Dependence Structure among Carbon Markets around the World: New Evidence from GARCH-Copula Analysis

Karishma Ansaram[a] *and Paolo Mazza*[b]

ABSTRACT

In this paper, we investigate the dependence structure among carbon markets globally through different copulas. The analysis examines the relationship between carbon prices being traded across different emission trading systems (ETS) worldwide. The novelty of our approach lies in assessing carbon allowances for both futures and spot prices across all the key carbon markets as well as the three Chinese carbon markets for the period from 2011 to 2019 for future prices and the period from 2015 to 2020 for spot prices. The results demonstrate an asymmetric relationship between most carbon markets. A low tail dependence was observed between the European Union ETS and Regional Greenhouse Gas Initiative ETS, California and Quebec carbon markets, while higher tail dependence was found in the Asian carbon markets. Furthermore, carbon markets that have linkage agreements, ongoing cooperation or are geographically close tend to have positive and higher tail dependence. Our findings suggest the formation of regional carbon clubs based on the dependence structure.

Keywords: Carbon markets, Carbon pricing, Copula models, Dependence structure

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1. INTRODUCTION

In the Paris Agreement, countries have pledged to reduce their carbon emissions to limit the global mean temperature increase to well below 2 degrees (Rogelj et al., 2017). The emission trading system (ETS), commonly known as the carbon market, is considered a pivotal tool for monitoring the commitments by the parties that ratified the agreement (Sousa et al., 2014). Since 2005, carbon markets have been mushrooming around the world (Michaelowa et al., 2019), and to date, there are 31 carbon markets that are currently in place or have been planned (Ramstein et al., 2020). Through carbon markets, the right to emit a given amount of CO_2 becomes a tradable commodity and is a factor of production that is subject to stochastic price changes. Since the advent of emission trading systems in 2005, several studies have analyzed the behavior of emission allowance prices. A segment of this vast literature focuses on cointegration in the same market (for example, Chevallier et al. (2010), Trück et al. (2014) and Wu and Hu (2014) for integration between spot and future carbon prices as well as Zhu et al. (2020) for the Chinese pilot carbon market's risk of spillovers). Another set of literature focuses on cointegration between two carbon markets and/or between one carbon

a IESEG School of Management, Univ. Lille, CNRS, UMR 9221—LEM—Lille Economie Management, F-59000 Lille, France, 3 rue de la Digue—59000 Lille (France). E-mail: k.ansaram@ieseg.fr.
UCLouvain, LFIN, Mons, Chaussee de Binche 161, B-7000 Mons, Belgium.

b Corresponding author. IESEG School of Management, Univ. Lille, CNRS, UMR 9221—LEM—Lille Economie Management, F-59000 Lille, France, 3 rue de la Digue—59000 Lille (France). E-mail: p.mazza@ieseg.fr.

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market and other energy markets. The following are examples: Kanamura (2016), Cherubini et al. (2011) and Zeng et al. (2021) for cointegration between the European carbon market and Certified Emission Reductions (CERs), Chun (2018) for spillovers between the European and Chinese carbon markets, and Balcılar et al. (2016) for cross-market correlations between the European carbon market and other energy markets. Establishing the stochastic relationships between carbon markets remains a challenging task.

This study is grounded in existing research on the cointegration between carbon markets and contributes to the literature by extending the analysis to eight mandatory carbon markets, the European Union ETS (hereafter EU ETS), Regional Greenhouse Gas Initiative ETS (RGGI ETS), and California ETS, to assess the interdependencies among future carbon prices as well as three additional carbon markets for spot prices, Canada (Quebec ETS), Korea (South Korean ETS) and China (three Chinese Pilots ETS, notably Shenzhen, Guangdong and Hubei). The data range from August 2011 to August 2019 and from January 2015 to June 2020 for future and spot prices, respectively. Rather than relying on traditional cointegration models such as Vector Error-Correction Model (VECM) and Vector Autoregressive (VAR) models, we measured the dependency across the different trading schemes using tail dependence (Frahm et al., 2005). Tail dependence is computed by fitting a parametric copula family to the data and by subsequently extracting the tail behavior of that copula. Copulas are a very flexible method to model the relationship between different variables through their marginal distributions and dependence structure separately, with the big advantage of accounting for different types of tail dependence from the return series under consideration (Aloui et al., 2013; Boako and Alagidede, 2017; Jondeau and Rockinger, 2006). GARCH-copula models have been extensively adopted in carbon pricing studies (Yu et al., 2020; Uddin et al., 2018;Wu and Hu, 2014). We followed these studies and first estimated, for each pair, the full-range tail dependence copulas through both lower and upper tail and tail asymmetry. Then, we selected the best copula model over the usual GARCH model based on the goodness-of-fit tests developed by Kojadinovic et al. (2010).

