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Abstract

Emission trading Scheme (ETS) 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 market has engaged a broad range of participants, including not only emissions-intensive energy corporations but also individual and institutional investors. As arbitrage opportunities arise, price fluctuations are likely to occur, which typically have a mutual spillover effect. This paper examines how market fluctuations (e.g., volatilities) in these markets interact with each other, among carbon prices across four jurisdictions – European Union, New Zealand, California, and Hubei (China) ETS. We use weekly return and volatility data, constructed by the daily prices from four markets, covering the period April 2014 - December 2021, and select the time-varying parameter (TVP)-VAR methodology to study the connectedness. We find that the dynamics of the carbon market is mainly explained by itself and not due to spillovers from other markets, indicating that the global carbon prices are largely (albeit not completely) dependent on themselves, not the cross-contribution due to individual shocks.

Keywords: Carbon markets integration; Volatility connectedness; TVP-VAR; Market risk.
JEL Classifications: C32; E44; G15; R11; Q43.

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1. Introduction

The Paris Agreement's objective is to keep global warming to 1.5 degrees Celsius above pre-industrial levels. However, the UNEP (2020) states that the world is heading for a temperature rise in excess of 3°C of the end of this century. In order to reduce this gap, numerous major energy consumers and CO_2 emitters announced their commitment to reaching carbon neutrality by the mid-21st century (Broadstock et al., 2021; National Development and Reform Commission, 2020). States and cities are actively crafting innovative policies to mitigate the effects of climate change.

Carbon pricing is one of the policies through which policy makers hope to achieve their objectives. In 2022, there were 25 regional emission trading schemes (ETS) developed[2], 9 under development, and 12 under consideration internationally (ICAP, 2022). 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 class in investment portfolios, the ETS market has engaged a broad range of participants, including not only emissions-intensive energy corporations but also individual and institutional investors. Trades between developing and developed emission markets increase the ties. Enterprises in certain markets may have to bear the carbon transaction cost caused by non-local shocks, namely, spillover effects (Guo and Feng, 2021). As arbitrage opportunities arise, price fluctuations are likely to occur, which typically have a mutual spillover effect (Liu and Gong, 2020). Hence, it is worth exploring whether there are spillover effects to make the prices of international carbon markets co-movement; if exist, which market is driving (mainly driven by) the others? This paper examines the carbon price interactions and its dynamic drivers among different cross-border ETS markets from the perspectives of return and volatility spillover.

Existing studies devoted to these impacts are not conclusive, few papers detect the correlations between developing and matured ETS markets. Previous studies have accounted for 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), EUA and CERs[3] prices integration (Mansanet Bataller et al., 2010; Nazifi, 2013, 2010; Sadefo Kamdem et al., 2016). However, less attention has been paid to the connectedness of carbon markets

[2] Explain the difference between developed, developing, and under consideration.

[3] EUA (EU Allowances) are carbon credits used in the European Union Emissions Trading Scheme (EU ETS). Certified Emission Reductions (CERs) is a primary product traded under the secondary market of the Clean Development Mechanism (CDM).

of Europe, China, US, and New Zealand. The paper most closely related to our work is Mizrach (2012), which investigates co-integration between European and US carbon prices. We will take the analysis one step further and studies how fluctuations in these markets interact with each other,

Most of the above studies adopt 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 (Nazifi, 2010; Mizrach, 2012; Diaz-Rainey and Tulloch, 2018; Lyu, 2021). However, standard vector autoregressive models or cointegration models are estimated with fixed parameters, and the GARCH models have drawbacks, namely imposing parameter restrictions that often violated by estimated coefficients, difficult in interpreting whether shocks to conditional variance persist or not (Nelson, 1991), as well as not accounting the directional and time-varying characteristics of spillovers (Diebold and Yılmaz, 2014).

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 over the course of our sample period. A steady carbon prices increase was observed since Covid-19 outburst (March 2020 - December 2021) from the four ETS we chose; the higher price of carbon in 2020 and 2021 can be jointly explained by uncertainty, a tight energy resources supply, and generally increasing energy prices. Consequently, this paper focuses theoretically on the time-varying parameter (TVP)-VAR methodology, and empirically the connectedness approach, in the field of the economics, finance, and connectedness literature. Our sample consists of emission trading prices across four jurisdictions – European Union, New Zealand, California, and Hubei (China), from April 2014 – December 2021. We examine patterns of the total, directional, and net return/volatility spillover effects among the four ETS schemes.

The relevance of our study is threefold: (1) 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 necessary for assessing the efficiency of existing market linkages and the possibility for future integration. (2) Understanding the return and volatility spillovers between these markets enables institutional and individual investors to manage risk more effectively and make better informed asset allocation decisions. (3) Examining such dynamic volatility interconnection among carbon markets is a prerequisite for correlating volatility connectedness to specific market characteristics, events, and regulatory policy.

The contribution of this study is fourfold: First, to the best of our knowledge, no previous studies have undertaken return and volatility connectedness analysis among these carbon markets. As such, this paper extends the work of Mizrach (2012) and Wang et al. (2021) by investigating more emerging cross-border carbon markets with the use of a more recent sample period. Second, this is the first study to employ the time-varying parameter (TVP) – VAR model with the connectedness approach introduced by Diebold and Yilmaz (2009; 2012) for the examination of the dynamics of carbon market returns and volatilities; a four-dimensional time varying parameter VAR model solves the defects of constant parameters and static analysis of the traditional measurement model. Third, from a practical standpoint, this study generates critical information to individual and institutional investors who are concerned about periods of significant volatility in carbon spot prices and their transmission across different carbon markets; these findings are of great significance to different stakeholders and provide practical suggestions to them. Finally, the detection of shock transmitter (receiver) from the return and volatility connectedness explains why and how the spillover effects change over time.

The remainder of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 presents the methodology to estimate the return and volatility spillover effects among different regional ETS. Section 4 describes the data and sample period. Section 5 discusses the empirical results. Section 6 concludes and provides policy implications.

2. Background

An ETS offers advantages in addressing the heterogeneity in marginal abatement costs, and provides the possibility of connecting national schemes across borders (Flachsland et al., 2009; Stern, 2007). The ETS operates on a 'cap and trade' principle, which sets a limit for the total allowable emissions for each regulated entities in a given area at the start of each compliance year. The initial emission allowances are either auctioned or freely allocated to the regulated entities. By creating the supply and demand for emission permits, an ETS sets a market price for GHG emissions. The Kyoto Protocol designed three carbon emission-trading mechanisms: International Emission Trade (IET), Joint Implement (JI), and Clean Development Mechanism (CDM). At present, there are now 25 ETS markets in force, covering 17 % of global GHG emissions. 22 ETSs are currently under development or under consideration, mainly in South America and South-East Asia (ICAP, 2022).

The ETS markets have developed into a significant component of the global financial system. The world's first cap-and-trade systems were introduced in the US to curb air emissions[4]. EU followed this

[4] Following Clean Air Act amendments of 1990, the sulphur dioxide allowance trading programme was built in the US (Borghesi and Montini, 2016; Schmalensee and Stavins, 2017).

application of cap-and-trade systems and built its own EU ETS in 2005[5]. The EU kept on extending its ETS system up to its present record dimensions, overtaking the US leadership in developing ETS. Subsequently, EU ETS has become the world's first international ETS, covering 31 countries and 11,500 installations; it remains the main driver of the other ETS and is considered as the prototype system for other ETSs (Borghesi and Montini, 2016). As for statewide ETS, 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, and readily implemented a unilateral linkage to Quebec's ETS in 2014. Compared to the above two developed ETS, the New Zealand's (NZ) ETS has a distinctive profile due to an economy dominated by the agriculture sector, responsible for almost 50% of New Zealand's GHG emissions. NZ ETS launched in 2008 and is designed to cover the whole New Zealand economy. It was bilaterally linked to other international ETS, meaning that the Kyoto units (e.g., Certified Emission Reductions and Emission Reduction Units) can be used for compliance in NZ ETS. However, after several changes of domestic market regulation, NZ ETS was withdrawn from the Kyoto protocol in December 2013[6]. As a young startup, the Chinese ETS developed at a fast pace. Its ETS is representative of the world's emerging ETS markets. With night regional ETS pilots running parallel to a national ETS, the whole system is surpassing EU ETS to be the largest ETS in market size[7]. The selected four ETS either allow cross-market linkage or the use of external offset credit for compliance, hence induce potential risk transmission (Gavard et al., 2016). The relationship between emerging and mature carbon markets is crucial for global environmental market integration and liberalization, particularly as emerging markets expand (Guo and Feng, 2021).

A long-term goal for developing ETS is to initiate an integrated market with comparable pricing across jurisdictions (ICAP, 2020). 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

[5] European Commission (2003). Directive 2003/87/EC Establishing a Scheme for Greenhouse Gas Emission Allowance Trading within the Community and Amending Council Directive 96/61/EC. Strasbourg: The European Parliament and the Council of Europe. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A32003L0087.

[6] From mid-2011, as the international price for carbon fell below domestic NZU prices, the unlimited ability to import offsets to NZ ETS has dragged down the price of emission allowances in NZ ETS, leading to a glut of imported international units for surrender for obligations. Thus, from Jan 2012, the government gradually introduced bans on various international carbon credit to strengthen the credibility of the NZ ETS, but ended up withdrawing from the second commitment period (CP2) of the Kyoto protocol in December 2013 (Diaz-Rainey and Tulloch, 2018)

[7] China's nine regional and one nationwide ETSs covers in total 5426 MtCO2e in China. The national ETS covers 4500 MtCO2e itself while the EU ETS covers 1597 MtCO2e.

price shocks from commodity or energy markets (Carbone et al., 2009; Flachsland et al., 2009; ICAP, 2020; Kachi et al., 2015). Smaller ETS could benefit from the improved market liquidity and more stable prices by linking to a mature ETS (Flachsland et al., 2009; the European Commision, 2019). Theoretical and qualitative studies showed a distinct preference toward linking regional emission-trading systems around the world (Doda et al., 2019; Heitzig and Kornek, 2018; Helm and Pichler, 2015; Holtsmark and Midttømme, 2021; Ranson and Stavins, 2016). The past decade has seen the organic growth of linkages between many regional ETS in the world. Some interconnections between carbon markets already exist and these linkages may expand in the future (Gavard et al., 2016), for instance, the California and Québec have linked their ETS markets (California Environmental Protection Agency, 2013); Switzerland and EU ETS signed a linking agreement in 2017, and the linking has been operating since January 2020 (European Commission, 2019). China is considering linking its regional ETS to its national ETS gradually (Lyu, 2021).

