Renewable and Sustainable Energy Reviews 191 (2024) 114102

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Integration of the international carbon market: A time-varying analysis

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ARTICLE INFO

Keywords:
Carbon markets integration
Volatility connectedness
TVP-VAR
Market risk
Emission trading scheme
Spillover effects

ABSTRACT

Emission Trading Schemes (ETSs) have become vital for meeting global emission reduction targets. They are gaining momentum, as witnessed by increasing market size and improving information mechanisms. Examining key emission markets — European Union, New Zealand, California, and Hubei (China) — from April 2014 to December 2021, a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model is applied to discern the markets' connectedness. In a novel approach to global carbon market research, this study uniquely combines the TVP-VAR with the connectedness approach, overcoming fixed parameters estimation and ensuring precise parameter estimates. The approach sheds light on patterns of total, directional, and net return/volatility spillovers, striving to identify which markets act as transmitters and which are receivers. Linking market spillovers to market characteristics, events, and policies offers insights for investors and policymakers. The total connectedness index of 10–12 % suggests a relatively low level of spillover, when compared to other market integration studies. The dynamic nature of return and volatility spillovers is evident, especially during the energy crisis and Covid-19 outbreak. The EU's ETS consistently acts as a net transmitter, predominantly in return connectedness, while New Zealand's ETS emerges as a major shock receiver in both return and volatility systems. Global climate negotiations and carbon market events have only a minor impact on the level of connectedness, in contrast to energy or financial crises and the Covid-19 outbreak. By highlighting the intricacies of carbon price volatility and market transmissions, the findings equip stakeholders with invaluable, actionable insights.

1. Introduction

The Paris Agreement's objective is to keep global warming to 1.5° Celsius above pre-industrial levels [1]. However, the UNEP [2] finds that the world is heading for a temperature rise in excess of 3 °C by the end of this century. To reduce this gap, numerous major energy consumers and CO_2 emitters committed to reaching carbon neutrality by the mid-21st century [3,4]. Many public and private sector organizations have committed to purchase electricity from renewable sources, adopt cleaner technologies, improve efficiency, and conserve water and other resources. However, they often need to supplement those efforts by purchasing carbon offsets or allowances [5].

In this regard, the Emissions Trading System (ETS) emerges as a quintessential policy instrument. An ETS incentivizes climate action by allowing entities to exchange emission allowances created by the reduction or removal of greenhouse gases (GHGs) from the atmosphere, such as through switching from fossil fuels to renewable energy or by increasing or conserving carbon stocks in ecosystems via afforestation [5,6]. The ETS is gaining momentum with its increasing market size and constantly improving information transmission mechanisms [6]. In 2022, there were 25 regional ETSs in operation, 9 under development, and 12 under consideration [6]. While existing literature has made attempts to explore spillover effects of price volatilities across carbon markets, the focus has been predominantly on the relationship between the European Union's market and Clean Development Mechanism markets, as well as the interactions among China's regional pilot markets [7–9]. Such studies paid limited attention to the connectedness of cross-border carbon markets. Hence, it is worth exploring whether there are spillover effects, which make the prices of international carbon markets co-move.

This study investigates the markets' connectedness, focusing on prominent ETSs, namely those of the European Union (EU ETS), California (CA-CaT), Hubei-China (HB-ETS), and New Zealand (NZ-ETS). The EU ETS, CA CaT, and China ETSs are the world's three largest such systems [6,10–12]. NZ ETS is unique in that it once permitted

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https://doi.org/10.1016/j.rser.2023.114102
Received 13 July 2022; Received in revised form 1 November 2023; Accepted 13 November 2023

Nomenclature

Abbreviations

ADF	Augmented Dickey–Fuller test
CA CaT	California's Cap and Trade
CCA	California Carbon Allowances
CER(s)	Certified Emission Reductions
ETS	Emission Trading Scheme
EUA	European Union Allowance
EU ETS	European Union Emission Trading Scheme
FEVD	Forecast error variance decompositions
GARCH	Generalized autoregressive conditional heteroskedasticity
GFEVD	Generalized forecast error variance decompositions
GHG	Greenhouse gases
GIRF	Generalized impulse response functions
HB ETS	Hubei (China) Emission Trading Scheme
HBEA	Hubei emission allowances
NZ ETS	New Zealand Emission Trading Scheme
RGGI	Regional Greenhouse Gas Initiative
TCI	Total connectedness index
TVP-VAR	Time-Varying Parameters Vector Autoregressive model

Symbols

%	Percentage

Units

MtCO2e	Metric tons of carbon dioxide equivalent
KtCO2e	Kilotonnes of carbon dioxide equivalent

unrestricted use of Kyoto credits, exposing it to global carbon price fluctuations while the other ETSs predominantly relate to localized emissions. These four markets are used to analyse global carbon market integration. This research examines the carbon price interactions and its dynamic drivers among different cross-border ETS markets regarding returns and volatility spillovers. It relies on a time-varying parameter (TVP)-VAR methodology. This study specifically examines patterns of the total, directional, and net return/volatility spillover effects among the four ETSs. The novelty of this research is underscored by its analytical framework that probes the interconnectedness of cross-border carbon markets. The study aims to investigate if international carbon markets are integrated and, if so, if and which (informational) spillover effects exist. The hypothesis posits the existence of spillover effects, potentially inducing synchronized fluctuations in the international carbon markets. The identification of market dynamics, specifically the determinants of these co-movements, is pivotal. If such effects exist, it is relevant to establish which market is driving the others.

To the best of our knowledge, this is the first study to utilize the TVP-VAR model combined with the connectedness approach in the context of global carbon market research. This innovative method not only facilitates a deeper exploration of the dynamics of total spillovers but also provides an acute understanding of the intricacies of cross-market connectedness. This approach helps identify aggregated and directional return and volatility connectedness, which differentiate which ETS markets are net transmitters, and which are net receivers.

Building on this foundation, our study contributes richly to both the academic and practical dimensions of the emission trading. Recognizing and appreciating the pivotal role of return and volatility spillover effect in market integration [13,14], this research offers an assessment of market linkages, enhancing our understanding of their efficiency. The study also delves into understanding the return and volatility spillovers between the markets, providing investors with valuable insights to manage risk more effectively and make informed asset allocation decisions. This examination of dynamic volatility interconnections within carbon markets links volatility trends to specific market characteristics, events, and policies. Notably, the expansive timeframe provides a unique vantage point to evaluate the impact of events like the Covid-19 pandemic. Furthermore, the study provides critical information for investors who are interested in periods with significant carbon price volatility and prices' transmission effect across different carbon markets. This is of great interest to different stakeholders and provides practical implications.

The remainder of the study is organized as follows: Section 2 reviews the background of the chosen ETS markets. Section 3 illustrates the state-of-the-art literature review. Section 4 presents the methodology to estimate the return and volatility spillover effects among different regional ETSs. Section 5 describes the data and sample period. Section 6 reports and discusses the empirical results. Section 7 is a robustness analysis. Section 8 concludes and provides policy implications.

2. Background

An ETS addresses the heterogeneity in marginal abatement costs of individual firms and plants, and provides the possibility of connecting national schemes [15,16]. A long-term goal for developing an ETS is to initiate an integrated market with comparable pricing across jurisdictions [17]. Potential benefits for market integration are likely to be substantial, including the support of international cooperation on climate change and the ability to better absorb price shocks [15,17–19].

The world's first cap-and-trade systems were introduced in the United States to curb air emissions [20,21]. The EU built its own ETS, EU ETS, in 2005 [22]. The EU ETS has become the world's first international ETS, covering 31 countries and 11,500 installations, and is considered as the prototype system for other ETSs [20]. California's cap-and-trade system has been operational since 2013 and has gradually expanded to regulate about 85 % of the state's total emissions. It expresses interest in linking its cap-and-trade system with those in other sub-national and national jurisdictions [23]. New Zealand's ETS, launched in 2008, has a distinctive profile due to an economy dominated by the agriculture sector, responsible for almost 50 % of New Zealand's GHG emissions. The NZ ETS used to be bilaterally linked to other international ETSs, meaning that the Kyoto units could be used for compliance in NZ ETS. However, after several changes of domestic market regulation, the New Zealand government introduced bans on various international carbon credits to strengthen the credibility of the NZ ETS. These changes began in January 2012, and subsequently the government withdrew the NZ ETS from the second commitment period of the Kyoto protocol in December 2013 [24]. As a young startup, the Chinese ETS developed at a fast pace. With nine regional ETS pilots running parallel to a national ETS, the Chinese system is surpassing the EU ETS in market size. The Chinese ETS covers 4500 MtCO2e, while the EU ETS covers 1597 MtCO2e [6]. The pilot ETSs either allow cross-market linkage or the use of external offset credit for compliance, hence induced potential risk transmission [25]. It is worth mentioning that pilot ETSs in China, such as Shanghai ETS (started from 2013.11.26), Shenzhen ETS (started from 2013.06.18), and Beijing ETS (started from 2013.12.28) have longer trading history. In 2013, when they started trading, breakpoints and missing data were observed due to the illiquidity and low trading volume, which impacted data quality. Additionally, the Shanghai, Shenzhen, and Beijing systems are city-wide ETSs; we argue that Hubei ETS, as a provincial ETS, is more comparable to the other markets in our study.

ETS markets have gradually developed into a significant component of the global financial system and provide it with investable carbon assets [26,27]. With the carbon assets becoming prominent as an alternative asset class in investment portfolios, the ETS market has engaged a broad range of participants, including not only emissions-intensive energy corporations but also investors. Enterprises in specific markets may have to bear a cost caused by non-local shocks, namely, spillover effects [28]. These effects, often prompted by arbitrage opportunities, can lead to price fluctuations. Such fluctuations, once initiated, are prone to reverberate across other markets [29]. Despite these observable dynamics, a comprehensive elucidation of the intricate interplays among these systems, especially on an international scale, remains conspicuously absent in the existing literature. The relationship between emerging and mature carbon markets is crucial for global environmental market integration and liberalization [28].

3. Review of the carbon market literature

The introduction of carbon markets has resulted in the emergence of a new class of investors who want to have financial exposure to GHGs [30,31]. There is rising interest in the risk management of carbon assets, which can be utilized for a variety of investment objectives, including portfolio diversification, arbitrage, hedging, and speculation [30,32, 33]. Liu et al. [31] study the mean and volatility spillovers by non-linear methods of Granger causality, showing there is a bidirectional spillover effect between European Union Allowance (EUA) spot and future prices for Phase II and III of the EU ETS. Arouri et al. [30] suggest that shocks to EUA spot markets have a greater influence on both spot and future market returns than shocks to the futures market. With respect to the empirical investigation of spillover effects among ETSs, previous studies have examined the price, return, and volatility dynamics among different markets — for example, carbon price dynamics between identical instruments trading on different exchanges [34,35], carbon spot and future prices on the same exchange [30,31], and EUA and Certified Emission Reductions (CERs) price integration [8,36–39]. In addition, much of the research up to now has studied the relationship between ETSs and other macroeconomic variables or energy markets [40–42].

The literature pays limited attention to the connectedness across major ETS systems around the world. In a pioneering study, Mizrach [43] finds that prices across exchanges in Europe are cointegrated, and the U.S. carbon market is Granger causing the EU market. However, this study predominantly focuses on the relationship between the earlier U.S. Regional Greenhouse Gas Initiative (RGGI) market and the EU ETS, employing static cointegration and causality tests. With the rapid evolution of carbon markets over the past decade – marked by changes in market mechanisms, improved liquidity, an expanded range of covered sectors, and the initiation of markets in developing economies – our research builds upon Mizrach's foundation. We not only extend the sample to include markets from China and New Zealand but also incorporate the U.S. California market, thereby significantly enriching the dataset. We have improved the static methodology to a time-varying estimation approach. In a related vein, Wang et al. [44] investigate the time-varying correlation and long-run price cointegration between the EUA price and Beijing ETS pilot in China from 2013 to 2020. Zeng et al. [8] analyse the dynamic volatility spillover effect between the EUA and CER from 2008 to 2017. They find the EUA market has a more significant volatility spillover effect on the CER market. Zhao et al. [7] examine the interaction among China's pilot ETSs.

Most of these studies mentioned so far primarily adopt static time-series econometrics (cointegration tests, Granger causality, vector autoregressive models, error correction models, and/or multivariate GARCH models) to examine spillover effects among carbon markets [24, 37,43], and [45]. However, standard vector autoregressive type models work under the assumption of fixed parameter, while the GARCH models impose parameter restrictions that can be violated by the estimated coefficients, making it challenging to interpret whether shocks to conditional variance are persistent [46].

Yet, past studies have struggled to analyse spillover effects, especially regarding their direction and time-dependent characteristics. Addressing this, Diebold and Yilmaz [47,48] establish a connectedness framework for analysing both idiosyncratic and extrinsic effects based on the estimation of the forecast error variance decompositions (FEVD) from a VAR model. Serving as a valuable tool in determining system connectedness, it essentially offers an indirect measure of the system risk, capturing the directionality of spillover effects. This approach has been subsequently applied across various sectors, such as electricity markets [14,49,50], crude oil markets [29], gas market volatility [51], and energy company stock returns and volatility [52–54].