The aim of this paper was to provide a thorough analysis of the dependence structure between prices in carbon markets around the world. Our main contribution is twofold. First, we investigated the dependence structure of prices across eight different carbon markets around the world. This significantly contributes to the available literature since, to the best of our knowledge, previous studies investigating dependence structure only included two markets. Second, we also extend the research to a very long time period which has never been explored. This contribution can help reduce price discrepancies across different markets to achieve the ultimate objective of a global, worldwide carbon emission trading scheme. Based on the assumption that the environmental cost of emitting one ton of CO_2 should be identical everywhere on Earth, price discrepancies between different markets might generate issues, such as carbon leakage, that would hinder the benefits of climate actions. Third, we applied five different copulas compared to previous studies which were limited to a single copula. The adoption of five different copulas strengthens the degree and structure of dependence, ensuring that any type of transformation is less likely to change it. Compared to multivariate GARCH-type models, copula-based GARCH models can better describe the nonlinear risk spillovers between the existing markets.

Our study showed that the European carbon market exhibited a positive tail dependence with uprising carbon markets (South Korea and Chinese pilot carbon markets), while the latter exhibited zero or weak tail dependence with the RGGI, California and Quebec carbon markets. In addition, a positive dependence was found among the RGGI, California and Quebec carbon markets, which might be due to existing linkage practices. Similarly, the Asian carbon markets are more likely to be dependent on each other. Our results suggested that the regional dependence structure, rather than the emergence of a global carbon market, has been lobbied for by several stakeholders. This clearly suggests the need for alternative policies to reach the ultimate goal of a global carbon market.

The remainder of this study is organized as follows. Section 2 provides an overview of the background of the study by describing methodologies to measure stochastic dependencies in carbon markets in the literature. Section 3 presents the methodology for measuring tail dependencies and introduces the copula model. Section 4 describes the data sources and empirical settings. Section 5 reports the empirical results. The final section concludes the paper.

2. BACKGROUND

For decades, economic theory has advocated for the use of carbon financial instruments to reduce carbon emissions through fixed instruments known as carbon taxes or quantity instruments known as emissions trading contracts (Weitzman, 1974; Newell and Pizer, 2003; Metcalf and Weisbach, 2009; Keohane, 2009; Aldy and Pizer, 2015; Schmalensee and Stavins, 2017). Carbon markets have been integrated into international climate agreements since the Kyoto protocol era under the clean development mechanism, joint implementation and international emissions trading (Capoor and Ambrosi, 2007). The motivation for this study stems from both political and economic dimensions. The world is witnessing the proliferation of carbon markets globally. The European Union Emissions Trading System (EU ETS) is the first and largest one, covering 11,000 emitters across all EU member states, as well as Norway, Iceland and Liechtenstein. California and Quebec share a market, which Ontario, Manitoba and provinces in Brazil and Mexico plan to join. Major Asian economies are following the trend, including Japan, South Korea, China, Kazakhstan, and India (Fankhauser, 2011; Jotzo et al., 2013; Wang, 2013). China is also associated with great potential for large-scale carbon trading. China has recently set up its national cap-and-trade system in June 2021, comprising more than 7,000 emitters. Since 2013, China has launched seven pilot carbon markets in Shenzhen, Beijing, Shanghai, Guangdong, Tianjin, Hubei, and Chongqing (Han et al., 2012; Lo, 2012). Coupled with the above, several countries that ratified the Paris Agreement expressed their intention to implement carbon markets. Many policymakers argue that the next logical step is to combine cap-and-trade efforts into one global carbon market. According to prevailing economic theory, linking markets together should promote trading, smooth financial flows and lower the overall cost of reducing emissions (Nordhaus, 1991; Golombek and Braten, 1994; Westskog, 1996; Jacoby et al., 1997; Bredin and Parsons, 2016; Grüll and Taschini, 2012). Rosendahl and Strand (2011) study Clean Development Mechanism (CDM) markets and note that higher market segregation leads to more carbon leakage, incentivizing a better link between trading systems. A global price on carbon emissions would emerge without the need for long and fractious diplomatic negotiations (Green et al., 2014). Before even embarking on a global carbon market, it is crucial to assess the dependence among the existing ones. This has not been widely studied in the literature; our study aims to fill that gap.