With respect to empirical investigation of spillover effects among ETS, previous empirical studies have examined the price, return, and volatility dynamics between separate emission markets. Mazza and Petitjean (2015) assess the integration dynamics of carbon future prices under EU ETS. They studied on European Union Allowance (EUA) futures traded on three platforms — European Climate Exchange (ECX), NASDAQ OMX, and European Energy Exchange (EEX), during Phase II of EU ETS (2008-2012). In the same vein, Benz and Hengelbrock (2008) compare the EUA future contract price across ECX and Nord Pool from 2005 to 2007. For the relationship between EU ETS and CDM market, Nazifi (2010) applies the generalized impulse response analysis to investigate dynamic interactions between EUA prices and CER prices, during Phase II of EU ETS (2008-2012).

Carbon futures markets are growing in significance because they play a critical role in risk mitigation and transfer between market participants, as well as in assisting the price discovery process in the spot market(s). The introduction of carbon futures markets has resulted in the emergence of a new class of individual and institutional carbon investor(s). There is rising concern over risk management of carbon assets or derivatives, as carbon-related derivatives can be utilized for a variety of investment objectives, including portfolio diversification, arbitrage, hedging, and speculation (Arouri et al., 2012; Conrad et al., 2012; Schultz and Swieringa, 2014). Existing literature has verified the close interrelation between carbon spot and futures under EU ETS. Liu et al. (2021) discuss the mean and volatility spillovers by non-linear methods of Granger Causality, showing there was a bidirectional mean spillover effect between EUA spot and future prices for phase 2 and 3 of the EU ETS. Arouri et al. (2012) suggest that shocks to EUA spot markets are observed to have a greater influence on both spot and future market returns than shocks to the futures market.

However, the literature seldom pays attention to the connectedness across major ETS systems around the world. Two papers closely related to our work are Mizrach (2012) and Wang et al. (2021). Mizrach (2012) proposes the first market integration study for cross-border ETS; the paper empirically found the prices across exchanges in Europe were cointegrated, and the U.S. carbon market was Granger Causal for the EU's market. Wang et al. (2021) investigated the time-varying correlation and long-run price cointegration between the EUA price (traded at European Climate Exchange) and Beijing ETS pilot in China, by the use of 61 (for EUA) and 76 (for Beijing) monthly data, from 2013 to 2020. Modelled by wavelet analysis, they indicate that Beijing's emission allowances prices are correlated to EUA price both in low-frequency domain and their co-movement on a longer time scale, however, their analysis doesn't include the examination of price relationship between EUA and other ETS pilots in China. Furthermore, the directional return and volatility connectedness are not examined in their study. The effects of improving clean technology, improving market efficiency, and the increasing scarcity of natural resources could lead the relationships between our variables to change during the sample period. It is natural to improve the standard VAR model which assumes a static structural relationship over time, while neglecting the shifting supply and demand dynamics, growing global market for emission permits, and changing climate change policies.

3. Methodology

To investigate the connectedness of international ETS's, we will use TVP-VAR methods. In recent years, scholars have been keen in developing TVP-VARs (see, among many others, Cogley and Sargent 2001, 2005; Nakajima 2011; and Primiceri, 2005). The connectedness approaches are proposed by Diebold and Yılmaz (2009, 2012, 2014). Diebold and Yilmaz (2019, 2012) intuitively establish a framework for analysing both idiosyncratic and extrinsic effects based on the estimation of the forecast error variance decompositions (FEVD) derived from a VAR model. It should be noted that, albeit they improved the Cholesky-type decomposition (Diebold and Yilmaz, 2009) to a generalised VAR approach (Diebold and Yilmaz, 2012), the rolling window analysis in both studies assumes that the parameters remain unchanged in each of the windows, causing potential loss of observations. Antonakakis et al. (2020), on the other hand, propose a dynamic connectedness approach based on TVP-VAR, which allows the variance-covariance matrix to vary via a Kalman filter estimation with forgetting factor[8]. This TVP-VAR-based connectedness approach has the following advantages: (i) it

[8] Kalman filter approaches have several desirable properties; for example, they are fast because state space models encapsulate the Markov property and reduce to a set of recursions. And the forgetting factor approaches have been commonly used with state space models; they do not require the use of Markov Chain Monte Carlo, which can be

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 (Antonakakis et al., 2020; Koop and Korobilis, 2013). The TVP-VAR approaches have been pursued in related cross-border or cross-region commodity markets (Umar et al., 2021a), stock markets (Bouri et al., 2022) , cryptocurrency markets (Asl et al., 2021), and energy markets (Akyildirim et al., 2022; Evrim Mandacı et al., 2020).

3.1 Overview

This paper follows the approach of Antonakakis et al. (2020). The objective 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:

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

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

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

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), $vec(\mathrm{A}_t)$ is the vectorisation of A_t which is an $N \times Np$ dimensional vector. The ξ_t is an $\mathrm{N}^2 p \times 1$ dimensional vector. Moreover, Ξ_t are $\mathrm{N}^2 p \times \mathrm{N}^2 p$ 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.

computationally demanding (Antonakakis et al., 2020; Koop and Korobilis, 2013; Dangl and Halling, 2012). Supporting the main purpose of our study — to empirically examine the interdependency among global carbon markets — the detailed algorithm of the TVP-VAR model with the use of Kalman filter and forgetting factors can be found in Koop and Korobilis, 2013. Different measures, for example, the rolling window VAR analysis, will be provided in the robustness checks.

Allowing for parameter change increases over-parameterization concerns. However, the existing TVP-VAR literature works with relatively small dimensional models, for example, models with three dependent variables. This study works with four dimensional models, and so the concern of over-parameterization and the need for prior shrinkage is less.

3.2 Estimation of TVP-VAR using forgetting factors

This study used the Primiceri (2005) and Del Negro and Primiceri (2015) prior, following Antonakakis et al. (2020). The mean and the variance of A_0 are chosen to be the OLS point estimates ($\hat{A}_{OLS}$) and its variance Σ^A_{OLS} in a time invariant VAR. Thus, the $\hat{A}_{OLS}$, Σ^A_{OLS}, and Σ_{OLS} are equal to the VAR estimation results of the initial subsample (first year): $A_0 \sim \mathrm{N}(\hat{A}_{OLS}, \Sigma^A_{OLS})$, and $\Sigma_0 = \Sigma_{OLS}$. Let $y^s = (y_1, \dots y_s)'$ 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 the equation (1) with prior information on A_t expressed through a prior distribution $\mathrm{p}(\mathrm{A}_t)$. Key steps in Kalman filtering[9] involve the result that:

$$\mathrm{A}_{t-1}|y^{t-1} \sim N(\mathrm{A}_{t-1|t-1}, V_{t-1|t-1}), \quad (3)$$

where formulae for $\mathrm{A}_{t-1|t-1}$ and $V_{t-1|t-1}$ are given in textbook sources (Koop and Korobilis, 2013). Kalman filtering then proceeds with the use of the below equation (4):

$$\mathrm{A}_t|y^{t-1} \sim N(\mathrm{A}_{t|t-1}, V_{t|t-1}), \quad (4)$$

$$\text{where } V_{t|t-1} = V_{t-1|t-1} + \Xi_t. \quad (5)$$

The prior density for $A_0|y^0$ which involves the choice of $A_{0|0}$ and $V_{0|0}$ is required for the Kalman filtering. In addition, the predictive density $\mathrm{p}(y_t|y^{t-1})$ provided by the Kalman filter can be used for forecasting y_t, given data through time t-1. Equation (5) is the only place where Ξ_t enters the Kalman filtering, and it can be removed by replacing the formulae as below:

$$V_{t|t-1} = \frac{1}{\lambda} V_{t-1|t-1}, \quad (6)$$

where λ is called a forgetting factor($0 < \lambda \leq 1$). The equation (6) implied that observations j periods in the past have weight λ^j in the filtered estimate of A_t. As we can see in equation (6), a forgetting factor approach negates the need to estimate Ξ_t. Now, to estimate the Σ_t, a similar approach involving a decay factor κ is applied. In particular, an exponentially weighted moving average (EWMA)

[9] For details of Bayesian inference for A_0 involving the Kalman filter, see Frühwirth-Schnatter (2006, chapter 13.3).

estimator is adopted. With the use of an EWMA estimate for Σ_t, prior information is required only for A_0:

$$A_0 \sim N(A_{0|0}, V_{0|0}).$$

$$\Xi_t = (\lambda^{-1} - 1)V_{t-1|t-1}, \quad (7)$$

$$\widehat{\Sigma_t} = \kappa\hat{\Sigma}_{t-1} + (1-\kappa)\widehat{\epsilon_t}\widehat{\epsilon_t}, \quad (8)$$

$$\Sigma_{t|t-1} = y_{t-1}V_{t|t-1}y'_{t-1} + \Sigma_t, \quad (9)$$

where $\widehat{\epsilon_t} = y_t - A_{t|t}Z_t$ is produced by the Kalman filtering method for inference on A_t. The EWMA estimators require the selection of the decay factor, κ; this study considers the benchmark values[10] for $\lambda = 0.99$ *and* $\kappa = 0.96$, and keeping them constant at fixed values[11].