Building upon this foundation, Antonakakis et al. [55] enhanced the Diebold and Yilmaz connectedness by proposing a non-parametric TVP-VAR estimation based on the connectedness framework. This method allows the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factor. Kalman filter approaches are fast because state space models encapsulate the Markov property and reduce to a set of recursions [55–57]. This innovative approach effectively examines systematic spillover dynamics. As such, the current research employs the TVP-VAR connectedness to analyse spillovers in various domains including cross-border or cross-region commodity markets [58], stock markets [59], cryptocurrency markets [60], and energy markets [61–63].

In line with the methodology of Antonakakis et al. [55], this study utilizes TVP-VAR connectedness to estimate the total, the directional, and the time-varying characteristics of spillovers among major carbon markets. Recent trends, including the effects of energy efficiency improvements, the evolution of carbon market mechanisms, and the increasing recognition of the scarcity of natural resources, lead to changing relationships among key variables. Taking stock of these dynamics, this research posits that the TVP-VAR base connectedness, as suggested by Antonakakis et al. [55], aligns more aptly with our designated subjects of study. Therefore, the main purpose of our study is to empirically examine the interdependency among global carbon markets. By leveraging the TVP-VAR model, this study successfully circumvents the constraints typical of the standard VAR-based connectedness, yielding more precise parameter estimates. This TVP-VAR-based connectedness approach has the following advantages: (i) it is insensitive to outliers due to the underlying Kalman filter, (ii) there is no need to arbitrarily choose the rolling-window size, (iii) no loss of observations, and (iv) it can be used for low frequency datasets [55,56]. However, the drawback of TVP-VAR is that it cannot accommodate the fat-tail feature of returns documented in financial markets [64,65]. Another limitation of our study is that we did not utilize the asymmetric TVP-VAR connectedness model proposed by Adekoya et al. [66]. The asymmetric TVP-VAR connectedness applied by Adekoya et al. [66] can identify three types of spillovers: normal, positive, and negative, offering a nuanced understanding of spillover dynamics, which might have provided additional insights in our research context.

While our paper is related to Refs. [7,8,45–47], it differs in several aspects. First, this study focuses on the time-varying measure of spillovers along the lines of [47], which is robust to outliers and does not require an arbitrary choice of the rolling window size. Second, while [8,45] predominantly focus on the relationship between two ETSs, this study considers various cross-border ETSs in the spillover indices. As such, this study analyses the net shocks transmitter or receiver within the system of the four various assets and extends our limited understanding of the nature and extent of the transmission of return and volatility shocks in light of the catastrophic event of the COVID-19 outbreak.

This study elaborates on the TVP-VAR connectedness empirical literature, as the aim is to provide a more flexible framework to analyse the time-variation in carbon markets. The next section details the research design.

4. Methodology

4.1. Overview

The TVP-VARs are state space models for which statistical methods based on the Kalman filter are available. To describe the dynamics of volatility spillovers, the baseline TVP-VAR model is as follows:

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

$$vec(\mathrm{A}_t) = vec(\mathrm{A}_{t-1}) + \xi_t, \xi_t|\Omega_{t-1} \sim N(0, \Xi_t), \tag{2}$$

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

In the models, p is the lag order, t is the sample length of the model, and $t = p+1, p+2, \ldots, T$. Ω_{t-1} represents all information available until $T = t-1$. y_t is an $N\times1$ 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 $N\times1$ and $N\times N$ matrix, respectively. In Equation (2), $vec(\mathrm{A}_t)$ is the vectorisation of A_t which is an $N \times Np$ dimensional vector. The ξ_t is an $\mathrm{N}^2p\times1$ dimensional vector. Moreover, Ξ_t are $\mathrm{N}^2p \times \mathrm{N}^2p$ time-varying variance-covariance matrices; ϵ_t and ξ_s are independent of one another for all s and t. Equation (2), which models the evolution of A_t, can be interpreted as a hierarchical prior for A_t. In our empirical model, we employed a first-order VAR model with a lag of 1, as informed by the Schwarz Information Criterion (SIC). However, we recognize that the choice of lags is crucial and can potentially affect the results, particularly in terms of model fit, parameter stability, and impulse response functions (IRFs). An inappropriate lag length might lead to issues of spurious regression, capturing noise rather than dynamics, or underfitting, overlooking important dynamics in the data. To address potential concerns regarding lag selection, we also explored other common information criteria for robustness checks. Specifically, while the main text adhered to the SIC-recommended lag of 1, the robustness analysis uses lags 1, 2, and 3, with the latter being selected by the Akaike Information Criterion (AIC) (see Fig. 10).

4.2. Estimation of TVP-VAR using forgetting factors

To estimate the TVP-VAR model, this study uses the Primiceri [67] and Del Negro and Primiceri [68] prior, following Antonakakis et al. [55]. The mean and the variance of A_0 are chosen to be the OLS point estimates ($\widehat{A}_{OLS}$) and its variance Σ^A_{OLS} in a time invariant VAR. Thus, the $\widehat{A}_{OLS}$, Σ^A_{OLS}, andΣ_{OLS} are equal to the VAR estimation results of the initial subsample (first year): $A_0 \sim \mathrm{N}(\widehat{A}_{OLS}, \Sigma^A_{OLS})$, and $\Sigma_0 = \Sigma_{OLS}$. Let $y^s = (y_1, \ldots y_s)'$ denote observations through time s. In this context filtering refers to inference on A_t through combining of the information contained in a single observation y from Equation (1) with prior information on A_t expressed through a prior distribution $p(A_t)$. This study considers the benchmark values (for example, for quarterly data, $\lambda = 0.99$ implies observations five years ago receive approximately 80 % as much weight as last period's observation [56]) for forgetting factor, $\lambda = 0.99$, and decay factor, $\kappa = 0.96$, and keeping them constant at fixed values. Koop and Korobilis [56] found that the value added by time-varying decay factors with respect to the forecasting performance was questionable and increased the computation burden of the Kalman filter algorithm, thus this study follows Antonakakis et al. [55] to keep the decay factors constant at fixed values.

4.3. TVP-VAR-based dynamic connectedness approach

The time-varying coefficients and error covariances are used to estimate the generalized connectedness procedure of Diebold and Yilmaz's spillover index. This procedure is based on generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) first developed by Koop et al. [64] and Pesaran and Shin [65]. The important step to calculate the GIRF and GFEVD is to transform the VAR to its moving average representation:

$$y_t = \sum_{j=0}^{\infty} \Upsilon_{j,t}\epsilon_{t-j}, \tag{3}$$

where $\Upsilon_{0,t} = I$, and $\Upsilon_{i,t} = A_{1,t}\Upsilon_{i-1,t} + A_{2,t}\Upsilon_{i-2,t} + \ldots + A_{p,t}\Upsilon_{i-p,t}$.

Where $\Upsilon_t = [\Upsilon_{1,t}, \Upsilon_{2,t}, \Upsilon_{3,t}, \ldots, \Upsilon_{p,t}]'$ and $A_t = [A_{1,t}, A_{2,t}, A_{3,t}, \ldots, A_{p,t}]'$. Both the $A_{i,t}$ and $\Upsilon_{i,t}$ are $\mathrm{N} \times \mathrm{N}$ dimensional matrices. The GIRFs represent the responses of all variables j, following a shock in variable i. Let $\Theta_{ij,t}(J)$ denote the J-step-ahead forecast error variances decompositions at time t. Each of the elements in the matrix can be obtained by the following formula:

$$\Theta_{j,t}(J) = \frac{\Upsilon_{J,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}}\frac{\varsigma_{j,t}}{\sqrt{\Sigma_{jj,t}}} = \Sigma_{jj,t}^{-\frac{1}{2}}\Upsilon_{J,t}\Sigma_t e_j, \varsigma_{j,t} = \sqrt{\Sigma_{jj,t}}, \tag{4}$$

where e_j is an $N\times1$ selection vector with unity in the jth position, and zero otherwise. $\Sigma_{jj,t}$ is the standard deviation of the error term of the ith equation, also the jth diagonal element in $\Sigma_{u,t}$ (same as Σ_t). The GFEVD represents the pairwise directional connectedness from j to i and illustrates the influence variable j has on variable i in terms of its forecast error variance share. Normalizing each element of the generalized variance decomposition matrix by the row sums as follows:

$$\widetilde{\varphi}_{ij,t}(J) = \frac{\Sigma_{t=1}^{J-1}{\Theta_{ij,t}}^2}{\Sigma_{j=1}^{N}\Sigma_{t=1}^{J-1}{\Theta_{ij,t}}^2}, \tag{5}$$

with $\Sigma_{j=1}^{N}\widetilde{\varphi}_{ij,t}(J) = 1$ and $\Sigma_{i,j=1}^{N}\widetilde{\varphi}_{ij,t}(J) = N$. 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, this study constructs the total connectedness index (TCI) by Equation (6):

$$C_t(J) = \frac{\Sigma_{\mathrm{i,j=1,i\neq j}}^{N}\widetilde{\varphi}_{ij,t}(J)}{N} \times 100, \tag{6}$$

This connectedness approach shows how a shock in one variable spills over to other variables. When variable i transmits its shock to all other variables j, this is called total directional connectedness to others ($C_{i\rightarrow j,t}(J)$) and it is defined as:

$$C_{i\rightarrow j,t}(J) = \frac{\Sigma_{\mathrm{j=1,i\neq j}}^{N}\widetilde{\varphi}_{ji,t}(J)}{\Sigma_{\mathrm{j=1}}^{N}\widetilde{\varphi}_{ji,t}(J)} \times 100. \tag{7}$$

The directional connectedness variable i received from variables j, total directional connectedness from others ($C_{i\leftarrow j,t}(J)$), can be defined as Equation (8):

$$C_{i\leftarrow j,t}(J) = \frac{\Sigma_{\mathrm{j=1,i\neq j}}^{N}\widetilde{\varphi}_{ij,t}(J)}{\Sigma_{\mathrm{i=1}}^{N}\widetilde{\varphi}_{ij,t}(J)} \times 100. \tag{8}$$

This research subtracts total directional connectedness to others from total directional connectedness from others to obtain the net total directional connectedness ($C_{ij,t}$):

$$C_{ij,t} = C_{i\rightarrow j,t}(J) - C_{i\leftarrow j,t}(J). \tag{9}$$

The sign of the net total directional connectedness illustrates whether variable i is driving the network ($C_{i,t} > 0$) or is driven by the network ($C_{i,t} < 0$).

5. Data

To study the regional carbon markets' co-movement and integration, this analysis uses carbon prices from four emission markets — CA CaT, EU ETS, HB ETS, and NZ ETS. This analysis concludes that Thomson Reuters, Wind Database, and Bloomberg provide the carbon prices for the four ETSs with the longest time periods. Daily spot prices for NZ ETS and EU ETS are sourced through Bloomberg and Reuters. Prices of Hubei emission allowance (HBEA) are found from Wind Database. Daily prices of CA CaT that traded on the ICE Future Exchange US are collected from California Carbon Info (https://www.californiacarbon.info/). The sample period covers the period April 30, 2014 through December 1, 2021. All prices used in this study are quoted in Euro. Table 1 summarizes the main features of four ETSs. It shows that EU ETS and CA CaT are the largest markets in scale, and HB ETS is smallest and has the lowest carbon price.

This study uses the spot price of the European emission allowances (EUAs) since EUA contracts are the major carbon product traded under EU ETS ([39,44,69]). NZ ETS trades in emission allowances known as New Zealand Units (NZUs), which can be held and sold by secondary market traders and auctions. The California Carbon Allowances (CCA) product represents a carbon emission equivalent in CA CaT, which is traded on the ICE Futures Exchange, US. Furthermore, this study chooses the spot price of HBEA as a representative of regional carbon price in China instead of other pilot ETSs, for these reasons: i) HB ETS regulates emission trading for a province whose economy is heavily based on secondary industries and coal; ii) Hubei's overall energy structure reflects China's as a whole country, hence it is deemed representative for the entire economy; iii) along with corporate and institutional investors, HB ETS attracted a substantial number of individual investors to the trading, with individual investors' daily trading volume accounting for over 30 % of total turnover; and iv) HB ETS is the largest pilot ETS in China in terms of trading volume, continuity, social capital invested, and incorporated firm participation.

