

[IS THE GLOBAL CARBON MARKET INTEGRATED? RETURN AND VOLATILITY CONNECTEDNESS IN ETS SYSTEMS]

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Overview

Carbon pricing is one of the policies through which policy makers claim to be able to achieve their objectives. In 2020, there were 25 regional emission trading schemes (ETS) developed, 9 under development, and 12 under consideration internationally (ICAP, 2020). Emission trading is gaining momentum with its increasing market size and constantly improving information transmission mechanisms. With carbon assets becoming prominent as an alternative asset in investment portfolios, the ETS model has engaged a broad range of market participants, including not only emissions-intensive energy corporations but also individual and institutional investors. Trades between developing and developed emission markets increase the ties. As arbitrage opportunities arise, price fluctuations are likely to occur, which typically have a mutual spillover effect (Liu and Gong, 2020). This paper examines the relations between carbon prices to help better understand the link between cross-border carbon markets.

Existing studies devoted to these impacts are not conclusive. With respect to empirical investigation on carbon market integration, previous studies have involved the price, return, and volatility dynamics between separate markets. For instance: carbon price dynamics between identical instruments trading on different exchanges (Benz and Hengelbrock, 2008; Mazza and Petitjean, 2015), carbon spot and future prices on the same exchange (Arouri et al., 2012; Liu et al., 2021), EU emission allowances and Certified Emission Reductions prices integration (Mansanet Bataller et al., 2010; Nazifi, 2010, 2013; Sadefo Kamdem et al., 2016). However, less attention has been paid to the connectedness of carbon markets of various countries. The paper most closely related to our work is Mizrach (2012), which investigates co-integration between European and US carbon prices. However, our paper takes the analysis one step further and studies how fluctuations in these markets interact with each other, among carbon prices across four jurisdictions – European Union, New Zealand, California, and Hubei (China) ETS.

To this extent, we investigate return and volatility connectedness between carbon prices across four jurisdictions – Guangdong Province (China), European Union, California, and New Zealand. The relevance of our study is threefold: (1) Understanding the return and volatility spillovers between these markets enables institutional and individual investors to manage risk more effectively and make more prudent asset allocation decisions. (2) Given that return and volatility spillover effects are considered as necessary characteristics of market integration (Ciarreta and Zarraga, 2015; Han et al., 2020), analysing these impacts is also necessary for assessing the efficiency of existing market linkages and the possibility for future integration through the ETS. (3) Furthermore, as we are interested in the relationship between short- and long-term market events and the variation in spillover effects between these markets, examining such dynamic volatility interconnection among carbon markets is a prerequisite for correlating volatility connectedness to specific market characteristics, events, and regulatory policy.

Methods

This paper follows the approach of Antonakakis et al. (2020). The object here is to provide a flexible framework for the estimation and interpretation of time variation in the systematic and non-systematic parts of carbon markets and their effects on the rest of the markets. The TVP-VARs are state space models and one of the advantages is that statistical methods for state space models (based on the Kalman filter) are available. To describe the dynamics of volatility spillovers, the baseline TVP-VAR model is set as follows:

$$y_t = Z_{t-1}A_t + \epsilon_t, \quad \epsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t), \quad (1)$$

$$vec(A_t) = vec(A_{t-1}) + \xi_t, \quad \xi_t | \Omega_{t-1} \sim N(0, \Xi_t), \quad (2)$$

$$\text{where } Z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix}, \text{ and } A_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \vdots \\ A_{pt} \end{pmatrix}.$$

In the above models, p is the lag order, t is the sample length of the model, and $t = p + 1, p + 2, \dots, T$. Ω_{t-1} represents all information available until $T = t-1$. y_t is an $N \times 1$ vector containing observations on N time series variables. Z_{t-1} represents $N \times p$ matrix. A_t are $N \times Np$ dimensional coefficient matrices while A_{it} are $N \times N$ matrices. ϵ_t and Σ_t are $N \times 1$ and $N \times N$ matrix, respectively. In equation (2), $vec(A_t)$ is the vectorisation of A_t

which is an $N \times Np$ dimensional vector. The ξ_t is an $N^2p \times 1$ dimensional vector. Moreover, Ξ_t are $N^2p \times N^2p$ time-varying variance-covariance matrices; ϵ_t and ξ_s are independent of one another for all s and t . The equation (2), which models the evolution of A_t can be interpreted as a hierarchical prior for A_t . The time-varying coefficients and error covariances are used to estimate the generalised connectedness procedure of Diebold and Yilmaz's spillover index. As mentioned above, this procedure is based on generalised impulse response functions (GIRF) and generalised forecast error variance decompositions (GFEVD) first developed by Koop et al. (1996) and Pesaran and Shin (1998).