3.3 TVP-VAR-based dynamic connectedness approach

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). The important step to calculate the GIRF and GFEVD is to transform the VAR to its moving average representation – VMA, see below:

$$y_t = \sum_{j=0}^{\infty} \Upsilon_{j,t}\, \epsilon_{t-j}, \quad (10)$$

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 $\Upsilon_t = \left[\Upsilon_{1,t}, \Upsilon_{2,t}, \Upsilon_{3,t}, \ldots, \Upsilon_{p,t}\right]'$ and $A_t = \left[A_{1,t}, A_{2,t}, A_{3,t}, \ldots, A_{p,t}\right]'$. Both the $A_{i,t}$ and $\Upsilon_{i,t}$ are $N \times N$ 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:

$$\Theta_{j,t}\,(J) = \frac{\Upsilon_{J,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}}\frac{\varsigma_{j,t}}{\sqrt{\Sigma_{jj,t}}} = \Sigma_{jj,t}{}^{-\frac{1}{2}}\Upsilon_{J,t}\Sigma_t e_j,\ \ \varsigma_{j,t} = \sqrt{\Sigma_{jj,t}}, \quad (11)$$

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[10] For example, for quarterly data, $\lambda = 0.99$ implies observations five years ago receive approximately 80% as much weight as last period's observation (Koop and Korobilis, 2013).

[11] Koop and Korobilis (2013) found that the value added by time-varying decay factors with respect to the forecasting performance was questionable and increased the computation burden of Kalman filter algorithm, thus, we follow Antonakakis et al. (2020) to keep the decay factors constant at fixed values.

where e_j is an $N \times 1$ 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 $\Sigma_{u,t}$ $(same\ as\ \Sigma_t)$. We compute the GFEVD ($\tilde{\phi}_{ij,t}(J)$), which 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. To match the traditional variance decomposition, we normalize each element of the generalized variance decomposition matrix by the row sums as follows:

$$\tilde{\phi}_{ij,t}(J) = \frac{\Sigma_{t=1}^{J-1}\Theta_{ij,t}{}^2}{\Sigma_{j=1}^{N}\Sigma_{t=1}^{J-1}\Theta_{ij,t}{}^2}, \quad (12)$$

with $\Sigma_{j=1}^{m}\tilde{\phi}_{ij,t}(J) = 1$ and $\Sigma_{i,j=1}^{m}\tilde{\phi}_{ij,t}(J) = N$. 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*** (TCI) by below:

$$C_t(J) = \frac{\Sigma_{\mathrm{i,j=1,i\neq j}}^{N}\tilde{\phi}_{ij,t}(J)}{\Sigma_{\mathrm{i,j=1}}^{N}\tilde{\phi}_{ij,t}(J)} \times 100 = \frac{\Sigma_{\mathrm{i,j=1,i\neq j}}^{N}\tilde{\phi}_{ij,t}(J)}{N} \times 100, \quad (13)$$

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 ($C_{i\to j,t}(J)$)*** and it is defined as:

$$C_{i\to j,t}(J) = \frac{\Sigma_{\mathrm{j=1,i\neq j}}^{N}\tilde{\phi}_{ji,t}(J)}{\Sigma_{\mathrm{j=1}}^{N}\tilde{\phi}_{ji,t}(J)} \times 100, \quad (14)$$

We could calculate the directional connectedness variable *i* received from variables *j*, called ***total directional connectedness from others*** ($C_{i\leftarrow j,t}(J)$) and defined as below:

$$C_{i\leftarrow j,t}(J) = \frac{\Sigma_{\mathrm{j=1,i\neq j}}^{N}\tilde{\phi}_{ij,t}(J)}{\Sigma_{\mathrm{i=1}}^{N}\tilde{\phi}_{ij,t}(J)} \times 100, \quad (15)$$

And so, we subtract *total directional connectedness to others* from *total directional connectedness from others* to obtain the ***net total directional connectedness*** ($C_{ij,t}$):

$$C_{ij,t} = C_{i\to j,t}(J) - C_{i\leftarrow j,t}(J), \quad (16)$$

The sign of the net total directional connectedness illustrates whether variable *i* is driving the network ($C_{i,t} > 0$) or driven by the network ($C_{i,t} < 0$). Table 1 is from Diebold and Yilmaz (2009; 2012). The upper left N*N block provides the J-step-ahead forecast error variance decomposition matrix. Based on this matrix, various spillover effects can be examined, as will be explained in Table 4 in Chapter 5 .

Table 1. Schematic of ta connectedness table

	EU ETS	NZ ETS	CA CaT	HB ETS	From Others
EU ETS	d_{11}^J	d_{12}^J	d_{13}^J	d_{14}^J	$\Sigma_{j\neq 1} d_{1j}^J$
NZ ETS	d_{21}^J	d_{22}^J	d_{23}^J	d_{24}^J	$\Sigma_{j\neq 2} d_{2j}^J$
CA CaT	d_{31}^J	d_{32}^J	d_{33}^J	d_{34}^J	$\Sigma_{j\neq 3} d_{3j}^J$
HB ETS	d_{41}^J	d_{42}^J	d_{43}^J	d_{44}^J	$\Sigma_{j\neq 4} d_{4j}^J$
To Others	$\Sigma_{i\neq 1} d_{i1}^J$	$\Sigma_{i\neq 2} d_{i2}^J$	$\Sigma_{i\neq 3} d_{i3}^J$	$\Sigma_{i\neq 4} d_{i4}^J$	$\Sigma_{i\neq j} d_{ij}^J$

Note: EU ETS, NZ ETS, CA CaT, and HB ETS stand respectively for EUA spot daily return/volatility under EEX, NZU daily return/volatility under New Zealand's ETS, spot daily return/volatility under California's Cap and Trade system, and Hubei Emission allowances daily return/volatility under Hubei ETS in China.

4. Data

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. These four markets are selected for the analysis of global carbon market integration[12]. We use the price of the European emission allowances (EUAs) spot since the EUA contracts are the major carbon product traded under EU ETS (Lutz et al., 2013; Sadefo Kamdem et al., 2016; Wang et al., 2021). Prices and traded volumes of EUAs exceed the other equivalent products under EU ETS while those instruments (EUAA or CERs[13]) can be used for acquiring 1 tonne of emission allowances. NZ ETS trades in carbon credits known as New Zealand Units (NZUs), which can be held and sold by secondary market traders and auctions. The carbon emission product California Carbon Allowances (CCA), which represents a carbon emission equivalent under CA CaT, is traded on the ICE Futures Exchange, US. Furthermore, we chose the spot price of Hubei pilot ETS as a representative of Chinese ETS instead of other pilot ETS, for these reasons: i) China's Hubei 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 its deemed representative for the entire economy. ii) Along with corporate and institutional investors, Hubei 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 iii) Hubei ETS is the largest pilot ETS

[12] It is worth mentioning that other pilot ETS in China, such as Shanghai ETS (started from 2013.11.26), Shenzhen ETS (started from 2013.06.18), and Beijing (started from 2013.12.28) have longer trading history, in 2013 when they started breakpoints and missing data were observed due to the illiquidity and low trading volume, which impacts the data quality. Furthermore, the Shanghai, Shenzhen, and Beijing ETS are city-wide ETS; we argue that Hubei ETS, as a provincial ETS, is more comparable to the other markets in our study.

[13] EUAA stands for European Union Aviation Allowances. CERs stands for Certified Emission Reductions. Both EUA and CERs are emission products.

in China in terms of trading volume, continuity, social capital invested, and incorporated firm participation. Table 2 summarizes the main differences across the four ETS in our study.

In the carbon market integration literature, Wang et al. (2021) identify a long-run cointegration relationship between Chinese ETS and EU ETS. However, only a limited sample of Chinese ETS — 34 months of data — are modelled in the cointegration test, which might lead to an inconclusive result. Mizrach (2012) examines the integration among carbon prices in EU and North America. While some evidence showed the foundation for global carbon market integration among EU, US, and China's (regional) ETS, the sample periods examined in the above two studies are different. And no research has included the California and New Zealand's ETS, respectively to the global carbon market integration.

Table 2. Market architecture – differences among four ETS

	EU ETS	NZ ETS	CA CaT	HB ETS
Start	2005	2008	2012	2014
Cap	1579 $\mathrm{MtCO_2e}$	34.5 $\mathrm{MtCO_2e}$	307.5 $\mathrm{MtCO_2e}$	166 $\mathrm{MtCO_2e}$
Market threshold	25 $\mathrm{ktCO_2e}$	low	25 $\mathrm{ktCO_2e}$	10 $\mathrm{MtCO_2e}$
Averagr 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 fluoridated GHG	CO_2

Source: Own elaboration based on information and data from Emission Trading Worldwide: Status Report, by International Carbon Action Partnership, 2022.

To study the regional carbon market co-movement and integration , we use carbon prices from four emission markets — EU ETS, NZ ETS, CA CaT, and Hubei ETS[14] (HB ETS). After examining several alternative data sources, we concluded Thomson Reuters and Bloomberg provide the carbon prices for the four ETSs with the longest time periods. Our sample covers the period 30 April 2014 through

[14] Daily spot prices for New Zealand Units and EU emission allowances (EUA) traded under European Energy Exchange (EEX) are sourced through Bloomberg and Reuters. Daily spot prices under Hubei ETS are found from Wind Database. Daily prices of California Carbon Allowance that traded on the ICE Future Exchange US are from California Carbon Info.