Weekly returns are calculated as the change in log price, from Friday-to-Friday. The continuously compounded returns of four sets are computed as $r_{i,j,t} = (lnP_{i,j} - lnP_{i,j-1})$, for market i, in week t. This study uses the realized (historical) volatility as proxy of volatility. This research obtains daily closing prices for the four markets; high frequency/intraday data are not available for CA CaT and HB ETS. By using the weekly highest, lowest, open, and close prices, this research calculates the realized/historical volatility. To be consistent with the frequency of the historical volatility, this study uses weekly returns. Three measures have been applied to estimate weekly volatility of the carbon price. Garman and Klass [70] and Parkinson [71] volatility measures are used as alternative proxies of volatility in the robustness analysis. Descriptive statistics of three volatilities are shown in Table 5. The main measure is the standard deviation of weekly return over the five-day interval during each week:

$$\widetilde{SD}_t = \sqrt{\frac{\sum_{i=1}^{M}\left(r_{ij,t} - \overline{r}_t\right)^2}{M-1}}, \tag{10}$$

where $\widetilde{SD}_t$ measures the market volatility on week t, $r_{i,j,t}$ is the jth daily return in week t, for market i; and M is the number of trading days (in most cases M = 5). The corresponding estimate of the annualized weekly volatility in percentage is $\widehat{SD}_t = 100\sqrt{52}\widetilde{SD}_t$. According to the calculations, the sample size is 397 observations for each series. The results in Section 5 are generated with the measure in Equation (10). The empirical results based on the Garman and Klass [70] and Parkinson [71] volatility can be found in Figs. 8 and 9 in Section 7 "Robustness". Figs. 1 and 2 plot the weekly return and realized weekly volatility for the four markets during the sample period. These figures show that all ETSs except HB ETS have high volatility after March 2020 (when Covid-19 hit). HB ETS had a lockdown from February 10 to March 20, 2020. Therefore, the movement of HB ETS during this period is not informative. Both the return and volatility in the NZ ETS in 2014 and 2015 are high after the withdrawal from the Kyoto Protocol. The descriptive statistics of the return and volatility series are in Table 2. Here, panel A shows that the means of all returns are positive, implying rising prices (see Fig. 1).

While the mean return on the HB ETS is positive but close to zero, the price of the HBEA remained rather stable, with the most significant t-statistics from the stationarity (ADF) test. Several facts emerge in the analysis of volatility (Panel B): 1) The EU ETS has the highest mean, min, and max return volatility of the four series; sharply rising prices and the EU's rapidly shifting carbon reduction policies might be identified as contributors to this high level of volatility. 2) The HB ETS has the second highest volatility. As a newly built pilot market which started trading in 2014, HB ETS has a flawed market structure, due to the lack of legislation through the provincial legislature in place. Thus high volatility is expected in such an emerging market [73]. 3) CA CaT volatilities increased simultaneously from mid-2021 to the end of the sample period, indicating a shift in the pattern of spillover effect from or to CA CaT in the post-Covid-19 period.

Table 1
Market architecture – differences among four ETSs.

	EU ETS	NZ ETS	CA CaT	HB ETS
Start	2005	2008	2012	2014
Cap	1579 $MtCO_{2e}$	34.5 $MtCO_2e$	307.5 $MtCO_2e$	166 $MtCO_2e$
Market threshold	25 $ktCO_2e$	low	25 $ktCO_2e$	10 $MtCO_2e$
Average price	54.76 Euro	30.91 Euro	20.65 Euro	4.92 Euro
Total revenue	31 billion Euro	1.9 billion Euro	16.78 billion Euro	42 million Euro
Covered emissions	39 %	49 %	85 %	45 %
Entities	9628	2475	500	373
GHGs covered	CO_2, N_2O, PFC_s	$CO_2, CH_4, N_2O, SF_6, HFC_s, PFC_s$	$CO_2, CH_4, N_2O, SF_6, HFC_s, PFC_s, NF_3$, *other GHG*	CO_2

Source: Own elaboration based on information and data from Emission Trading Worldwide: Status Report, by International Carbon Action Partnership, 2022. Note: The market threshold of NZ ETS is not clear; the report by International Carbon Action Partnership presents it as "low."

6. Results

This section reports the results of empirical analysis by the method presented in Section 4. The results are generated with the first measure (i.e., $\widetilde{SD}_t$, from Equation (10)). The empirical results measured by the other two volatilities can be found in Section 7 "Robustness" (or are available upon request to the authors). Section 6.1 presents the total connectedness index (TCI), which measures the influence of one market on all others on average (see Equation (6)). Sections 6.2 and 6.3 show the total directional connectedness, which reflects the spillover relationship between one market and all other markets, including total directional connectedness to others ($C_{i\to j,t}(J)$ in Equation (7)) and total directional connectedness from others ($C_{i\leftarrow j,t}(J)$ in Equation (8)), and net total directional connectedness from others ($C_{ij,t}$ in Equation (9)).

6.1. Dynamic total connectedness index

In the following empirical model, this analysis uses first-order VARs (p = 1) (selected by Schwarz information criterion), with 10-step-ahead forecasts (H = 10). A different choice of forecasting horizon, H from 2 to 9, is assessed in the robustness analysis (see Fig. 11). Following most of the literature [74], this study uses a 10-step-ahead horizon in the main text. This research defines that if this TCI rises, so does network member

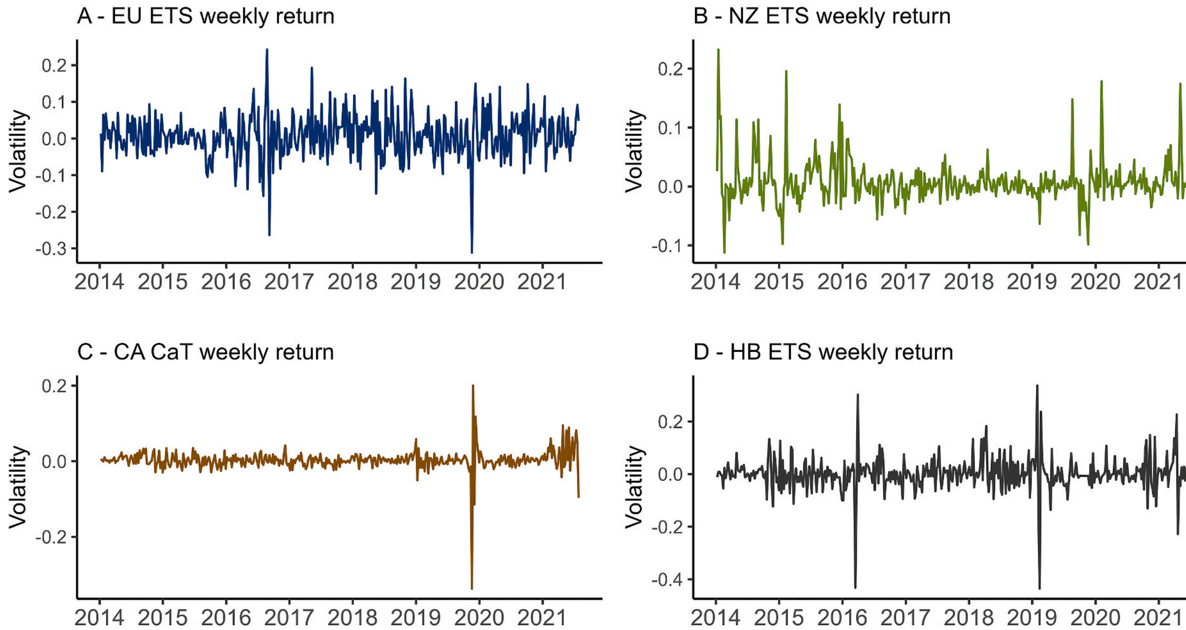

Fig. 1. Weekly return from four ETSs.
Source: Own elaboration based on data from Bloomberg, Reuters, and Wind Database. Reported are the weekly log-return series, range from April 30, 2014 to December 1, 2021.

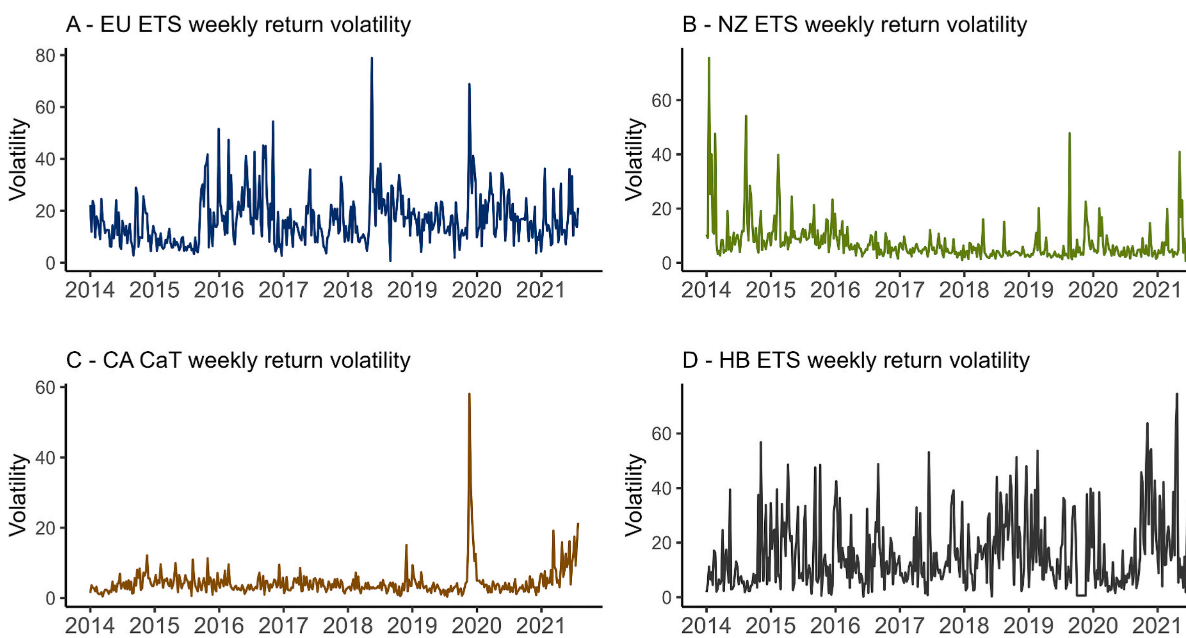

Fig. 2. Weekly realized (annualized) volatility from four ETSs.
Source: Own elaboration based on data from Bloomberg, Reuters, and Wind Database. Reported are the weekly volatility series, range from April 30, 2014 to December 1, 2021.

dependency, and therefore market risk. Alternatively, if TCI decreases the dependence between the members decreases and hence market risk. Table 3 presents the averaged connectedness measures for the markets. The main diagonal of Table 3 shows own-variance shares of shocks, while the off-diagonal elements reflect the interaction across global ETSs. The number in the bottom right corner represents TCI of the system. For example, the EU ETS in the return connectedness analysis (see Table 3 Panel A) has received a total of 11.01 % shocks from three other markets: 2.88 % from NZ ETS, 4.98 % from CA CaT, and 3.15 % from HB ETS, respectively. EU ETS spilled in total 13.16 % to the three markets: 3.46 % to NZ ETS, 5.16 % to CA CaT, and 4.54 % to HB ETS. The average return (volatility) TCI is 10.42 % (12.10 %). A total spillover of no more than 10.42 % (12.10 %) indicates that internal cross-contribution due to individual shocks is not a major driver of future performance across four ETSs. Both dynamics of each of the carbon markets are mainly explained by themselves and not due to spillovers from other markets, which indicates that the global carbon prices are largely (albeit not completely) dependent on themselves. In other words, the degree of systemic risk among emission allowance markets is not high.

Our results of carbon market return and volatility TCI are lower than those of the other commodity market TCIs, because this study concentrates on carbon markets as such where others connect carbon with

Table 2
Descriptive statistics for the carbon price return and volatility.

	Mean	Min	Max	St.dev.	Skew.	Kurt.	ADF
Panel A: Return							
EU ETS	0.007	−0.312	0.243	0.060	−0.312	5.996	−14.37***
NZ ETS	0.008	−0.112	0.232	0.036	1.944	12.041	−10.27***
CA CaT	0.003	−0.326	0.202	0.028	−3.064	59.992	−12.74***
HB ETS	0.001	−0.437	0.342	0.063	−0.764	17.080	−18.74***
Panel B: Volatility							
	Mean	Min	Max	St.dev.	Skew.	Kurt.	ADF
EU ETS	16.734	1.368	78.881	10.081	1.782	8.622	−4.07***
NZ ETS	7.167	0.690	75.503	7.474	4.350	29.793	−5.74***
CA CaT	4.842	0.819	57.247	5.266	5.718	46.145	−4.09***
HB ETS	15.604	0.002	56.364	12.531	1.098	3.557	−5.45***

Source: Own elaboration based on data from Bloomberg, Reuters, and Wind Database. Note: Sample including carbon prices series from EU ETS, NZ ETS, CA CaT, and HB ETS from April 30, 2014, to December 1, 2021. The hypothesis of the Augmented Dicky Fuller (ADF) test is H0: non-stationary against H1: stationary. The lag length is determined by BIC criterion. *** denotes significance at 1 % level [72].

Table 3
Average connectedness matrix of the system.

