fluctuations in the international commodity market and is the main secondary risk industry

2) The side effects of volatility between different industries in the Chinese stock market and the international commodity market are asymmetric.

3) In general, the Chinese stock market and the international commodity market show a strong dynamic side effect and have significant time variability. The overall dynamic index of secondary effects ranges from 60% to 95%.

4) The correlation coefficient between international commodity futures and 11 industries in the Chinese stock market as a whole is relatively small, so it is a more suitable risk hedging tool.

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