1 December 2021. All prices use in this study are quoted in Euro. We calculate weekly returns as the change in log price, from Friday-to-Friday. The continuously compounded returns of four sets are computed as $r_{i,j,t} = \left(lnP_{i,j} - lnP_{i,j-1}\right)$, for market i, in week t. We use the realized (historical) volatility as proxy of volatility[15]. Four measures have been applied to estimate weekly volatility of carbon price[16]. The first measure is the standard deviation of weekly return over the five-day interval during each week:

$$\widetilde{SD}_t = \sqrt{\frac{\sum_{i=1}^{M}\left(r_{i,t}-\bar{r}_t\right)^2}{M-1}}, \quad (17)$$

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 case M=5). The corresponding estimate of the annualized weekly volatility in percentage is $\widehat{SD}_t = 100\sqrt{52}\widetilde{SD}_t$. The second measure is the weekly range of price that considers five prices in a week. Following Diebold and Yilmaz (2012) and Parkinson (1980), we use weekly high and low prices obtained from daily data, from Monday open to the Friday close, to estimate weekly variance:

$$\tilde{\sigma}_{it}^2 = 0.361[\ln(P_{it}^{max}) - \ln(P_{it}^{min})]^2, \quad (18)$$

where P_{it}^{max} is the Monday-Friday highest price, P_{it}^{min} is the Monday-Friday lowest price, $\tilde{\sigma}_{it}^2$ is an estimator of weekly variance at market i, same as above. We calculated the annualized daily percentage volatility (standard deviation) $\hat{\sigma}_{it} = 100\sqrt{52\tilde{\sigma}_{it}^2}$. According to the calculations above, the sample size is 397 observations for each series. The empirical results reported in Chapter 5 are generated with the first measure[17] (i.e., $\widetilde{SD}_t$, from Equation 18). All return and volatility series are stationary, tested by the Augmented Dicky-Fuller (ADF) test. Figures 1 and 2 plot the weekly return and realized volatility for the four markets during the sample period[18]. The two figures show that all ETS except HB ETS have high volatility after March 2020 (when Covid-19 hit); however, because HB ETS had a 40-day lockdown from February 10 to March 20, 2020, the movement of HB ETS during this period is not informative. Both the return and volatility in the NZ ETS in 2014 and 2015 appear to be high due to the withdrawal from the Kyoto Protocol.

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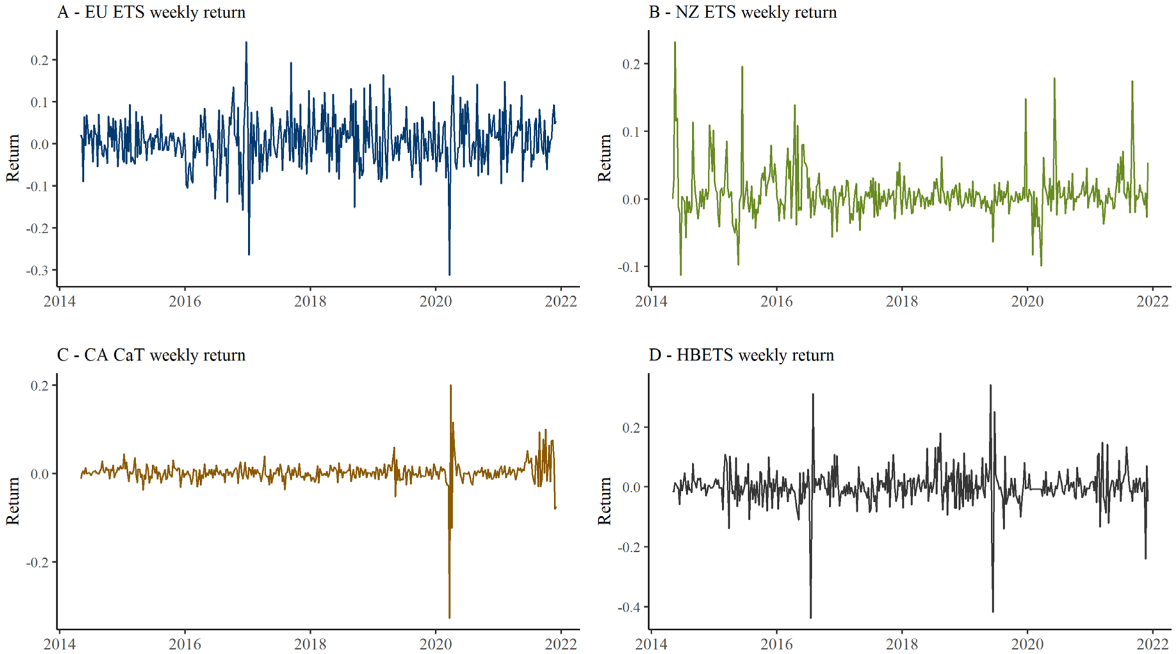
[15] We can obtain only daily closing prices for the four markets; high frequency/intraday data are not available for CA CaT and HB ETS. By using the weekly highest, lowest, open, and close prices, we calculated the realized/historical volatility. To be consistent with the frequency of the historical volatility data, we use weekly returns.

[16] Note that we use Garman and Klass (1980) volatility as another proxy of volatility for the robustness check, descriptive statistics shown in Appendix in Section 7.

[17] The empirical results based on the two measures are very similar. The results based on the second measure (i.e., $\hat{\sigma}_{it}$) can be found in Appendix Table A1 and Figure A1 in Section 7 or are available upon request to the authors.

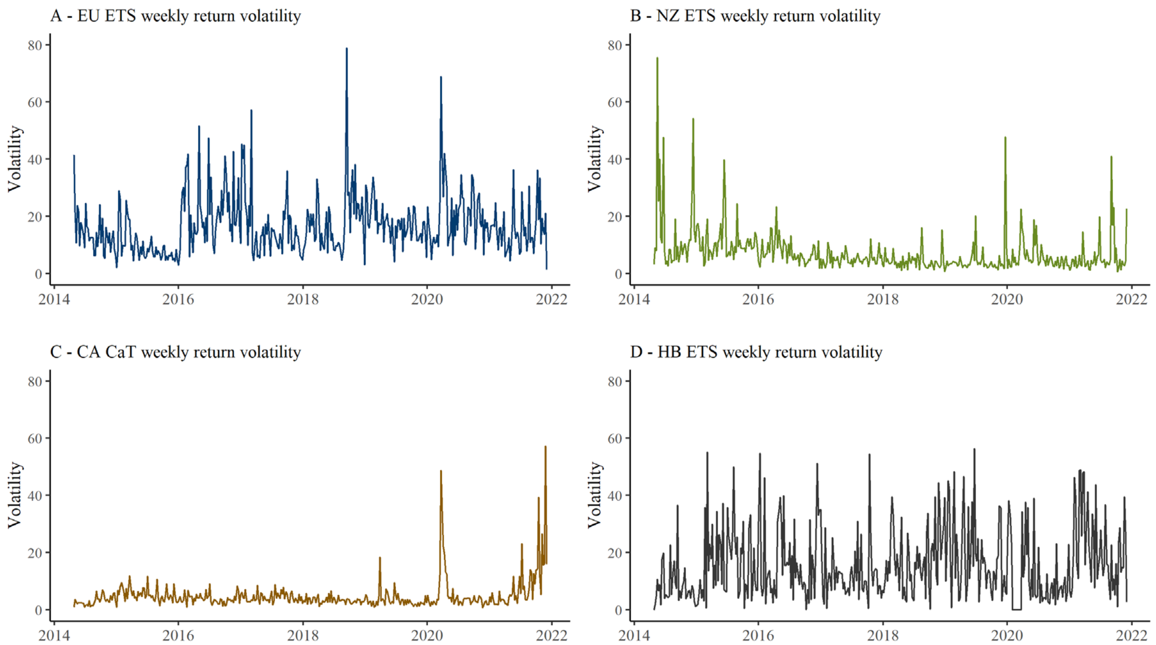
[18] Plots of Parkinson (1980) volatility (i.e., $\hat{\sigma}_{it}$), $\widetilde{SD}_t$ based volatility, and Garman and Klass (1980) volatilities are provided in Figure A2 in Appendix.

Figure 1: Weekly return from four ETS



Source: Own elaboration based on data from Bloomberg, Reuters, and Wind Database. Reported are the descriptive statistics of the weekly log-return and volatility series, range from 30 April 2014 to 1 December 2021.

Figure 2: Weekly realized (annualized) volatility from four ETS



Source: Own elaboration based on data from Bloomberg, Reuters, and Wind Database. Reported are the descriptive statistics of the weekly log-return and volatility series, range from 30 April 2014 to 1 December 2021.

To dig into more details of the series, we report the descriptive statistics of the return and volatility series in Table 3, in which panel A shows that the means of all returns are positive, implying rising prices. Indeed, the prices of EUA, NZU, and CCA rose from 4.34, 1.03, and 11 Euro/ton emission allowances to 76.8, 41.34, and 26.21 Euro/ton, respectively. While the mean return on the HB ETS is positive but close to zero, the price of the Hubei emission allowances (HBEA) remained rather stable, with the most significant t-statistics from stationarity (ADF) test. Furthermore, several interesting facts emerge in the analysis of volatility: 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 one of the newly built Chinese pilot markets which started trading in 2014, Hubei ETS has a flawed market structure, due to the lack of legislation through the provincial legislature in place and a large share of over the counter (OTC) trading. Thus high volatility is expected in such emerging market (Zhang, 2015). 3) CA CaT volatilities increased simultaneously from mid-2021 to end of sample period, indicating a shift in the pattern of spillover effect from or to CA CaT in the post-Covid-19 period.

Table 3. 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 H_0: non-stationary against H_1 : stationary. The lag length is determined by BIC criterion. * denotes significance at 10% level, ** denotes significance at 5% level, *** denotes significance at 1% level.*

5. Results

In this section we report the results of empirical analysis by the method presented in Section 3. Specifically, Section 5.1 presents the total connectedness index (TCI), which measures the influence of one market on all others on average (see Equation 13 in Section 3.3). Sections 5.2 and 5.3 show the total directional connectedness, which reflect the spillover relationship between a market and all other markets, including total directional connectedness to others ($C_{i\rightarrow j,t}(J)$ from Equation 14), total directional connectedness from others ($C_{i\leftarrow j,t}(J)$ from Equation 15), and net total directional connectedness from others ($C_{ij,t}$ from Equation). The results reported in the following main text are generated with the first measure[19] (i.e., $\widetilde{SD}_t$, from Equation 18).

5.1 Dynamic total connectedness index

In the following empirical model, we use first-order VARs (p=1) (selected by Schwarz information criterion), with 10-step-ahead forecasts[20] (H=10). We define the total connectedness index (TCI) by summing all the non-diagonal elements of the generalized variance matrix (see Table 1, Section 3). We define that if this TCI rises, so does network member dependency, and therefore market risk. On the other hand, if the TCI decreases then the dependence between the members decreases and hence in turn the market risk decreases. Table 4 presents the averaged connectedness measures for the markets.

Table 4. 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

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:*

[19] The empirical results based on the other two measures are very similar. The results based on the second measure (i.e., $\hat{\sigma}_{it}$) can be found in Appendix A (or are available upon request to the authors).