	EU ETS	NZ ETS	CA CaT	HB ETS	From Others
Panel A: Return connectedness (%)					
EU ETS	88.99	2.88	4.98	3.15	11.01
NZ ETS	3.46	92.03	2.72	1.79	7.97
CA CaT	5.16	2.63	87.59	4.62	12.41
HB ETS	4.54	1.53	4.22	89.70	10.30
To others	13.16	7.04	11.93	9.57	41.70
Net total	2.14	−0.93	−0.48	−0.73	TCI = 10.42
	EU ETS	**NZ ETS**	**CA CaT**	**HB ETS**	**From Others**
Panel B: Volatility connectedness (%)					
EU ETS	89.40	2.95	5.71	1.94	10.60
NZ ETS	3.72	86.03	7.36	2.89	13.97
CA CaT	5.36	5.75	84.69	4.21	15.31
HB ETS	2.38	2.51	3.60	91.50	8.50
To others	11.46	11.21	16.67	9.04	48.38
Net total	0.86	−2.76	1.36	0.54	TCI = 12.10

other assets. For example, Ji et al. [75] conclude a 39.47 % (30.52) return (volatility) TCI between carbon and energy markets. Tan et al. [41] find 42.26 % (34.82) total return (volatility) TCI. Studies regarding other commodity markets' connectedness conclude 24.58 % return connectedness across beverage, fertilizers, food, metals, precious metals, raw materials, and oil market [76], and 53.71 % among four crude oil markets globally [29]. In the agricultural market connectedness, Umar et al. [58] report 18.5 % (27.6 %) return (volatility) TCI of the dominant agricultural markets.

Source: This spillover table is generated based on 10-step-ahead generalized VAR forecast error variance decomposition. The ij^{th} entry estimates the fraction of 10-step-ahead error variance in forecasting market i due to exogenous shocks to market j (the spillover from market j to market i: d_{ij}^{J}).

As the objective of this study is to investigate the behaviour of return and volatility spillovers over time, this study moves beyond the aggregated spillovers for the full sample. This research demonstrates the TCI's dynamic evolution over time, which is particularly relevant for examining the TCI's response to major changes in carbon market regulation, economic and energy events, occurrence of extreme weather conditions, and disasters like the Covid-19 pandemic. The dynamic total return and total volatility connectedness are plotted in Figs. 3 and 4 respectively. They show that the overall degree of return (volatility) total average connectedness/effects of spillover ranges from 3 % (2 %) to 35.74 % (35.69 %) across the sample period. The literature suggests that the driving factors of the supply and demand in an ETS are: (i) economic

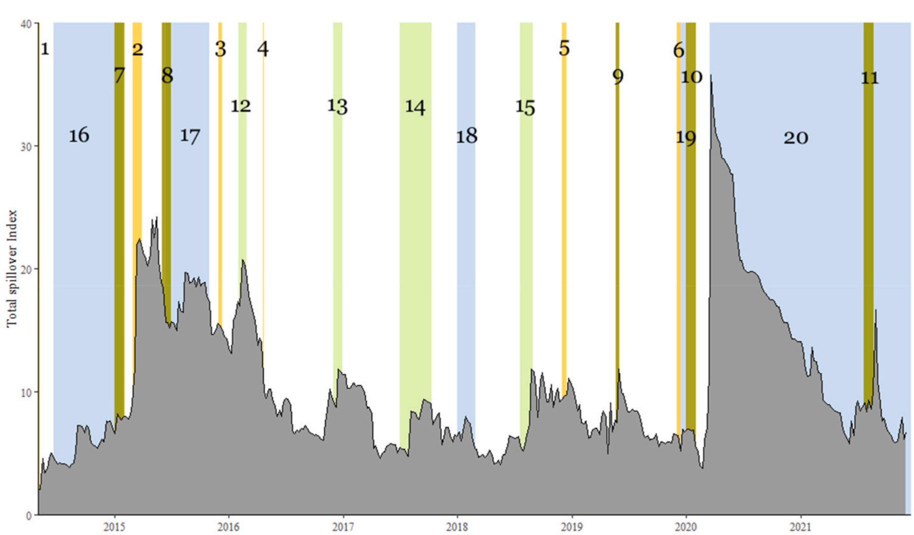

Fig. 3. Dynamic total return connectedness
Note: Fig. 3 plots the dynamics of spillover index (measured by TCI). X axis shows our sample period, 2014–2021. Y axis shows the TCI in the network (numbers in y axis are in percentages). Shaded areas with numbers refer to Table 4.

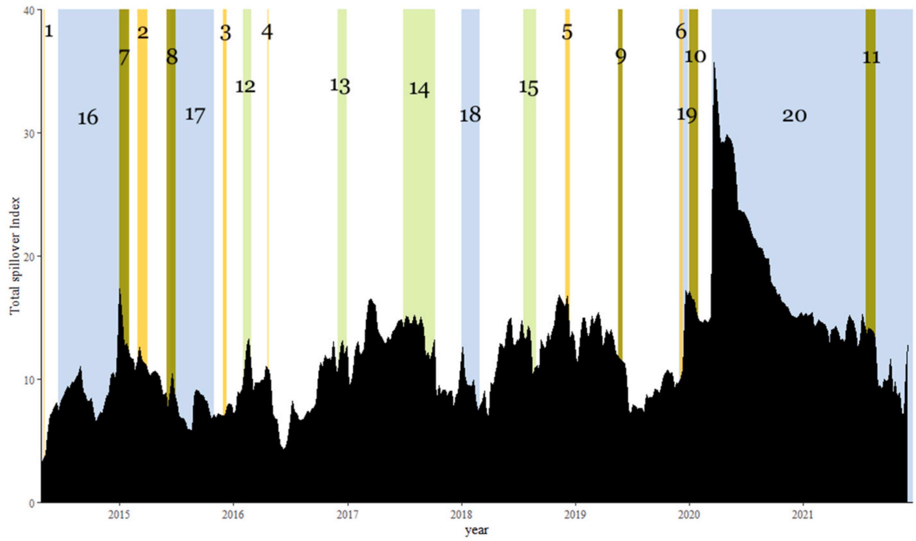

Fig. 4. Dynamic total volatility connectedness
Note: Fig. 4 plots the dynamics of spillover index (measured by TCI). X axis shows our sample period, 2014–2021. Y axis shows the TCI in the network (numbers in y axis are in percentages). Shaded areas with numbers refer to Table 4.

growth and government constraints; (ii) international climate change agreements; (iii) regulatory change and arbitrageurs; and (iv) market fundamentals, such as energy prices and weather [45,77,78]. Therefore, this study focuses on events related to (i) global politics, (ii) carbon market linkage/delinked changes, (iii) temperature and weather, and (iv) public health crises — e.g., Covid-19. Periods with a high degree of connectivity corresponding to the events in Table 4 connect to the event number and are shaded in Figs. 3 and 4.

Fig. 3 shows that the dynamic connectedness of return network changes considerably over time, especially from 2015 to mid-2016 and following the Covid-19 outbreak, which suggests that the spillovers across carbon markets are time-dependent. The first peak occurred in March 2015 (return spillovers jumped instantly, rising from 9.07 % to 21.88 %), when the Chinese government shut down the last coal-fired power facilities in inner Beijing as part of a national trend to close over 2000 coal-fired power facilities by 2015 (Event 2). Coal power plants were the most important participants in Hubei carbon markets. Changes in TCI indicate that phasing them out impacts China's carbon markets, which in turn affects international carbon markets, given China's dominant role in global carbon emissions. The second peak is associated with Event 17, the global stock market selloff in the second half of 2015. Notably, the stock market crashes initially began in China, resulting in abnormal fluctuations in the world's economies. The return TCI went up to the second peak and remained at around 19 %. The third peak of return TCI occurs along with Event 12, when the Global Land-Ocean Temperature Index surged from January to February 2016 (NASA recorded that the average global surface temperature in February 2016 was 1.35C warmer than the average for the month between 1951 and 1980). Fourth, and highest, connectedness is associated with the Covid-19 outburst and sparking fears of the lockdown policies all over the world (Event 20). During March 2020, the return spillovers jumped from 7.09 % to 35.74 %, and global carbon market spillovers reached their highest so far.

Notably, three moderate intensifications in the return connectedness start from December 2016, July 2017, and August 2018 respectively, coinciding with several extreme weather events (Events 13, 14, and 15). Elevated concerns about global warming and decarbonisation led the TCI to respond. Two other carbon markets events (Events 9 and 11) caused small spikes in the index. In June 2019, the HB ETS experienced a huge price spike, causing volatility in its return series (see Fig. 1, Panel D). A reasonable explanation is that the compliance period of China's pilot ETS is in June, and the price of the Hubei carbon market surged due

Table 4
Chronology of events for high connectedness.

Year	No.	Event	Date	Category
2014	1	G7 Energy Ministers Summit, Rome	2014.05.05	global politics
2015	2	China coal power plant closure	2015.03.01–31	global politics
2015	3	COP21- Paris agreement	2015.11.30–12.12	global politics
2016	4	High-level UN debate on achieving the SDGs + Paris Agreement open for signature	2016.04.21–22	global politics
2018	5	COP24	2018.12.2–14	global politics
2019	6	COP25	2019-12.2-13	global politics
2015	7	Korea built ETS	2015.01.01–02.01	carbon market
2015	8	New Zealand delinked	2015.06.01–07.01	carbon market
2019	9	Hubei carbon price spike	2019.05.20–06.03	carbon market
2020	10	Swiss ETS linked to EU ETS	2020.01.01–02.01	carbon market
2021	11	China national ETS operation	2021.07.21–08.21	carbon market
2016	12	Big jump occurred in Global Land-Ocean Temperature Index	2016.02.01–28	weather
2016	13	Worst air pollution episode in China, schools and factories ordered shut, 200 flights cancelled	2016.12.01–30	weather
2017	14	Yangtze River flooding; Hurricanes Harvey, Irma, and Maria	2017.06.30–10.01	weather
2018	15	Multiple deadly heat waves hit East Asia + Monsoon flood in India where Kerala state reported 500 deaths	2018.07.20–08.30	weather
2014	16	Oil price crisis	2014.06–2015.01	energy
2015	17	Stock market selloff (initially began in China)	2015.06.12–08.26	finance
2018	18	2018 cryptocurrency crash- Bitcoin ultimately fell by approximately 65 %	2018.01–02	finance
2019	19	Covid hit China	2019.12.31	covid-19
2021	20	Covid-19 pandemic started	2021.03–2022.12	covid-19

Table 5
Descriptive statistics for three volatility measures – three measures of historical volatility.

Statistic	EU ETS	NZ ETS	CA CaT	HB ETS
Panel A: Standard Deviation of Weekly Returns				
N	398	398	398	398
Min	1.4	0.7	0.8	0.002
Mean	16.7	7.2	4.8	15.6
Max	78.9	75.5	57.2	56.4
St.Dev.	10.1	7.5	5.3	12.5
Skewness	1.78	4.35	5.72	1.09
Kurtosis	8.62	29.79	46.14	3.56
Panel B: Parkinson (1980)				
Min	2.8	0.67	0.65	1.14
Mean	23.53	10.73	6.86	21.03
Max	125.39	100.66	127.29	166.78
St.Dev.	15.83	11.42	9.11	20.42
Skewness	1.98	3.64	7.70	2.88
Kurtosis	9.75	20.73	86.83	16.08
Panel C: Garman and Klass (1980)				
Min	26.04	15.95	28.59	15.64
Mean	43.70	34.02	33.28	34.81
Max	153.67	120.33	154.66	197.93
St.Dev.	14.86	9.66	7.97	21.04
Skewness	2.53	4.21	10.57	3.56
Kurtosis	14.42	29.29	145.33	21.62

Source: Based on data from Bloomberg, Reuters, and Wind Database. Note: sample including carbon price volatility series from EU ETS, NZ-ETS, CA-CaT, and HB-ETS from April 25, 2014, to December 1, 2021. The corresponding estimate of the annualized weekly volatility in percentage is $\widehat{SD}t=10052\widehat{SD}t$.

to unusual activity of participant enterprises trading for compliance before the end of the compliance year. This unusual movement led to spikes in both return and volatility TCIs. Moreover, China launched its national ETS in July 2021, taking 34 power entities away from Hubei ETS at its opening, which caused a loss in allowances demand, and a decrease in the trading volume of emission allowances in Hubei ETS. The results were not surprising in a sense that the national ETS has a higher priority since launched, and its existence will inevitably reduce the size and liquidity of pilot ETSs and weaken their influence. Carbon market regulation changes might alter investment decisions, resulting in market return changes. For instance, the decreased market threshold incentivizes investors to participate in carbon trading.

Fig. 4 shows the volatility TCI. There is a slight upward move in volatility total connectedness from the September 2014 to January 2015 period, reflecting the effects of continued crude oil price crises (2014–2016). We observe that the first peak (TCI = 17.31 %) of the carbon market volatility connectedness index occurred at the troughs ($44.08 a barrel in January 2015) of the crude oil price (Event 16). The dependence between the markets increases with the decreasing petroleum prices, from September 2014 to January 2015, which in turn results in lower market risk in the carbon market volatility network. Akyildirim et al. [79]'s analysis of global energy market connectedness index also shows an increase from October 2014 to January 2015, which suggests that the carbon and energy market connectedness indices share the same features during global oil price crises. During 2016 and 2020, the volatility spillover index moves up and down. The fluctuation of carbon market volatility in the spillover index can be the joint consequences of extreme weather events/awareness of global warming (Events 12–15), cryptocurrency crash (Event 18), and uncertainty brought about by Covid-19 in China (Event 19). Noticeably, an instant upward move from 9.66 % to 17.15 % is witnessed following COP 25 (Event 6). However, in December 2019 when Switzerland quit the EU ETS and Covid-19 first hit China, the index falls again (European Commission, 2019). In March 2020, an extraordinary shift occurred when the Covid-19 virus began spreading globally: volatility TCI rose from 14.55 % to 35.69 %. Following the Covid-19 outbreak (Event 20), the total risk in the ETS markets, as measured by the TCI level, reached historic highs owing to the quick and furious reaction to growing uncertainty at both the individual and national level. The unprecedented increase in the TCI as a result of the Covid outbreak is supported by other studies in energy markets [79–81].

