[Time-varying co-movements between energy-related stock market and low-carbon economy in China]

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Overview

Early studies on the relationship between energy stock prices and stock market mainly concentrated on advanced economies, while the emerging stock markets, particularly China, are seldom involved. One of the criticisms of previous studies is that majority of works have not examined the existence of structure breaks of the variables. To fill these gaps, a novel time-varying parameter vector autoregressive model with stochastic volatility (TVP-VAR-SV) is employed to evaluate the dynamics relationships among between stock prices of fossil fuel prices, new energy and technology stock prices, and low carbon economy in China. This paper contributes to the current literature by considering the structural changes and the volatility of the shocks. The results show that the new energy index correlate more highly with technology stock prices than with fossil fuel prices. Increasing coal and oil prices could cause a surge in the stock prices of new energy and high technology due to new energy is the substitution of fossil fuel. Moreover, the development of low-carbon economic could promote the improvement of low-carbon technologies and create a stimulus for the switch to clean energy from fossil fuels in the long term.

Keywords:New energy index; high technology index; fossil fuel index; Low-carbon economy; TVP-VAR-SV model

Methods

According to (Nakajima, 2011a; Nakajima, 2011b; Primiceri, 2005), the TVP-VAR model is constructed form the standard VAR model while it allows the parameters to change over time. The extended TVP-VAR model with stochastic volatility is employed to capture possible structure changes of stock markets. A basic structural VAR model is defined as follows.

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + u_t, t = s+1, \ldots, n \quad (1)$$

Where y_t is a $k \times 1$ vector of observed variables; $A, F_1, \ldots, F_s$ denote $k \times k$ matrices of coefficients; the disturbance u_t is a $k \times 1$ structural shock which follows a normal distribution. We set $u_t \sim N(0, \Sigma\Sigma)$ and A is lower-triangular to study the relationship of the structural shock by recursive identification. Thus, we rewrite the Eq. (1) as follows:

$$y_t = \mathrm{B}_1 y_{t-1} + \cdots + \mathrm{B}_s y_{t-s} + A^{-1}\Sigma\varepsilon_t, \varepsilon_t \sim N(0, I_k) \quad (2)$$

Where $B_i = A^{-1}F_i$ for $i = 1, \ldots, s$ (s is the number of the lag phase of y_t). Then, Eq. (2) can be written as follows:

$$y_t = X_t\beta + A^{-1}\Sigma\varepsilon_t \quad (3)$$

With β is a ($k^2 s \times 1$) vector obtained by stacking the elements in the rows of the $B_i^{'}s$ and $X_t = I_s \otimes (y'_{t-1}, \ldots, y'_{t-s})$.

It can be observed that all the coefficients in Eq. (3) are invariable, suggesting the coefficients change over time. Furthermore, we extend the TVP-VAR model with stochastic volatility to consider the heteroscedasticity. The TVP-VAR-SV model is given by:

$$y_t = X_t\beta_t + A_t^{-1}\Sigma_t\varepsilon_t, t = s+1, \ldots, n. \quad (4)$$

Where the coefficients β_t, and the parameters A_t, and $\sum_t$ are all time varying. There would be many ways to model the process for these time-varying parameters. We define a_t a stacked vector of the lower-triangular elements in A_t and $h_t = (h_{1t}, \ldots, h_{kt})'$ where $h_{kt} = \log\sigma_{jt}^2$, for $j = 1, \ldots, k, t = s+1, \ldots, n$. Following (Primiceri, 2005), we assume that the parameters in (6) follow a random walk process:

$$\begin{cases} \beta_{t+1} = \beta_t + \mu_{\beta t} \\ \alpha_{t+1} = \alpha_t + \mu_{\alpha t} \\ h_{t+1} = h_t + \mu_{ht} \end{cases} \quad (7)$$

$$\begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right) \quad (8)$$

Where $t = s+1, \ldots, n$, $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0}), \alpha_{s+1} \sim N(\mu_{\alpha_0}, \Sigma_{\alpha_0})$ and $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$. The shocks to the innovations of the time-varying parameters are assumed uncorrelated among the parameters β_t, α_t and h_t. We further assume that Σ_β, Σ_α and Σ_h is all diagonal matrices. The drifting coefficients and parameters are modeled to fully capture possible changes of the VAR structure over time.

Results

(1) The new energy index and the high technology index have the highest volatility and new energy index exhibits largest swing. Because China's new energy sector is still a fledgling industry and the level of new energy technology is low in the early stages.
(2) The responses of new energy stock prices and technology stock prices to low carbon economy shock are increasing throughout the response horizons. The results indicate that the development of low-carbon economic could promote the improvement of low-carbon technologies and create a stimulus for the switch to clean energy from fossil fuels in the long term.
(3) The effects of new energy price on stock prices of low carbon economic and high technology are positive in most cases and time-varying. However, the effect of new energy prices shock on coal and oil index is negative but related small in most situations. It shows that the new energy index correlate more highly with technology stock prices than with fossil fuel prices
(4) The responses of the new energy price and low carbon economic index to the high technology shock show a similar tendency while vary in the different ways over time. High technology index shock has a positive and persistent impact on promoting the development of new energy and low carbon economic index.
(5) High technology prices shock has a positive influence on the coal and oil index in most years, however, this influence becomes negative in 2016 and close to zero since 2017.

Conclusions

(1) The development of low-carbon economic could promote the improvement of low-carbon technologies and create a stimulus for the switch to clean energy from fossil fuels in the long term.

(2) The new energy index correlate more highly with technology stock prices than with fossil fuel prices. While, the energy technology could promote the efficient and clean utilization of coal resources.
(3) Increasing coal and oil prices could cause a surge in the stock prices of new energy and high technology. Because the new energy sources are regarded as the substitution of fossil fuel. Moreover, the high fossil fuel prices could promote energy technology innovation(Cheon and Urpelainen, 2012) and foster the development of the green economy (Reboredo, 2015).

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