[20] A different choice of forecasting horizon, H from 2 to 9 will be assessed in the robustness check in the Appendix A, at Section 7 Following most of the literature (see for example Yilmaz, 2009), we use 10-step-ahead horizon in the main text.

d_{ij}^{J}). *According to Equation 16 (*$C_{ij,t} = C_{i\to j,t}(J) - C_{i\leftarrow j,t}(J)$*), we obtain the net total directional connectedness,* $C_{ij,t}$.

The main diagonal of Table 4 shows own-variance shares of shocks, while the off-diagonal elements reflect the interaction across global ETS. The number in the bottom right corner represents TCI of the system. As such, 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 ETS. Both the dynamics of each of the carbon market 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 return and volatility TCI are 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.

As the objective of this paper is to learn more about the behavior of return and volatility spillovers over time, we move beyond the aggregated spillovers for the full sample. In particular, we demonstrate 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, respectively. The dynamic total return and total volatility connectedness are plotted in Figures 3 and 4. As shown in the figures 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. Periods with a high degree of connectivity corresponding to the events in Table 5 are upscaled by the event numbered and the shaded areas in Figure 3 and 4. Therefore, we focus on events shaded to to (i) global politics, (ii) carbon market linkage/delinked changes, (iii) temperature and weather, and (iv) public health crises — e.g., Covid-19. Table 5 shows the key features of the events shaded. As confirmed by the literature, the driving factors of the supply and demand in an ETS are: (i) economic growth and government constraints; (ii) international climate change agreements; (iii) regulatory change and arbitrageurs; and (iv) market fundamentals, such as energy prices and weather (Benz and Trück, 2009; Mansanet-Bataller et al., 2007; Lyu, 2021).

Table 5: 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[21]	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 hits China	2019.12.31	covid-19
2021	20	Covid-19 pandemic started	2021.03-2022.12	covid-19

Repeatedly, the return connectedness can be observed in Figure 3, the dynamic connectedness of return network changes considerably over time, especially from 2015 to mid-2016 and following the Covid-19 outbreak, which is suggests that fact that the spillovers across carbon markets are time-dependent.

[21] levels of fine particle pollution in Shijiazhuang, capital of northern Hebei province, hit 1,000 micrograms per cubic meter—40 times the WHO standard, in December 2016.

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 shut down over 2,000 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[22]. Fourth and, highest connectedness is associated with the Covid-19 outburst and sparking fears of the lockdown policies all over the world (Event 20). March 2020, the return spillovers jump from 7.09% to 35.74%, global carbon market spillovers reached the highest point so far.

It is worth to notice three moderate intensifications in the return connectedness starting from Dec 2016, Jul 2017, and Aug 2018 respectively, coinciding several extreme weather events (Events 13, 14, and 15). Elevated concerns about global warming and decarbonisation have led the TCI to an respond. Two other carbon markets events (Events 9 and 11) have caused the index to small spikes. In June 2019, the HB ETS experienced a huge price spike, causing volatility in its return series (see Figure 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 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, its existence will inevitably reduce the size, as well as reduce the liquidity of pilot ETS and weaken its influence. Carbon market regulation changes might alter investment decisions, resulting in market return changes. For instance, the decreased market threshold incentivizes institutional and individual investors to participate in carbon trading.

[22] NASA recorded that the average global surface temperature in February 2016 was 1.35C warmer than the average for the month between 1951-1980. Sourced by NASA, retrieved from https://data.giss.nasa.gov/gistemp/.

Figure 3: Dynamic total return connectedness

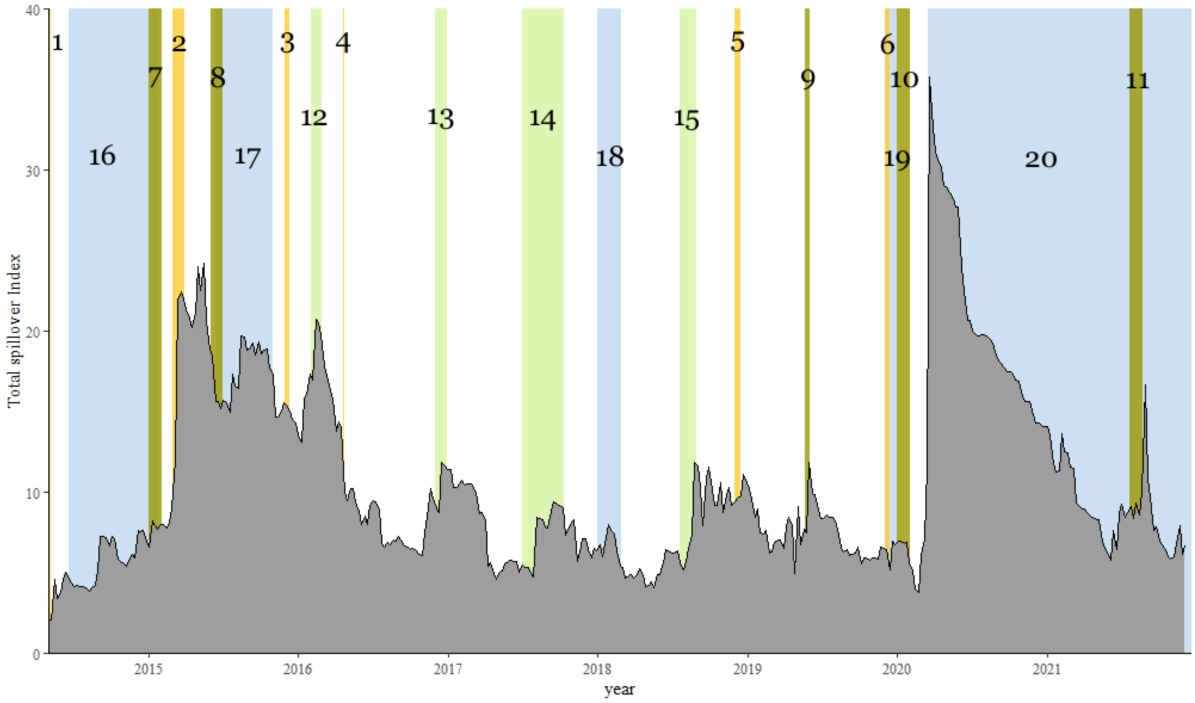
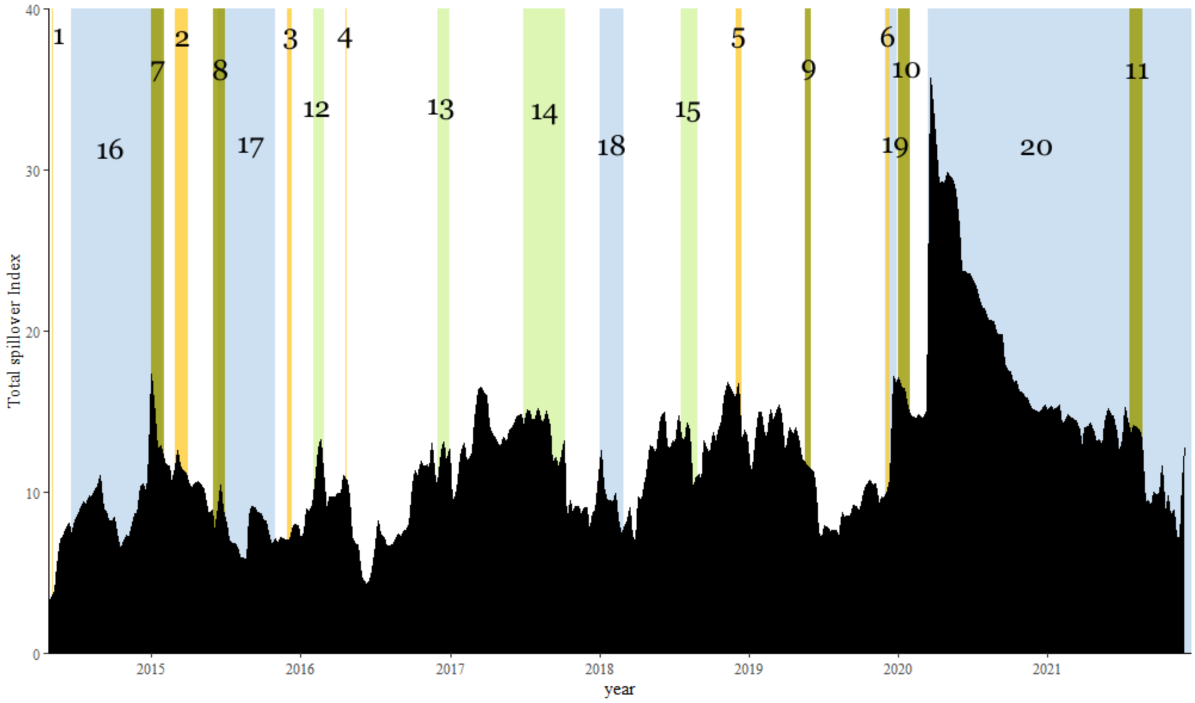


Figure 4: Dynamic total volatility connectedness



The volatility TCI, shown in Figure 4, jumps in a different pattern. A slight upward moves in volatility total connectedness from the September 2014 to January 2015 period reflects the effects of continued crude oil price crises(2014-2016). We observe that the first peak (TCI=17.31%) of carbon market volatility connectedness index occurred at the troughs ($44.08 a barrel in January 2015) of the crude oil price (Event 16). From Figure 4, it appears that 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. (2022)'s analysis of global energy market connectedness index also shows an increase from October 2014 to January 2015, this suggests that the carbon and energy market connectedness indices share the same features during global oil price crisis.

During 2016 and 2020, the volatility spillover index moves up and down. The fluctuation of carbon market volatility the spillover index can be the joint consequences of extreme weather events in which booming the awareness of global warming (Event 12 - 15), cryptocurrency crash (Event 18), and uncertainty brough 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 EU ETS, as well as Covid-19 first hit China, the index fall again. 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 (e.g., Akyildirim et al., 2022; Bouri et al., 2021; Tiwari et al., 2022).