These findings suggest that global negotiations and other political issues (e.g., Events 1, 3, 4, and 5) and carbon market events (Events 7–11) have only a minor impact on the level of connectedness. Their impacts are far less than that of the energy or financial crises and Covid-19 outbreak. In particular, the return spillover index (TCI) is less influenced by the global crude oil crises during mid-2014 and early 2015, but more so by financial market crashes and extreme weather events (e.g., Events 12–15). The volatility spillovers seem mostly impacted by the crude oil crisis and cryptocurrency crash (Events 16, 18). Both return and volatility spillovers are heavily impacted by the Covid-19 outburst, which resulted in increasing market risk across the carbon market network.

6.2. Connectedness for 'from' and 'to'

This section investigates dynamic spillovers and their directions for each of the ETSs. Recall that the diagonal of Table 3 represents the shocks from each of the markets themselves, while the upper and lower parts of the off diagonal show the spillovers across the markets. The highest value of the (aggregated) return spillovers from others are for CA CaT ($\Sigma_{j\neq3}d^J_{3j} = 12.41$ %), and the lowest value of the (aggregated) return spillovers from others are for NZ ETS ($\Sigma_{j\neq2}d^J_{2j} = 7.97$ %). In terms of the (aggregated) return spillovers to others, EU ETS and NZ ETS remain the highest ($\Sigma_{i\neq1}d^J_{i1} = 13.16$ %) and the lowest ($\Sigma_{i\neq2}d^J_{i2} = 7.04$ %). The volatility connectedness measures (see Table 3, Panel B) reveals that NZ ETS received 13.96 % (aggregated) volatility spillover from the other three markets. The highest value of spillovers to other markets are for CA CaT (16.67 %), while HB ETS has taken an aggregated average value of 9.04 % spillover. All the numbers shown in Table 3 are average aggregated measures.

As this study is interested in the conduct of return and volatility spillovers over time, this study also plots the directional evolution through time. Figs. 5 and 6 respectively show the directional return and the volatility spillovers from and to four ETSs over time. The plots in Fig. 5, except for HB ETS, reveal marked increases of spillovers from other markets right after the Covid-19 outbreak, for both the return and volatility networks. Although the average level of connectedness "From Others" remains at 7–13% for the markets, the spillovers "From Others" peaked at almost 50 % for EU ETS and CA CaT in March 2020. The general pattern of HB ETS regarding return and volatility appears to be unaffected by the Covid-19 outbreak. This is due to the strict lockdown, which shielded the Chinese market temporarily from further shocks. Considering that the Covid-19 policies in China were unique in terms of the strict lockdown, the carbon market movement could not be impacted by the other markets in other countries. Furthermore, there is a slight upward trend in return (volatility) systems of NZ ETS since mid-2017 (mid-2016), showing that delinking NZ ETS to global markets increased the market risks in NZ ETS.

In terms of the directional spillovers from each of the four to all markets, the EU ETS has the largest (aggregated) share of spillovers (13.16 %) to all others in the return system while CA CaT has the largest (16.67 %) to the others in the volatility system. Since March 2020, the return (volatility) spillovers from EU ETS and CA CaT to all others reached the unprecedented points 55.30 % (50.86 %) and 54.04 % (69.69 %), respectively. There has been a steady decline of return spillovers from HB ETS to the others, from approximately 10 % to nearly 2 %, since mid-2019.

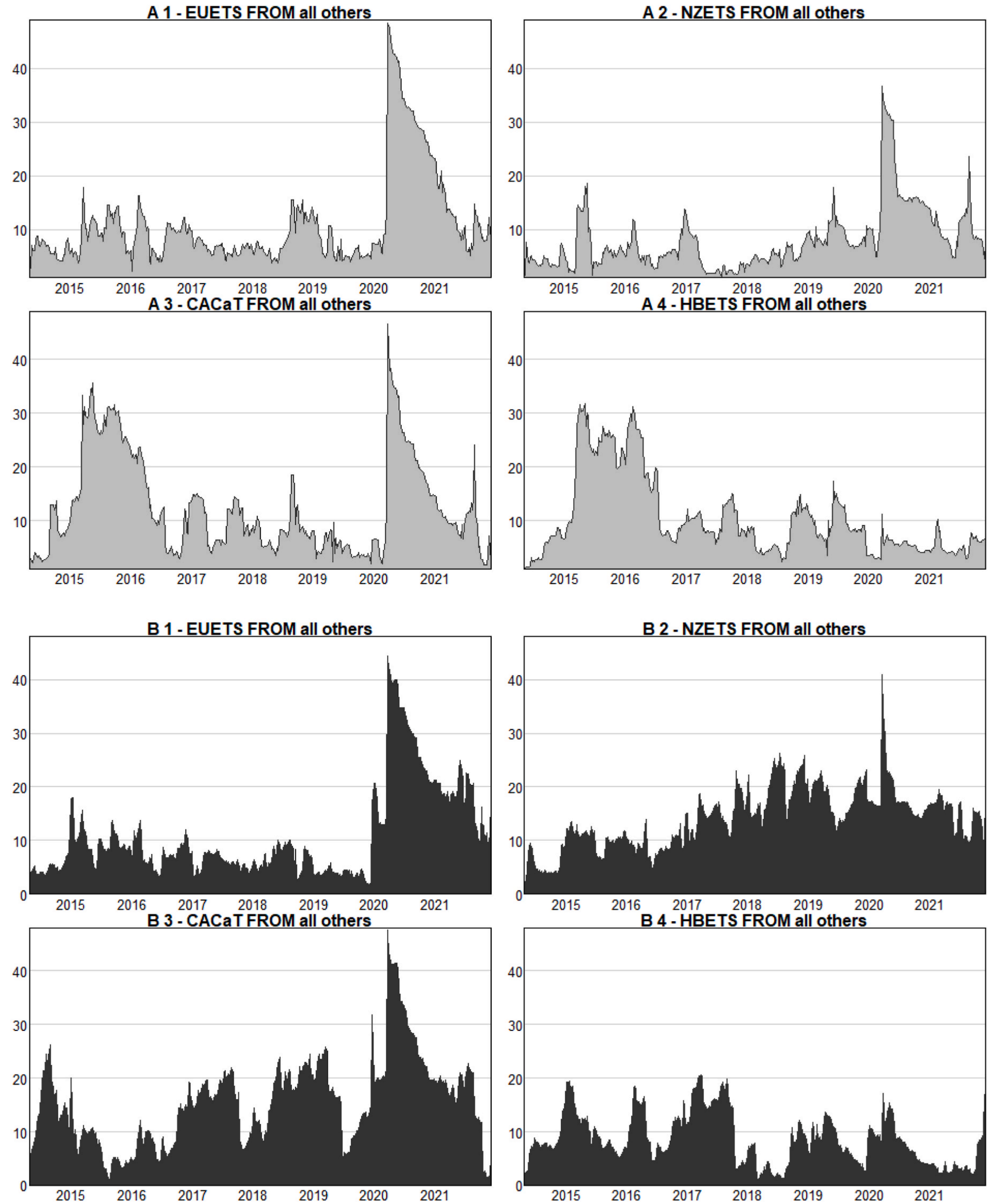

Fig. 5. Dynamic directional return and volatility spillovers FROM four markets
Note: Panels A1 to A4 in grey relate to the return connectedness system; Panels B1 to B4 in black relate to the volatility connectedness system. X axis gives the sample period, 2014–2021. Y axis shows the connectedness level in the network (numbers in y axis are percentages). The return series contains 397 observations (each) starting from May 2, 2014 to December 1, 2022 while the volatility series contains 398 observations (each) starting from April 25, 2014 to December 1, 2022. The predictive horizon for the underlying variance decomposition is H = 10, both are first-ordered VAR (p = 1).

6.3. Net total connectedness

Here this analysis reports the results for the four markets' net total directional connectedness. This is defined in Equation (9) and calculated by subtracting total directional connectedness to others ($C_{i\leftarrow j,t}(J)$) from total directional connectedness from others ($C_{i\rightarrow j,t}(J)$). Given that a net positive (negative) value in the last row of Table 3 means that the market (from one of the four columns) is a net transmitter (receiver) of the shocks, hence, leading (being led by) the network. Therefore, the results shown in the rows Net Total in panels A and B of Table 3 point at the difference between the transmitting and the receiving shocks of each market considering the entire network. Table 3 suggests that EU ETS is the largest transmitter (2.14 %) while NZ ETS is the largest receiver (−0.93 %) in the return connectedness systems. Notably, the EU ETS is the only return

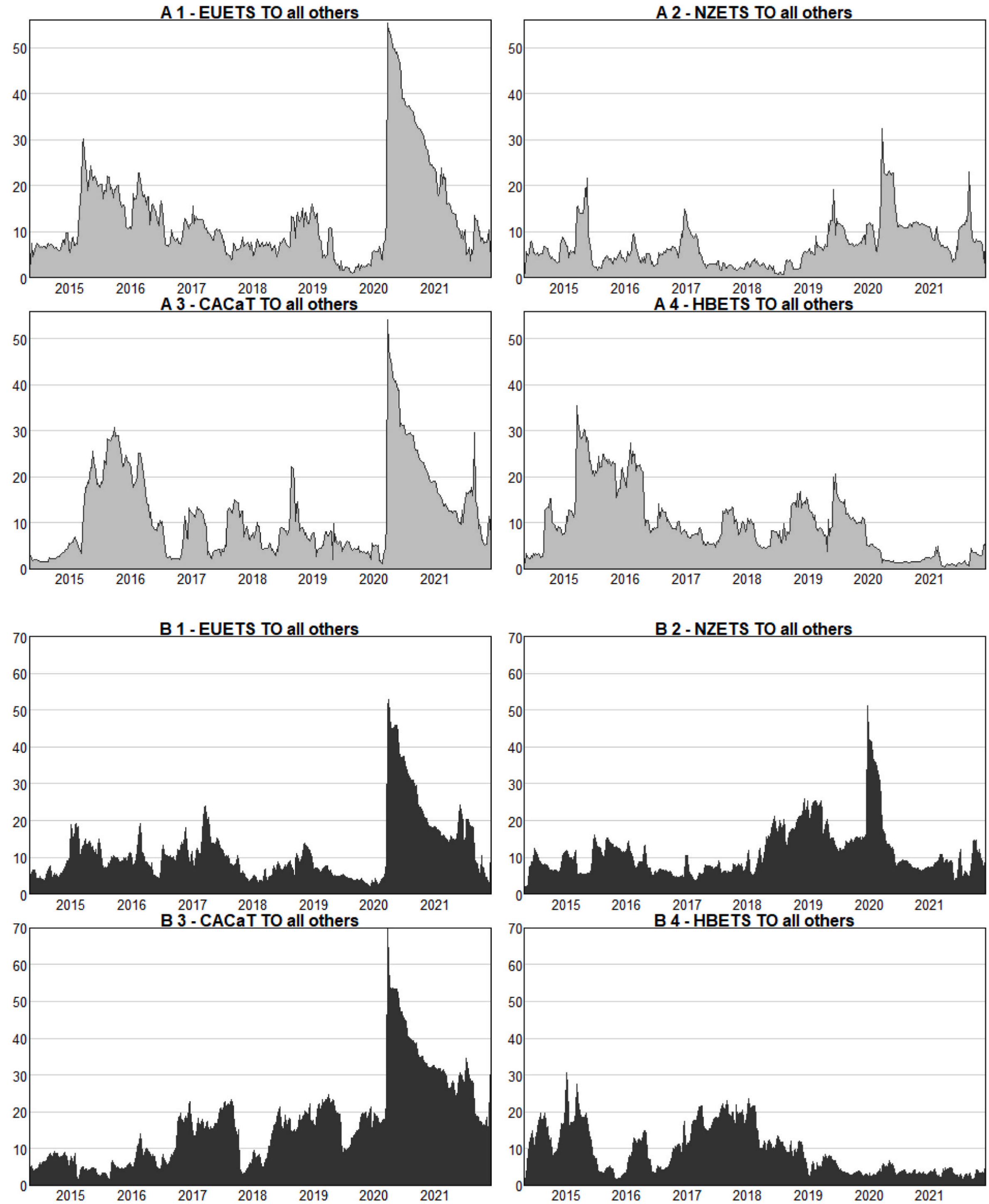

Fig. 6. Dynamic directional return and volatility spillovers *TO* four markets
Note: Panels A1 to A4 in grey relate to the return connectedness system; Panels B1 to B4 in black relate to the volatility connectedness system. X axis shows the sample period, 2014–2021. Y axis shows the connectedness level in the network (numbers in y axis are percentages). The return series contains 397 observations (each) starting from May 2, 2014 to December 1, 2022 while the volatility series contains 398 observations (each) starting from April 25, 2014 to December 1, 2022. The predictive horizon for the underlying variance decomposition is H = 10, both are first-ordered VAR (p = 1).

spillovers transmitter, confirmed by the positive value shown at the bottom of Table 3 Panel A. In terms of the volatility connectedness system, CA CaT is the largest transmitter (1.35 %), followed by EU ETS (0.86 %), while NZ ETS is again the largest receiver (−2.76 %). NZ ETS has the least and only negative value in the last row – Net Total, which means all other three markets are identified as volatility transmitters, while NZ ETS receives more spillovers from the system than it transmits.