A second motivation for the study is based on the increasing attention given to linking carbon markets. Linkages across carbon markets have not escaped policy makers discussions or scholars' attention. To date, some links have been formed, such as the approved integration of the Swiss ETS by the EU ETS. California's carbon market also has an established link with the Quebec carbon market. Jotzo and Betz (2009) evaluated a plan to bilaterally integrate the Australian ETS with the EU ETS, which was afterwards abandoned in 2012. The impact of linking the EU ETS to the U.S. system was evaluated in Zetterberg et al. (2012). The studies of Marschinski et al. (2012) and Hübler et al. (2014) investigated a proposal for integrating the EU ETS with a Chinese ETS. Similarly, Gavard et al. (2016) modeled a sectoral ETS on electricity and energy-intensive industries in the EU, the U.S. and China, simulating different linkage scenarios. Empirical evidence also suggested a multiregional integrated ETS in which the EU ETS takes part (Anger, 2008; Dellink et al., 2014; Yu and Xu, 2017). Ellerman and Trotignon (2009) investigated cross-border trading and borrowing in the EU ETS and found that there were widespread trading activities as well as preconditioned efficient abatement costs.

The literature on carbon market integration has grown significantly over the last decade. Three dimensions of the carbon markets' integration and dependency have been extensively studied: carbon prices in a single market, bilateral market integration and dependence on other energy commodities. Different methods have been used in all these studies. Chevallier et al. (2010) employed autoregressive methods to measure the cointegration between European Union Allowances (EUA) futures and spot prices. Rittler (2012) measured spillover effects from futures to the spot market using 10-minute and 30-minute data for the EU carbon market. Bredin and Parsons (2016) studied the term structure between spot and future carbon prices and highlighted the fact that spot prices were higher than future prices until the financial crisis of 2008. The relationship between EUA and CERs has also been studied, and a positive spillover effect was identified. Kanamura (2016) adopted a supply and demand correlation model to examine the EUA and CER returns integration. Trück et al. (2014) added to the empirical analysis of the relationship between EUA futures and spot contracts traded on the EEX and presented a convenience yield model for the volatilities between the two assets. Zhu et al. (2020) adopted a vine copula approach to measure the risks and spillovers in Chinese pilot carbon markets and found that the conditional value at risk (CVaR) was a better measure than traditional risk. Wu and Hu (2014) explored the dynamic interdependence between European carbon spot and futures prices using the copula-GARCH model. Hu et al. (2015) investigated the dependency characteristics of EU carbon markets using the R-vine copula model and found that R-vine copula methods could better depict the dependency structure of the carbon market.

As highlighted here above, GARCH and copula models have been extensively used in the carbon markets literature. To this set of studies, we may also add Zeng et al. (2021), who adopted the copula approach to analyze the dynamic volatility spillover effect between the EUA and CER markets during the second and third phases of trading of the EU ETS, showing that there was a spillover effect across the two carbon markets. Benz and Trück (2009) further captured the regime changes in the EU ETS through an AR-GARCH Markov switching price return model. Paolella and Taschini (2008) measured the tails and volatility clustering between the U.S. SO_2 permits and EUA price returns through GARCH modeling. Chevallier et al. (2011) used a Dynamic Conditional Correlation (DCC) model to analyze the dynamic correlation between EUAs and CERs and found that the correlation coefficient between the two markets changes dynamically over time in the range of [0.01; 0.90]. Chun (2018) used a DCC(1,1) model to analyze the volatility spillover effect between the market prices of the EU ETS and Chinese carbon market for the period ranging from 2014 to 2017. The results demonstrated that there were agglomeration effects in the two markets, but the market concentration and price volatility were more significant.