Our findings also suggest that global negotiations and other political issues (e.g., Events 1, 3, 4, and 5) and carbon market events (Event 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., Event 12-15,). The volatility spillovers, on the other hand, seem mostly impacted by the crude oil crisis and cryptocurrency crash (Event 16, 18). Both return and volatility spillovers are heavily impacted by the Covid-19 outburst, which resulted in increasing market risks across carbon market network.

5.2 Connectedness for 'From' and 'To'

In this section, we investigate dynamic spillovers and their directions for each of the ETS's. In Table 4, the time averaged values of To Others, From Others, and Net measures are computed from $\tilde{\phi}_{ij,t}(J)$ (see Equation (12)). Recall what the diagonal of Table 4 represents the shocks from each of the markets themselves, while the upper and lower part of the off diagonal show the spillovers across the markets. For example, the EU ETS in the return connectedness analysis (see Table 3 Panel A), has received in total of 11.01% shocks from three other markets, 2.88% from NZ ETS, 4.98% from CA CaT, and 3.15%

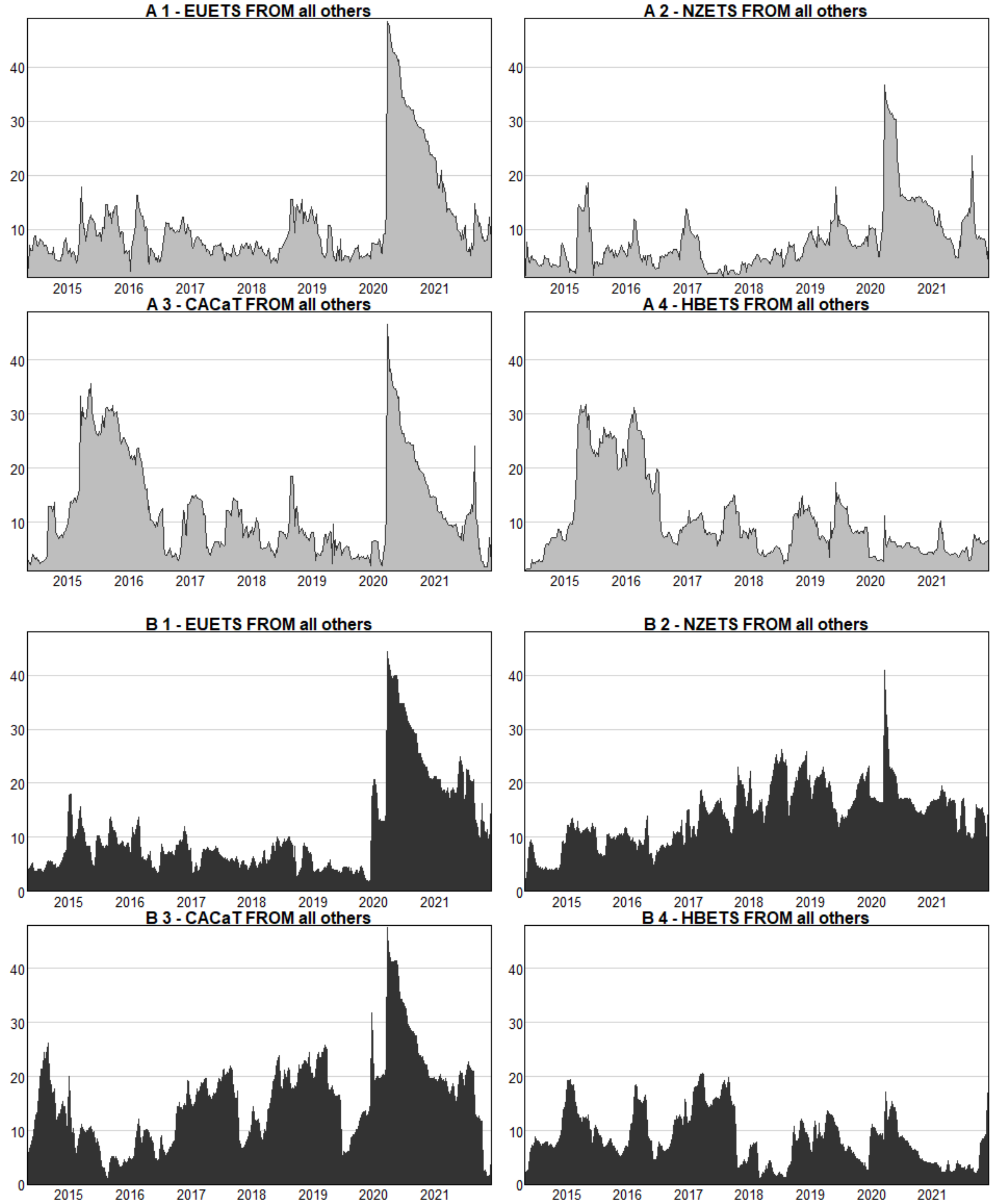
from HB ETS, respectively. On the other hand, EU ETS spilled in total 13.16% to the above three markets: 3.46% to NZ ETS, 5.16% to CA CaT, and 4.54% to HB ETS.

The highest value of the (aggregated) return spillovers from others are for CA CaT ($\Sigma_{j\neq 3} d_{3j}^{J}$=12.41%), and the lowest value of the (aggregated) return spillovers from others are for NZ ETS ($\Sigma_{j\neq 2} d_{2j}^{J}$ =7.97%). In terms of the (aggregated) return spillovers to others, EU ETS and NZ ETS remain the highest ($\Sigma_{i\neq 1} d_{i1}^{J}$ =13.16%) and the lowest ($\Sigma_{i\neq 2} d_{i2}^{J}$ =7.04%). The volatility connectedness measures (see Table 4, Panel B) reveals that NZ ETS received 13.96% (aggregated) volatility spillover from 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 4 are average aggregated measures. As we wish to show more about the behaviour of return and volatility spillovers over time, we also plot the directional evolution through time. Figure 5 and Figure 6 show the directional return and volatility spillovers from and to four ETS over time.

All plots in Figure 5, except for HB ETS reveal that there have been marked increases of spillovers from other markets right after the Covid-19 outbreak, both for the return and volatility networks. Although the average level of connectedness *From Others* remains 7-13 percentage for the markets, the spillovers *From Others* peaked at almost 50% for EU ETS and CA CaT in March 2020. What is interesting in these plots is that general patterns of HB ETS in both return and volatility systems, which have shown hardly impacted by the Covid-19 outbreak. Considering that the Covid-19 policies in China are unique in terms of the strict lock down, the carbon market movement could not be impacted by the other markets in other countries. Furthermore, there is a slight upward trend shown in return (volatility) systems of NZ ETS since mid-2017 (mid-2016), showing that delinking NZ ETS to global markets has increase the market risks in NZ ETS.

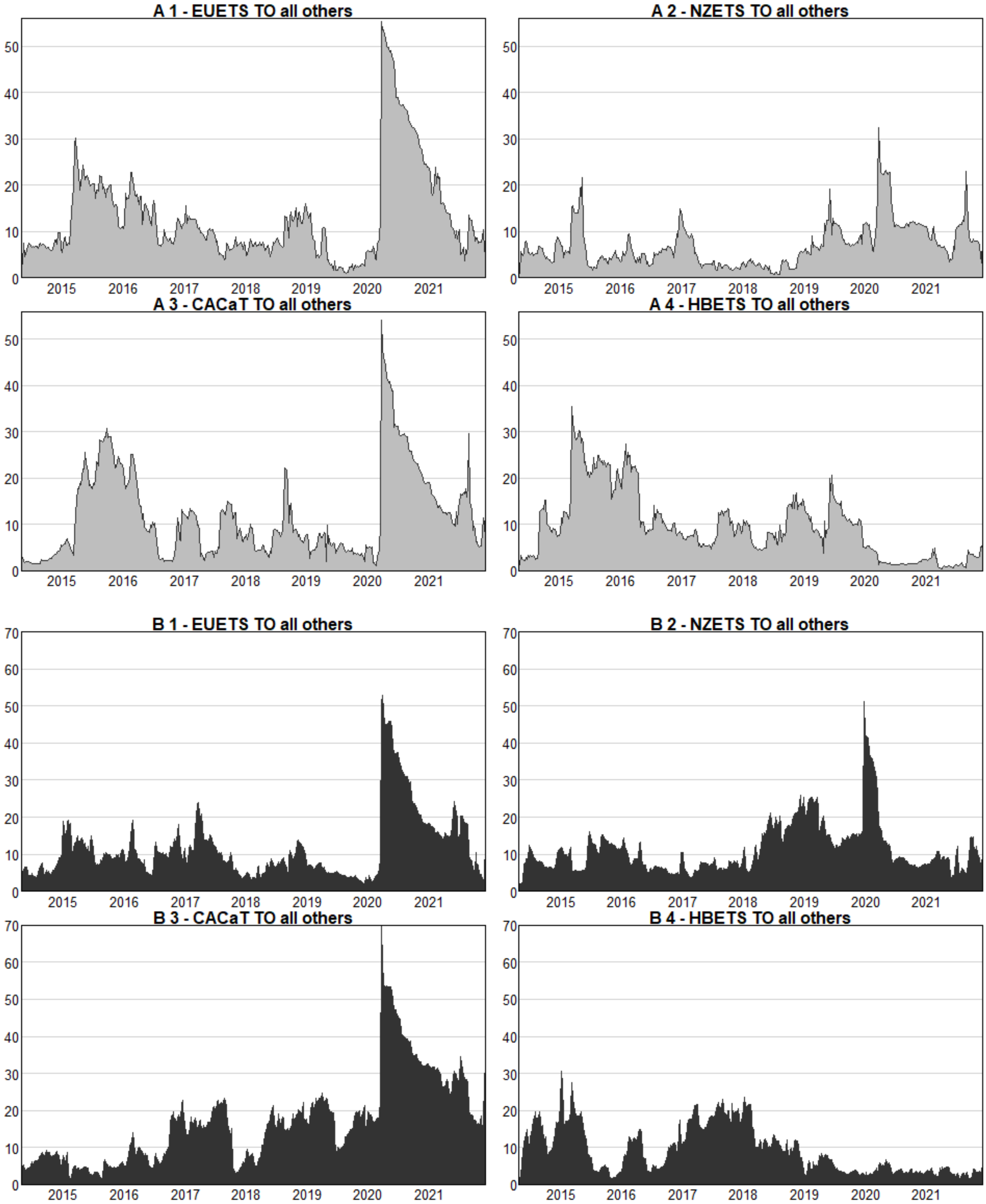
In terms of the directional spillovers from each of the four to all markets, the EU ETS has the largest (aggregated) share of spillovers (13.16%) to all others in the return system while CA CaT has the largest (16.67%) to the others in the volatility system. Since March 2020, the return (volatility) 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 approx. 10% to nearly 2%, since mid-2019.