Fig. 7 displays the evolution of net return and volatility spillover of the four ETSs. Positive values indicate periods when a specific carbon market acts as a net-transmitter, whilst negative values indicate the period when one of the markets receives, on net terms, from all others. An inspection of Fig. 7 leads to the following observations: First is that EU ETS has a persistent net-transmitting role in the return connectedness system. The phenomena could be explained by the maturity of the

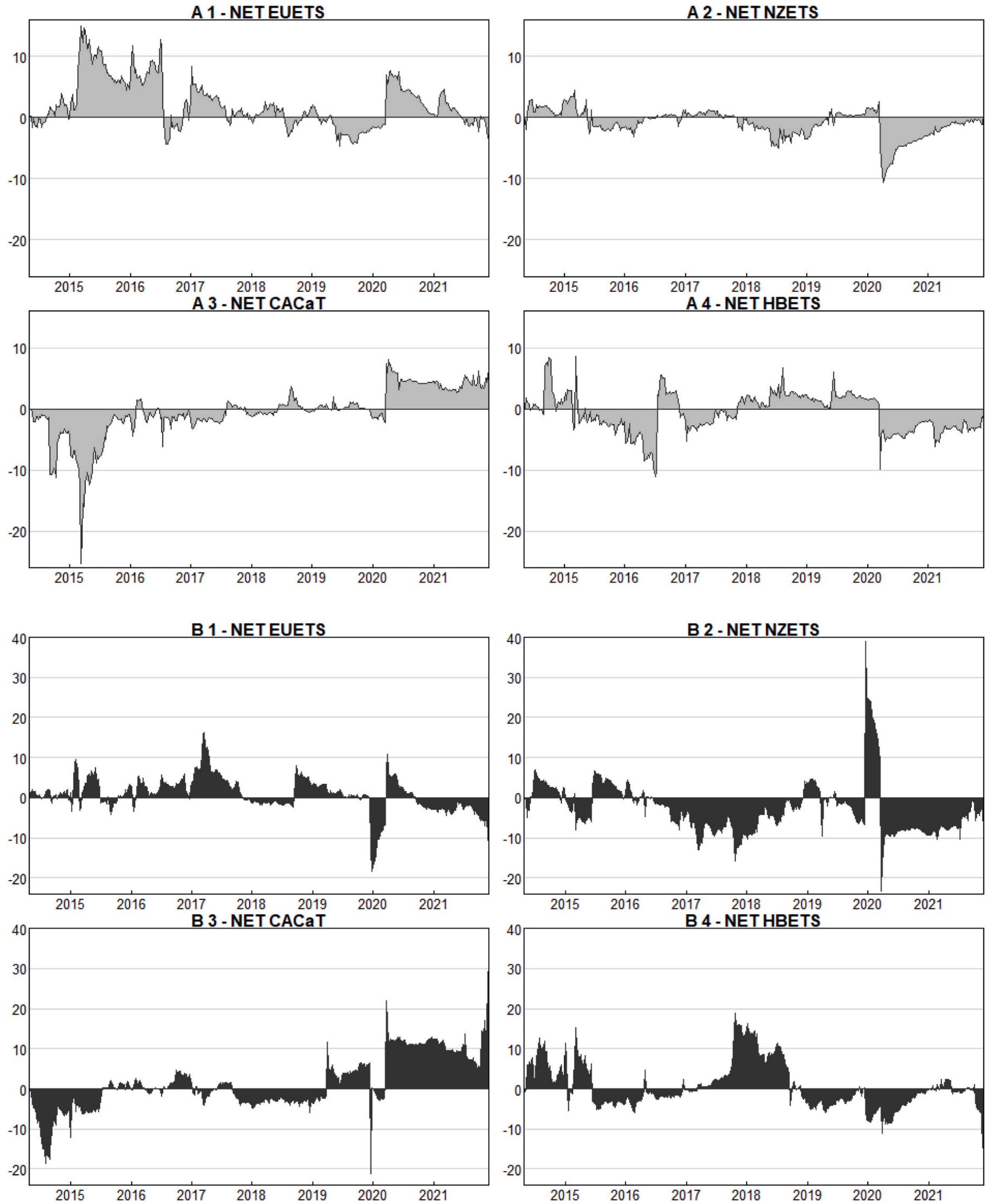

Fig. 7. Net return and volatility spillovers — four markets
Note: Panels A1 to A4 in grey relate to the return connectedness system; Panels B1 to B4 in black relate to the volatility connectedness system. The return series contains 397 observations (each) starting from May 2, 2014 to December 1, 2022 while the volatility series contains 398 observations (each) starting from April 25, 2014 to December 1, 2022. The predictive horizon for the underlying variance decomposition is H = 10, both are first-ordered VAR (p = 1). X axis shows the sample period, 2014–2021. Y axis shows the connectedness level in the network (numbers in y axis are percentages).

market performance and the market size (in terms of total participants, price, and revenues) of the EU ETS. Second, in terms of volatility net total spillovers, what stands out in Fig. 7 is the spike of 39.5 % on December 13, 2019 of the Net Total spillovers of NZ ETS. Albeit NZ ETS is a net receiver in the aggregated level, in December 2019 it was leading the network in the short-term. This discovery matches the volatility jumps (from 1.72 to 47.81 %) in New Zealand ETS's volatility series (Fig. 2), where the market volatility was substantially impacted by Covid-19 when it first hit the world. Third, it shows that after the Covid-19 outbreak, the CA CaT became a net transmitter while the NZ ETS and

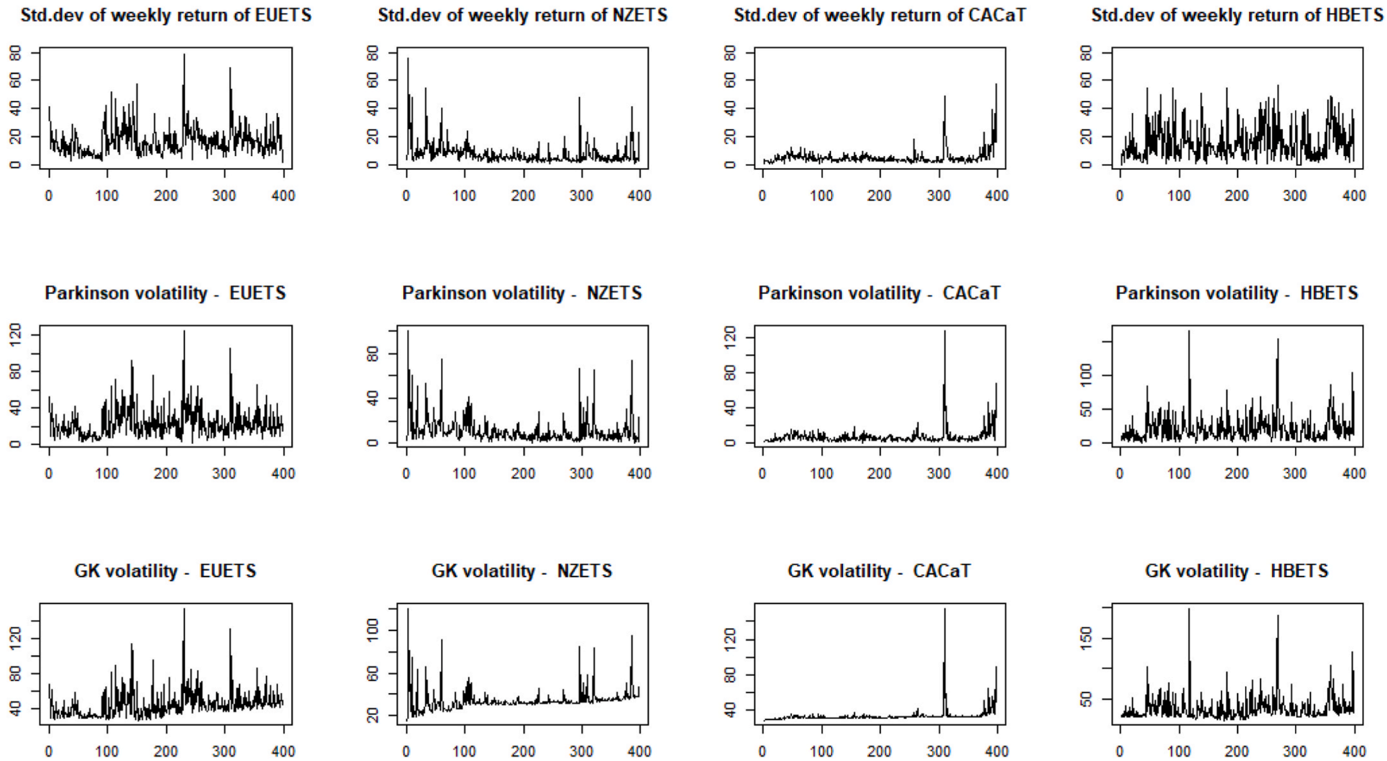

Fig. 8. Plots of three volatility measures – St. Dev., Parkinson, and Garman and Klass.
Source: Based on data from Bloomberg, Reuters, and Wind Database. Note: sample including carbon price volatility series from EU ETS, NZ-ETS, CA-CaT, and HB-ETS from April 25, 2014, to December 1, 2021. The corresponding estimate of the annualized weekly volatility in percentage is SD̃t=10052SD̃t.

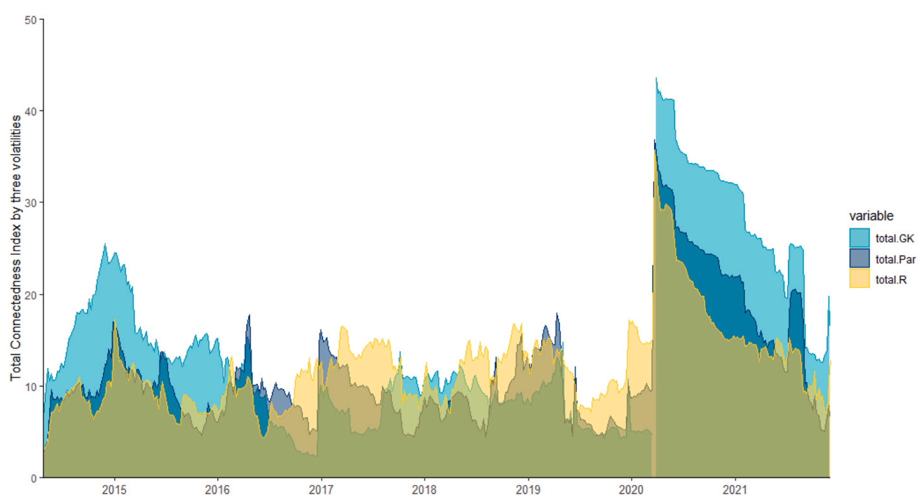

Fig. 9. Robustness check – total connectedness index from three volatility measures.

HB ETS remained in their roles as shocks receiver in the carbon trading system.

7. Robustness

This analysis uses the realized (historical) volatility as proxy of volatility. This analysis employs daily closing prices for the four markets; high frequency/intraday data are not available for CA CaT and HB ETS. By using the weekly highest, lowest, open, and close prices, this research calculates the realized/historical volatility. To be consistent with the frequency of the historical volatility data, this study uses weekly returns. Three measures have been applied to estimate weekly volatility of carbon price. The first measure is the standard deviation of weekly return over the five-day interval during each week (Equation (10) in Section 5).

The second measure is the weekly volatility that considers five prices in a week. Following [71,82], this study uses weekly high and low prices obtained from daily data, from Monday open to the Friday close, to estimate Parkinson-type weekly variance:

$$\tilde{\sigma}^2_{it} = 0.361\left[\ln\left(P^{max}_{it}\right) - \ln\left(P^{min}_{it}\right)\right]^2, \tag{11}$$

where P^{max}_{it} is the Monday-Friday highest price, P^{min}_{it} is the Monday-Friday lowest price, $\tilde{\sigma}^2_{it}$ is an estimator of weekly variance at market i.

Fig. 10. Sensitivity of the Total Connectedness Index to VAR lag structure

Note: The indices were calculated based on the volatilities generated with the first measure (i.e., $\widetilde{SD}_t$, from Equation (10)). In the main text we used lag 1 as selected by Schwarz information criterion. Here in the robustness check we tried lag 1, lag 2, and lag 3 in the model (lag 3 was chosen by Akaike information criterion).