To match the traditional variance decomposition, we normalize each element of the generalized variance decomposition matrix by the row sums as follows:

$$\tilde{\phi}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \theta_{ij,t}^2}{\sum_{j=1}^N \sum_{t=1}^{J-1} \theta_{ij,t}^2}, \quad (3)$$

with $\sum_{j=1}^m \tilde{\phi}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^m \tilde{\phi}_{ij,t}(J) = N$. The denominator represents the cumulative effect of all the shocks, while the numerator illustrates the cumulative effect of a shock in variable i . Using the GFEVD, we construct **the total connectedness index** by below:

$$C_t(J) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij,t}(J)}{\sum_{i,j=1}^N \tilde{\phi}_{ij,t}(J)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\phi}_{ij,t}(J)}{N} \times 100, \quad (4)$$

Results (preliminary)

Our results of return and volatility TCI are relatively lower than those of the other commodity market TCIs. Among studies regarding carbon, energy, and financial market connectedness, Ji et al. (2018) concludes 39.47% (30.52) return (volatility) TCI between carbon and energy markets, while system Tan et al. (2020) shows 42.26% (34.82) total return (volatility) spillover index in Carbon-Energy-Finance. Studies regarding other commodity markets' connectedness conclude 24.58% return connectedness across beverage, fertilizers, food, metals, precious metal, raw materials and oil market (Zhang and Broadstock, 2020), 53.71% among four crude oil markets globally (Liu and Gong, 2020); and 12.5% across U.S. stock, bond, foreign exchange, and commodities markets (Diebold and Yilmaz, 2012). In the agricultural market connectedness, Umar et al. (2021) reports 18.5% (27.6%) return (volatility) TCI of the dominant agricultural markets, and in another study Umar et al. (2021) shows 31.2% (17.7%) return (volatility) connectedness in fifteen selected agricultural markets and oil price stocks.

Conclusions

This paper studies the connectedness among four Emission Trading Schemes: the EU ETS, New Zealand ETS, California's Cap-and-Trade, and Hubei (China) ETS, from 2014 to 2021. The EU ETS, CA CaT, and China's ETS are the world's three largest ETS systems. New Zealand's ETS (NZ ETS) is unique in that it once permitted unrestricted use of Kyoto credits, exposing it to global carbon price fluctuations. The sample period examined in our study covered a wide range of events, for example, the stock market plunge in 2015, global climate change negotiations/conferences, carbon market regulatory changes, and the Covid-19 outburst. Given the effects of increasing clean technology adoption, improving emission market efficiency, and the organic growth of linkages between ETS systems, the spillover effects among our four variables may change throughout our sample period. In this regard, this paper employs a time-varying parameter (TVP)-VAR methodology to measure the connectedness across the four above ETS, following Antonakakis et al. (2020). This method extends Diebold and Yilmaz's (2009, 2012) connectedness approaches by improving the rolling-window VAR, and further allows us to examine patterns of the average, directional, and net total return (volatility) spillover effects among the four ETS schemes. The following conclusions can be drawn from the empirical results:

- The average return (volatility) TCI is 10.42% (12.10%), which indicates that the global carbon prices are largely (albeit not completely) dependent.
- Changes in global climate change politics and carbon market reforms have minor impact, whereas occurrence of energy and financial crises have greater effect on TCIs, both in return and volatility networks.
- EU ETS has a persistent net-transmitting role, it is the largest and only transmitter (2.14%) in return connectedness system while CA CaT is the largest transmitter in the volatility connectedness system (1.35%). CA CaT and EU ETS share several similarities in resilience.
- NZ ETS is the largest shock receiver in both the return (-0.93%) and volatility (-2.76%) connectedness systems.
- It was observed that the spillover patterns *From* and *To* HB ETS have hardly been impacted by the Covid-19 outbreak, unlike the other three markets. A likely explanation is that the Covid-19 policies in China are unique in terms of strictly locking down, and closing the boarder for other countries, the carbon market movement can hardly be impacted by the markets in other countries.