Figure 5: Dynamic directional return and volatility spillovers - *FROM* four markets



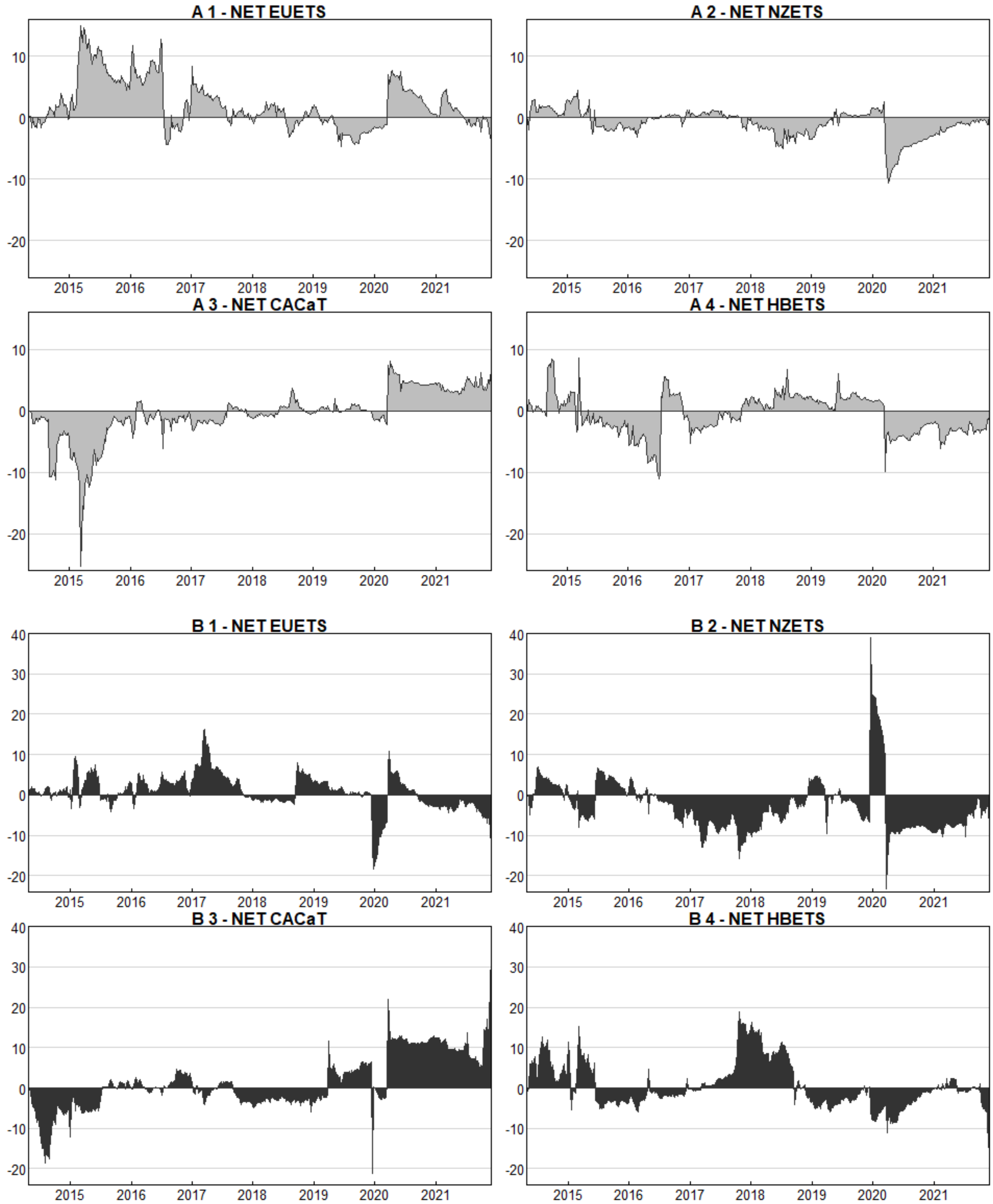
Note: Panel A1 to A4 in grey colour are from the return connectedness system, Panel B1 to B4 in black colour are for the volatility connectedness system. The return series contains 397 observations (each) starting from 2 May 2014 to 1 December 2022 while the volatility series contains 398 observations (each) starting from 25 April to 1 December 2022. The predictive horizon for the underlying variance decomposition is H=10, both are first-ordered VAR (p=1).

Figure 6: Dynamic directional return and volatility spillovers – *TO* four markets



Note: Panel A1 to A4 in grey colour are from the return connectedness system, Panel B1 to B4 in black colour are for the volatility connectedness system. The return series contains 397 observations (each) starting from 2 May 2014 to 1 December 2022 while the volatility series contains 398 observations (each) starting from 25 April to 1 December 2022. The predictive horizon for the underlying variance decomposition is H=10, both are first-ordered VAR (p=1).

Figure 7: Net return and volatility spillovers - four markets



Note: Panel A1 to A4 in grey colour are from the return connectedness system, Panel B1 to B4 in black colour are for the volatility connectedness system. The return series contains 397 observations (each) starting from 2 May 2014 to 1 December 2022 while the volatility series contains 398 observations (each) starting from 25 April to 1 December 2022. The predictive horizon for the underlying variance decomposition is H=10, both are first-ordered VAR (p=1).

5.3 Net total connectedness

Net total directional connectedness (see Equation (16)) 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 4 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 4 point at the difference between the transmitting and the receiving shocks of each markets considering the entire network. Note that positive values in Figure 7 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.

Table 4 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 spillovers transmitter, confirmed by the positive value shown at the bottom of Table 4 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. Figure 7 displays the evolution of net return and volatility spillover of the four ETSs. An inspection of Figure 7 leads to several concise conclusions:

(i) the EU ETS is persistently transmitting shocks to others (with few exceptions) in the return connectedness system, leading to a result that EU ETS has a persistent net-transmitting role. The phenomena could be explained by the maturity of the market performance and the market size (in terms of total participants, price, and revenues) of the EU ETS. The result is in line with the findings of Borghesi and Montini (2016) who suggest that EU ETS is the driver of international ETS and considered as the prototype system.

(ii) In terms of volatility net total spillovers, what stands out in Figure 7, is the spike of 39.5% on 13 December 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 (see. Figure 2), where the market volatility was substantially impacted by Covid-19 when it first hit China.

(iii) After Covid-19 outbreak, the CA CaT became a net transmitter while the NZ ETS and HB ETS remained in their roles as shocks receiver in systems. Ca CaT and EU ETS share several similarities, for example, they are both structured upon three compliance phases, sector coverage is similar, as well as the market threshold of EU ETS and CA CaT are evidently higher than those in the other two, which means their participants are larger in scale, hence, less vulnerable to public crisis. Moreover, both EU ETS and CA CaT allow the use of other project based GHG emission offset programs, while NZ and HB ETS are relatively isolated markets (Hua and Dong, 2019; Leining et al., 2020; Zhang, 2015).

6. Conclusion

This paper studies the connectedness among four Emission Trading Schemes: the EU ETS, New Zealand ETS, California's Cap-and-Trade, and Hubei ETS, from 2014 to 2021. Our examined sample period (2014-2021) covers a wide range of events, for example, the stock market crashes, global climate change negotiations, political events, carbon market regulation, 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 markets may be affected during the sample period. To find out, we employ a time-varying parameter (TVP)-VAR methodology to measure the connectedness along the four markets. This method extends Diebold and Yilmaz's (2009, 2012) connectedness approach by improving the rolling-window VAR, and allows us to examine patterns of the average, directional, and net total return (volatility) spillover effects among the four ETS schemes. We find that the dynamic connectedness of return and volatility networks changes considerably over time, especially during Covid-19 outbreak, this suggests that the fact that the spillovers across carbon markets is time-dependent. It shows that 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 appear to have only minor impact, whereas the occurrence of energy and financial crises have a substantial effect on TCI (both in return and volatility). The EU ETS has a persistent net-transmitting role, it is the largest and only transmitter (2.14%) in return connectedness while CA CaT is the largest transmitter in the volatility connectedness (1.35%). Ca CaT and EU ETS share several common features regarding their resilience. They are both structured upon three compliance phases, e.g., EU ETS (CA CaT) phase one 2005-2008 (2013-2014), phase two 2008-2012 (2015-2017), phase three 2012-2020 (2018-2020); sector coverage is similar, and the market threshold of EU ETS and CA CaT are evidently higher than the other two, which means their participants are larger in scale, hence, less vulnerable to public crisis. NZ ETS is the largest shock receiver in both the return (-0.93%) and volatility (-2.76%) connectedness systems. Furthermore, we establish 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 the strict lock down, and especially closing the boarder for other countries, the carbon market movement can hardly be impacted by the markets in other countries.

Most studies in the field of carbon markets have focused on the relationship between carbon market and energy/financial markets (Ji et al., 2018; Tan et al., 2020; Tiwari et al., 2022). Several studies are limited to local/domestic carbon markets (Conrad et al., 2012; Diaz-Rainey and Tulloch, 2018; Lyu, 2021). To the best of our knowledge, there are only three studies investigating the relationship among cross-border/cross-region carbon markets, which are (Guo and Feng, 2021; Lyu, 2021; Mizrach, 2012; Wang et al., 2021). No attempt was made to dealt with the directional return and/or volatility spillovers (from/to a particular market) across the four countries we examined. This study improves the carbon market integration literature by investigating four important emerging cross-border carbon markets with the use of a more recent sample period. A novel model, our four-dimensional time varying parameter VAR model solves the defects of constant parameters and static analysis of the traditional measurement model. Examining such directional dynamics among carbon markets is a prerequisite for correlating volatility connectedness to specific market characteristics, events, and regulatory policy. From a practical standpoint, the findings are not only relevant to the four selected study regions but also globally, as the establishment of ETS and improving market integration among regional markets through direct physical interconnections is ongoing globally.