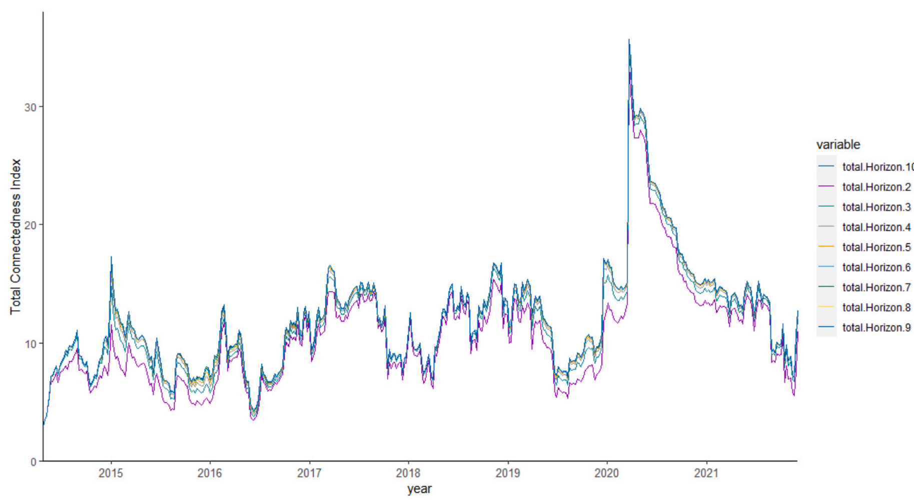

Fig. 11. Sensitivity of the Total Connectedness Index to Forecast Horizon

Note: The indices were calculated based on the volatilities generated with the first measure (i.e., $\widetilde{SD}_t$, from Equation (10)). This study used VAR (1) for these estimations. 2 to 10-week Horizons are chosen and plotted.

This study calculated the annualized weekly volatility as $\widehat{\sigma}_{it} = 100\sqrt{52\widetilde{\sigma}_{it}^2}$. The third measure, following [70,83], we use weekly high, low, opening and closing prices obtained from collected daily price data to estimate Garman and Klass-type weekly variance:

$$\widetilde{\omega}_{it}^2 = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2, \tag{12}$$

where H is the Monday-Friday highest price, L is the Monday-Friday lowest price, O is the Monday open and C is the Friday close price. All prices are transformed to natural logarithms. This study calculates the annualized weekly volatility as $\widehat{\omega}_{it} = 100\sqrt{52\widetilde{\omega}_{it}^2}$. The descriptive statistics for the volatilities are reported in Table 5.

8. Conclusion

Emission Trading Schemes (ETSs) incentivize climate action by allowing entities to exchange emission allowances created by the reduction or removal of greenhouse gases (GHGs) from the atmosphere. As such, ETSs bring together companies, investors, and policy makers to ensure a clean (er) transition to meet net-zero emissions targets. Understanding the interactions between such carbon markets for emission allowances promotes their efficient and effective operation. This study investigates the connectedness among four Emission Trading Schemes: California's Cap-and-Trade (CA CaT), China's Hubei ETS (HB ETS), the EU ETS, and New Zealand's ETS (NZ ETS), from 2014 to 2021. This sample period covers a wide range of events, for example, stock market crashes, international climate negotiations, political events, carbon market regulation, and the Covid-19 outburst.

Most studies in the field of carbon markets focus on the relationship between the carbon market and other energy and/or financial markets [40,41,75], and [81]. Other studies concentrate on local/domestic carbon markets [24,32], and [45]. These studies did not account for return and/or volatility spillovers across the carbon markets. The four-dimensional time varying parameter VAR model in this study addresses the shortcomings of relying on constant parameters and static analysis that are inherent with the conventional approaches employed. Given the effects of increasing energy efficiency and clean technology adoption, improving emission market efficiency, and the organic growth of linkages between ETS systems, the spillover effects among the four markets might be affected. This study employs a TVP-VAR methodology to measure the connectedness along the four markets.

The key findings are as follows. This research finds that the dynamic connectedness of return and volatility networks varies considerably over time. In particular, events like the energy crisis and Covid-19 outbreak accentuate the time-dependent nature of spillovers across carbon markets. This research establishes that the total connectedness index stands at around 10–12 %, suggesting a relatively low level of spillover, when compared to other market integration studies. It indicates that the global carbon prices are largely (albeit not completely) dependent on themselves. The changes in global climate politics and carbon market reforms appear to have only minor impact on their connectedness, whereas the occurrence of energy and financial crises have a substantial effect (both regarding return and volatility). The EU ETS consistently acts as a net transmitter in return connectedness, while the CA CaT emerges as a primary transmitter for volatility connectedness. NZ ETS is the dominant receiver of shocks, indicating vulnerability during market unrests. HB ETS exhibited unique resilience during the Covid-19 pandemic, probably due to China's strict border control and lockdown measures (with the border closed, the movement at HB ETS could hardly be impacted by other ETSs).

From a practical perspective, CA CaT and EU ETS share several features regarding their resilience: They are both structured upon three compliance phases; their sector coverage is similar, and their market threshold (25 ktCO_2e) is substantially higher than that of the other two, which means their participants are larger in scale, hence, less vulnerable to public crisis.

The results lead to important policy implications. Firstly, investors and portfolio managers may diversify their portfolio risks by investing in carbon market pairings that are unlikely to transfer shocks to one another during anomalous events. Investors should attach special attention to New Zealand and EU's ETSs when formulating portfolio strategies since they have been in the role of net receiver and transmitters, respectively, in the system; net receivers are vulnerable under market unrest. Secondly, efficient coordination and monitoring mechanisms among cross-country carbon markets shall be put in place during periods with higher uncertainty, namely energy crises and extreme weather events, to help policymakers design timely interventions to alleviate the contagion risk in carbon market networks. Thirdly, albeit Hubei ETS has the smallest market size compared to the other three in our study, extreme prices spike in Hubei ETS, and the launch of China's national ETS could increase the market risk transmission in carbon market networks. Hence, a smooth transmission from China's pilot ETSs to national pilots is needed in a sense that the carbon market regulation change might alter investment decisions, resulting in market return changes.

This paper offers valuable insights and recommendations for other global ETSs by studying these four markets. In fact, even as our samples focus on these four markets, they cover a diverse range of participants, trading phases, project types, and market sizes. The empirical results can be applied to other developed and developing ETSs. For developing ETSs, examples include the other eight pilot ETSs in China, South Korea ETS, Indonesia ETS, and Vietnam ETS. For more developed ETSs: Switzerland ETS and the UK ETS. However, using weekly data, as opposed to daily data, might lead to a lag in capturing market dynamics. This is because finer details or daily fluctuations within the week could be missed, which can pose challenges for accurate forecasting and informed decision-making. From a policy-making perspective, this choice of data granularity might inadvertently overlook critical short-term events or shifts, potentially affecting decisions related to climate change objectives.

As for future work, this study envisions several directions for extension. There is a definite need for constructing high frequency data to analyse the connectedness on a daily frequency. Another direction for future research would be to incorporate the asymmetric TVP-VAR connectedness model in carbon market research. This asymmetric model has the capacity to discern three distinct types of spillovers: normal, positive, and negative. Utilizing this model could offer a more nuanced comprehension of spillover dynamics, potentially unveiling additional insights pertinent to the study of ETSs. Furthermore, it is interesting to include more carbon markets in the panel, for example, the South Korea ETS, which is another nationwide ETS in Asia; Regional Greenhouse Gas Initiative (RGGI) in North America; and UK ETS that, with Brexit, quit the EU ETS.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Credit author statement

Chenyan Lyu: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Writing–review & editing, Visualization. Bert Scholtens: Conceptualization, Methodology, Validation, Supervision, Project administration, Writing–review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

We acknowledge the useful comments and suggestions of Bing Xu, Ismir Mulalic, Lisbeth La Cour, Myriam Marending, Stefano Tripodi, Tooraj Jamasb, and Lammertjan Dam. This study was invited for presentation at the 43rd International Association of Energy Economics (IAEE) conference in Tokyo, July 2022, and the International Conference on Sustainability, Environment, and Social Transition in Economics and Finance conference in Southampton, 14–16 December 2023.

References

[1] UNFCCC. In report of the conference of the parties to the united nations framework convention on climate change. Jul. 04, 2022. [Online]. Available: https://unfccc.int/documents/184656.

[2] United Nation Environment Project. Emissions gap report 2020. Jul. 05, 2022. [Online]. Available: https://www.unep.org/emissions-gap-report-2020.

[3] Broadstock D, Ji Q, Managi S, Zhang D. Pathways to carbon neutrality: challenges and opportunities. Resour Conserv Recycl Jun. 2021;169:105472. https://doi.org/10.1016/j.resconrec.2021.105472.

[4] National Development, Reform Commission. 14th five-year plan on national economic and social development. Jul. 05, 2022. [Online]. Available: https://www.ndrc.gov.cn/xxgk/zcfb/ghwb/202103/P020210323538797779059.pdf.

[5] Kreibich N, Hermwille L. Caught in between: credibility and feasibility of the voluntary carbon market post-2020. Clim Pol Aug. 2021;21(7):939–57. https://doi.org/10.1080/14693062.2021.1948384.

[6] International Carbon Association Partnership. Emissions trading worldwide: Status report 2022 [Online]. Available: https://icapcarbonaction.com/en/publications/emissions-trading-worldwide-2022-icap-status-report. [Accessed 27 May 2022].

[7] Zhao L, Wen F, Wang X. Interaction among China carbon emission trading markets: nonlinear Granger causality and time-varying effect. Energy Econ Sep. 2020;91:104901. https://doi.org/10.1016/j.eneco.2020.104901.

[8] Zeng S, Jia J, Su B, Jiang C, Zeng G. The volatility spillover effect of the European Union (EU) carbon financial market. J Clean Prod Feb. 2021;282:124394. https://doi.org/10.1016/j.jclepro.2020.124394.

[9] Mizrach B. Integration of the global carbon markets. Energy Econ Jan. 2012;34(1):335–49. https://doi.org/10.1016/j.eneco.2011.10.011.