The results lead to below policy implications. Firstly, strategies to enhance market design might involve the introduction of a price floor, market stability reservice, and banking and/or borrowing mechanisms in the emerging markets. Learning from our empirical results, a price floor turns out to be useful to prevent California's carbon prices from decreasing/increasing even further during the recent Covid-19 crisis. If such mechanisms are not in place, the allowances prices may keep falling/increasing and would not reflect the true value of emission allowances. ETS participants, for instances the power generators would most likely pass through the carbon cost to end users. Secondly, 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 would increase the market risk transmission in carbon market networks. Hence, a smooth transmission from China's pilot ETS to national pilots is needed in a sense that the carbon market regulation change might alter investment decisions, resulting in market return changes.

Due to data availability, we only obtained daily closing prices for each ETS, which further constrains the volatility series to a weekly frequency since the measure of daily realized volatilities can only be calculated by intraday data. There would therefore seem to be a definite need for high frequency data.

In addition, possible future studies in this area would be 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 quit EU ETS since Brexit. Another possible area of future research would be to investigate the directional spillovers from compliance carbon markets to voluntary carbon markets.

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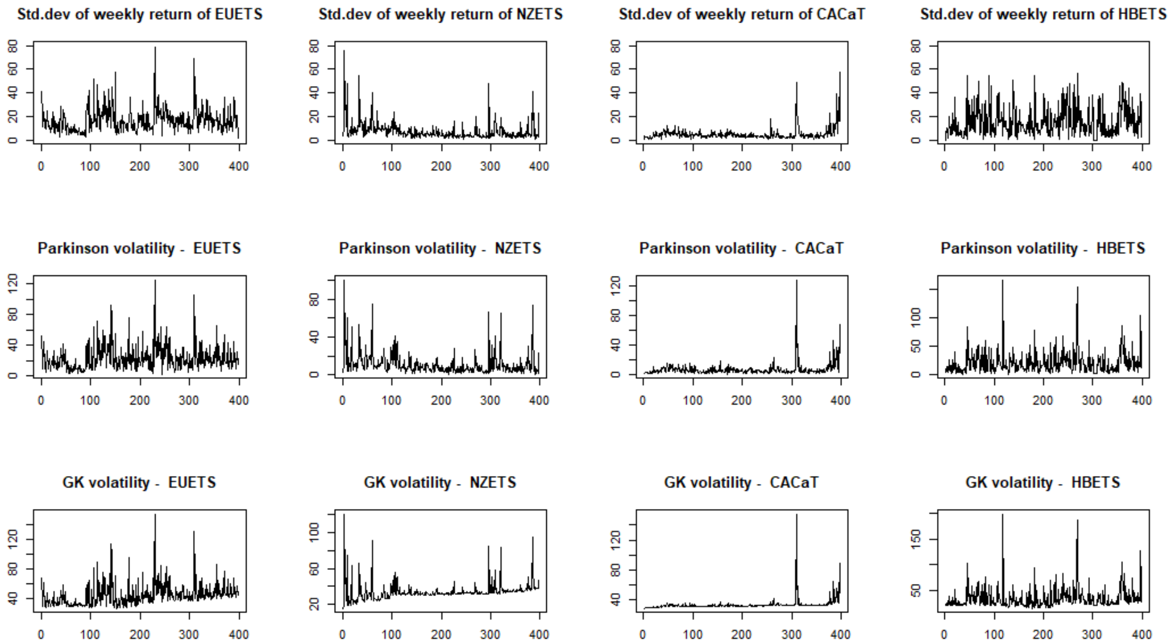
Appendix A

Table A1. Descriptive statistics for three volatility measures – three measures of historical volatility

Panel A: Standard Deviation of Weekly Returns				
Statistic	EU ETS	NZ ETS	CA CaT	HB ETS
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: Own elaboration 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 $\widehat{SD}_t = 100\sqrt{52}\widetilde{SD}_t$.

Figure A1. Plots of three volatility measures – St.Dev., Parkinson, and Garman and Klass



Source: Own elaboration 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 $\widehat{SD}_t = 100\sqrt{52}\widetilde{SD}_t$.

Figure A2. Robustness check – total connectedness index from three volatility measure

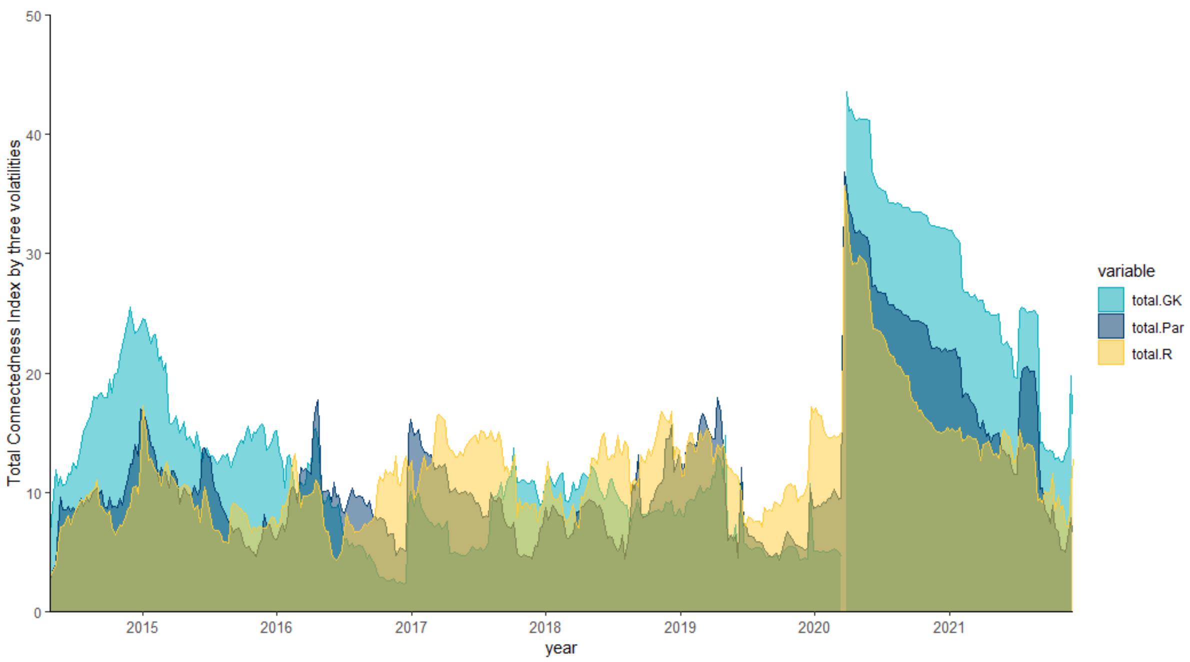
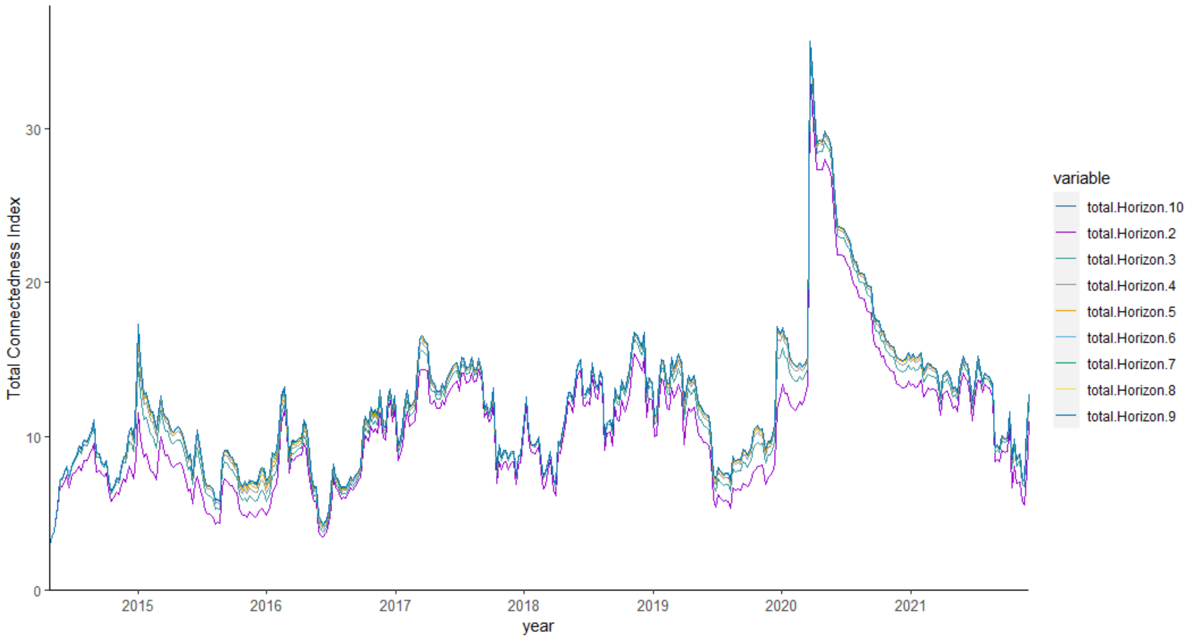


Figure A3. Sensitivity of the Total Connectedness Index to VAR lag structure

Note: The indices were calculated based on the volatilities generated with the first measure (i.e., $\widetilde{SD}_t$, from Equation 18). In the main text we used lag 1 as selected by Schwarz information criterion. Here in the robustness check we tried lag 1, lag2, and lag3 in the model (lag 3 was chosen byAkaike information criterion)

Figure A4. 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 18). We used VAR (1) for these estimations. 2 to 10-week Horizons are chosen and plotted.