[10] Ibikunle G, Gregoriou A, Hoepner AGF, Rhodes M. Liquidity and market efficiency in the world's largest carbon market. Br Account Rev Dec. 2016;48(4):431–47. https://doi.org/10.1016/j.bar.2015.11.001.
[11] Nogrady B. China launches world's largest carbon market: but is it ambitious enough? Nature 2021;595(7869). https://doi.org/10.1038/d41586-021-01989-7. 637–637, Jul.
[12] Hernandez-Cortes D, Meng K. Do environmental markets cause environmental injustice? Evidence from California's carbon market. Cambridge, MA: National Bureau of Economic Research; May 2020, w27205. https://doi.org/10.3386/w27205.
[13] Ciarreta A, Zarraga A. Analysis of mean and volatility price transmissions in the MIBEL and EPEX electricity spot markets. Energy J 2015;36(4). https://doi.org/10.5547/01956574.36.4.acia. Oct.
[14] Han L, Kordzakhia N, Trück S. Volatility spillovers in Australian electricity markets. Energy Econ 2020;90:104782. https://doi.org/10.1016/j.eneco.2020.104782. Aug.
[15] Flachsland C, Marschinski R, Edenhofer O. To link or not to link: benefits and disadvantages of linking cap-and-trade systems. Clim Pol Jan. 2009;9(4):358–72. https://doi.org/10.3763/cpol.2009.0626.
[16] Stern N. The Economics of climate change: the Stern review. Cambridge: Cambridge University Press; 2007. https://doi.org/10.1017/CBO9780511817434.
[17] International Carbon Association Partnership. On the way to a global carbon market: linking emissions trading systems. Jul. 06, 2022. [Online]. Available: https://icapcarbonaction.com/en/?option=com_attach&task=download&id=711.
[18] Carbone JC, Helm C, Rutherford TF. The case for international emission trade in the absence of cooperative climate policy. J Environ Econ Manag Nov. 2009;58(3): 266–80. https://doi.org/10.1016/j.jeem.2009.01.001.
[19] Kachi A, Niels B, Kateryna S, Constanze H, Michel F, Charlotte U. Linking emissions trading systems: a summary of current research. Oct. 11, 2023. [Online]. Available: https://icapcarbonaction.com/en/?option=com_attach&task=download&id=241.
[20] Borghesi S, Montini M. The Best (and worst) of GHG emission trading systems: comparing the EU ETS with its followers. Front Energy Res 2016;4(Jul). https://doi.org/10.3389/fenrg.2016.00027.
[21] Schmalensee R, Stavins RN. The design of environmental markets: what have we learned from experience with cap and trade? Oxf Rev Econ Pol Nov. 2017;33(4): 572–88. https://doi.org/10.1093/oxrep/grx040.
[22] Directive 2003/87/EC of the European Parliament and of the Council of 13 October 2003 establishing a scheme for greenhouse gas emission allowance trading within the Community and amending Council Directive 96/61/EC. Official Journal of the European Union; 2003. Oct. 18, 2023. [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32003L0087.
[23] California Environmental Protection Agency. California-Québec agreement to integrate and harmonize their cap-and-trade programs. Jul. 05, 2022. [Online]. Available: https://ww2.arb.ca.gov/sites/default/files/cap-and-trade/linkage/ca_quebec_linking_agreement_english.pdf.
[24] Diaz-Rainey I, Tulloch DJ. Carbon pricing and system linking: lessons from the New Zealand emissions trading scheme. Energy Econ 2018;73:66–79. https://doi.org/10.1016/j.eneco.2018.04.035. Jun.
[25] Gavard C, Winchester N, Paltsev S. Limited trading of emissions permits as a climate cooperation mechanism? US–China and EU–China examples. Energy Econ Aug. 2016;58:95–104. https://doi.org/10.1016/j.eneco.2016.06.012.
[26] Yu P, Hao R, Cai Z, Sun Y, Zhang X. Does emission trading system achieve the win-win of carbon emission reduction and financial performance improvement? —evidence from Chinese A-share listed firms in industrial sector. J Clean Prod Jan. 2022;333:130121. https://doi.org/10.1016/j.jclepro.2021.130121.
[27] Lovcha Y, Perez-Laborda A, Sikora I. The determinants of CO2 prices in the EU emission trading system. Appl Energy Jan. 2022;305:117903. https://doi.org/10.1016/j.apenergy.2021.117903.
[28] Guo L-Y, Feng C. 'Are there spillovers among China's pilots for carbon emission allowances trading?'. Energy Econ Nov. 2021;103:105574. https://doi.org/10.1016/j.eneco.2021.105574.
[29] Liu T, Gong X. Analyzing time-varying volatility spillovers between the crude oil markets using a new method. Energy Econ Mar. 2020;87:104711. https://doi.org/10.1016/j.eneco.2020.104711.
[30] Arouri MEH, Jawadi F, Nguyen DK. Nonlinearities in carbon spot-futures price relationships during Phase II of the EU ETS. Econ Modell May 2012;29(3):884–92. https://doi.org/10.1016/j.econmod.2011.11.003.
[31] Liu J, Tang S, Chang C-P. Spillover effect between carbon spot and futures market: evidence from EU ETS. Environ Sci Pollut Res Mar. 2021;28(12):15223–35. https://doi.org/10.1007/s11356-020-11653-8.
[32] Conrad C, Rittler D, Rotfuß W. Modeling and explaining the dynamics of European Union Allowance prices at high-frequency. Energy Econ 2012;34(1):316–26. https://doi.org/10.1016/j.eneco.2011.02.011.
[33] Schultz E, Swieringa J. Catalysts for price discovery in the European union emissions trading system. J Bank Finance May 2014;42:112–22. https://doi.org/10.1016/j.jbankfin.2014.01.012.
[34] Benz EA, Hengelbrock J. Liquidity and price discovery in the European CO2 futures market: an intraday analysis. SSRN Electron J 2008. https://doi.org/10.2139/ssrn.1143923.
[35] Mazza P, Petitjean M. 'How integrated is the European carbon derivatives market?'. Finance Res Lett 2015. https://doi.org/10.1016/j.frl.2015.07.005.
[36] Mansanet Bataller M, Chevallier J, Hervé-Mignucci M, Alberola E. The EUA-sCER spread: compliance strategies and arbitrage in the European carbon market. SSRN Electron J 2010. https://doi.org/10.2139/ssrn.1540599.
[37] Nazifi F. The price impacts of linking the European union emissions trading scheme to the clean development mechanism. Environ Econ Pol Stud Dec. 2010;12(4): 164–86. https://doi.org/10.1007/s10018-010-0168-3.
[38] Nazifi F. Modelling the price spread between EUA and CER carbon prices. Energy Pol May 2013;56:434–45. https://doi.org/10.1016/j.enpol.2013.01.006.
[39] Sadefo Kamdem J, Nsouadi A, Terraza M. Time-frequency analysis of the relationship between EUA and CER carbon markets. Environ Model Assess 2016;21 (2):279–89. https://doi.org/10.1007/s10666-015-9478-y. Apr.
[40] Chang K, Ge F, Zhang C, Wang W. The dynamic linkage effect between energy and emissions allowances price for regional emissions trading scheme pilots in China. Renew Sustain Energy Rev 2018;98(September):415–25. https://doi.org/10.1016/j.rser.2018.09.023.
[41] Tan X, Sirichand K, Vivian A, Wang X. How connected is the carbon market to energy and financial markets? A systematic analysis of spillovers and dynamics. Energy Econ 2020;90:104870. https://doi.org/10.1016/j.eneco.2020.104870. Aug.
[42] Wang Y, Guo Z. The dynamic spillover between carbon and energy markets: new evidence. Energy 2018;149:24–33. https://doi.org/10.1016/j.energy.2018.01.145. Apr.
[43] Mizrach B. Integration of the global carbon markets. Energy Econ 2012;34(1): 335–49. https://doi.org/10.1016/j.eneco.2011.10.011.
[44] Wang Y, Fu Q, Chang C-P. The integration of carbon price between European and Chinese markets: what are the implications? Int J Environ Res Aug. 2021;15(4): 667–80. https://doi.org/10.1007/s41742-021-00342-0.
[45] Lyu C. Dynamics of regional carbon markets in China. SSRN Electron J 2021;37. https://doi.org/10.2139/ssrn.3996155.
[46] Nelson DB. Conditional heteroskedasticity in asset returns: a new approach. Econometrica 1991;59(2):347. https://doi.org/10.2307/2938260. Mar.
[47] Diebold FX, Yilmaz K. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ J 2009;119(534):158–71. http://www.jstor.org/stable/20485298.
[48] Diebold FX, Yilmaz K. Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast Jan. 2012;28(1):57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.
[49] Do HX, Nepal R, Jamasb T. Electricity market integration, decarbonisation and security of supply: dynamic volatility connectedness in the Irish and Great Britain markets. Energy Econ Oct. 2020;92:104947. https://doi.org/10.1016/j.eneco.2020.104947.
[50] Ma R, Liu Z, Zhai P. Does economic policy uncertainty drive volatility spillovers in electricity markets: time and frequency evidence. Energy Econ Mar. 2022;107: 105848. https://doi.org/10.1016/j.eneco.2022.105848.
[51] Broadstock DC, Li R, Wang L. Integration reforms in the European natural gas market: a rolling-window spillover analysis. Energy Econ Oct. 2020;92:104939. https://doi.org/10.1016/j.eneco.2020.104939.
[52] Geng J-B, Liu C, Ji Q, Zhang D. Do oil price changes really matter for clean energy returns? Renew Sustain Energy Rev 2021;150:111429. https://doi.org/10.1016/j.rser.2021.111429. Oct.
[53] Geng J-B, Du Y-J, Ji Q, Zhang D. Modeling return and volatility spillover networks of global new energy companies. Renew Sustain Energy Rev Jan. 2021;135: 110214. https://doi.org/10.1016/j.rser.2020.110214.
[54] Wu F, Zhang D, Ji Q. Systemic risk and financial contagion across top global energy companies. Energy Econ May 2021;97:105221. https://doi.org/10.1016/j.eneco.2021.105221.
[55] Antonakakis N, Chatziantoniou I, Gabauer D. Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. J Risk Financ Manag 2020;13(4). https://doi.org/10.3390/jrfm13040084.
[56] Koop G, Korobilis D. Large time-varying parameter VARs. J Econom Dec. 2013;177 (2):185–98. https://doi.org/10.1016/j.jeconom.2013.04.007.
[57] Dangl T, Halling M. Predictive regressions with time-varying coefficients. J Financ Econ Oct. 2012;106(1):157–81. https://doi.org/10.1016/j.jfineco.2012.04.003.
[58] Umar Z, Jareño F, Escribano A. Dynamic return and volatility connectedness for dominant agricultural commodity markets during the COVID-19 pandemic era. Appl Econ Sep. 2021:1. https://doi.org/10.1080/00036846.2021.1973949. –25.
[59] Bouri E, Demirer R, Gabauer D, Gupta R. Financial market connectedness: the role of investors' happiness. Finance Res Lett Jan. 2022;44:102075. https://doi.org/10.1016/j.frl.2021.102075.
[60] Asl MG, Bouri E, Darehshiri S, Gabauer D. Good and bad volatility spillovers in the cryptocurrency market: new Evidence from a TVP-VAR asymmetric connectedness approach. SSRN Electron J 2021. https://doi.org/10.2139/ssrn.3957317.
[61] Akyildirim E, Cepni O, Molnar P, Uddin GS. Connectedness of energy markets around the world during the COVID-19 pandemic. Energy Econ; Mar. 2022, 105900. https://doi.org/10.1016/j.eneco.2022.105900.
[62] Evrim Mandacı P, Cagli EÇ, Taşkın D. Dynamic connectedness and portfolio strategies: energy and metal markets. Resour Pol Oct. 2020;68:101778. https://doi.org/10.1016/j.resourpol.2020.101778.
[63] Li R, Joyeux R, Ripple RD. International steam coal market integration. Energy J 2010;31(3). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol31-No3-10. Jul.
[64] Barro RJ. Rare disasters and asset markets in the twentieth century. Q J Econ Aug. 2006;121(3):823–66. https://doi.org/10.1162/qjec.121.3.823.
[65] Guo D, Zhou P. Green bonds as hedging assets before and after COVID: a comparative study between the US and China. Energy Econ Dec. 2021;104:105696. https://doi.org/10.1016/j.eneco.2021.105696.
[66] Adekoya OB, Akinseye AB, Antonakakis N, Chatziantoniou I, Gabauer D, Oliyide J. Crude oil and Islamic sectoral stocks: asymmetric TVP-VAR connectedness and investment strategies. Resour Pol Sep. 2022;78:102877. https://doi.org/10.1016/j.resourpol.2022.102877.

[67] Primiceri GE. Time varying structural vector autoregressions and monetary policy. Rev Econ Stud 2005;72(3):821–52. https://doi.org/10.1111/j.1467-937X.2005.00353.x. Jul.
[68] Del Negro M, Primiceri GE. Time varying structural vector autoregressions and monetary policy: a Corrigendum. Rev Econ Stud Oct. 2015;82(4):1342–5. https://doi.org/10.1093/restud/rdv024.
[69] Lutz BJ, Pigorsch U, Rotfuß W. Nonlinearity in cap-and-trade systems: the EUA price and its fundamentals. Energy Econ 2013;40:222–32. https://doi.org/10.1016/j.eneco.2013.05.022.
[70] Garman MB, Klass MJ. On the estimation of security price volatilities from historical data. J Bus 1980;53(1):67–78. http://www.jstor.org/stable/2352358.
[71] Parkinson M. The extreme value method for estimating the variance of the rate of return. J Bus 1980;53(1):61–5. http://www.jstor.org/stable/2352357.
[72] Dickey DA, Fuller WA. Distribution of the estimators for autoregressive time series with a unit root. J Am Stat Assoc 1979;74(366):427–31. https://doi.org/10.2307/2286348.
[73] Zhang Z. Carbon emissions trading in China: the evolution from pilots to a nationwide scheme. Clim Pol 2015;15(sup1):S104–26. https://doi.org/10.1080/14693062.2015.1096231. Nov.
[74] Yilmaz K. Return and volatility spillovers among the East Asian equity markets. J Asian Econ Jun. 2010;21(3):304–13. https://doi.org/10.1016/j.asieco.2009.09.001.
[75] Ji Q, Zhang D, Geng J. Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. J Clean Prod Oct. 2018;198:972–8. https://doi.org/10.1016/j.jclepro.2018.07.126.
[76] Zhang D, Broadstock DC. Global financial crisis and rising connectedness in the international commodity markets. Int Rev Financ Anal Mar. 2020;68:101239. https://doi.org/10.1016/j.irfa.2018.08.003.
[77] Benz E, Trück S. Modeling the price dynamics of CO2 emission allowances. Energy Econ Jan. 2009;31(1):4–15. https://doi.org/10.1016/j.eneco.2008.07.003.
[78] Mansanet-Bataller M, Pardo A, Valor E. 'CO2 prices, energy and weather'. Energy J 2007;28(3). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No3-5. Jul.
[79] Akyildirim E, Cepni O, Molnar P, Uddin GS. Connectedness of energy markets around the world during the COVID-19 pandemic. Energy Econ; Mar. 2022, 105900. https://doi.org/10.1016/j.eneco.2022.105900.
[80] Bouri E, Cepni O, Gabauer D, Gupta R. Return connectedness across asset classes around the COVID-19 outbreak. Int Rev Financ Anal Jan. 2021;73:101646. https://doi.org/10.1016/j.irfa.2020.101646.
[81] Tiwari AK, Aikins Abakah EJ, Gabauer D, Dwumfour RA. Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: implications for hedging and investments strategies. Global Finance J Feb. 2022;51:100692. https://doi.org/10.1016/j.gfj.2021.100692.
[82] Diebold FX, Yilmaz K. Better to give than to receive: predictive directional measurement of volatility spillovers. Int J Forecast Jan. 2012;28(1):57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006.
[83] Diebold FX, Yilmaz K. Measuring financial asset return and volatility spillovers, with application to global equity markets. Econ J 2009;119(534):158–71. http://www.jstor.org/stable/20485298.