The GARCH-Copula methodology has also been applied in other energy commodities' markets to assess tail dependency. For example, Uddin et al. (2018) modeled the multivariate tail dependence structure and spillover effects across energy commodities, such as crude oil, natural gas, ethanol, heating oil, coal and gasoline. Yu et al. (2020) used the copula and VAR-BEKK-GARCH models to study the volatility spillovers between the oil and stock markets. Balcılar et al. (2016) relied on the MS-DCC-GARCH model to find time-varying cross-market correlations and volatility spillover effects between EU carbon futures prices and electricity, coal and natural gas futures prices.

Based on the above evidence, we deduced that GARCH models have been the most favored and adopted models in carbon market integration studies. Among these investigations, some went even further by including copula-based modeling. Our contribution falls into that category. The widespread finance literature vouch for two-step copula modeling, which involves marginal estimations prior to deducting the dependence parameters (Embrechts et al., 2002; Meucci, 2011). Copula models address the drawbacks of the Pearson correlation coefficient, as they do not require random variables to be elliptically distributed. They are also invariant to increasing and continuous transformations (Durante et al., 2010; Schmid et al., 2010; Cai and Wei, 2012). For the purpose of this study, we selected a methodology that has been used in most seminal papers and is known to be robust and appropriate to assess the dependence structure across carbon markets.

While the above empirical studies focused on carbon price models and the empirical analysis of a single carbon market, they did not assess the characteristics of price dependency across different carbon markets. With the emergence of new carbon markets around the world, there is a need to consider in a wider range of carbon markets, rather than investigating bilateral integration as was done in previous studies. By studying both spot and future prices across eight carbon markets, we provide novel insight into the cointegration of carbon markets. Furthermore, given the extensive application of the GARCH-Copula methodology in energy commodities and carbon markets, we relied on the best methodology, to the best of our knowledge, to test the empirical integration of the global carbon market.

3. METHODOLOGY

The primary objective of this study is to test the dependence structure across carbon markets using the EGARCH copula model, which has been extensively adopted in the literature (see Chevallier et al. (2011); Arouri et al. (2012); Mou (2019); Zhu et al. (2019)). This modeling approach is advantageous because it allows us to separately model the margins (GARCH-based model) and the association structure of different variables (copula models). Furthermore, the model provides more flexibility for constructing the joint distribution of multiple returns. Copulas are favorable for assessing the dependence structure since they allow for greater flexibility in modeling and estimating margins compared to multivariate distributions. Both the degree and structure of dependence are also considered. Simple linear correlation analyses only examine how carbon prices move together on average across marginal distributions assuming multivariate normality. In the following subsections, the copula functions are briefly explained. The specifications of the EGARCH model are provided and the five copula estimations are discussed.

3.1 Copulas

In this study, we employed the two-step estimation process of copula models suggested by Aloui et al. (2013). A copula is a function that combines marginal distributions to form a joint multivariate distribution (Min and Czado, 2010). The concept was initially introduced by Sklar

(1996) but has only gained popularity in modeling financial or economic variables over the last two decades.[1]

Sklar (1996) showed that the concept of copulas could deviate from a rich set of joint distributions. Assuming that $X = (X_1.....X_d)$ is a random vector with continuous marginal cumulative distribution functions $F_1.....F_d$, Sklar (1996) shows that the joint distribution H of X could be represented as:

$$H(X) = C(F_1(x_1),........,F_d(x_d)) \tag{1}$$

in terms of a unique function $C : [0,1]^d \rightarrow [0,1]$ called a copula. Copula functions can conveniently construct a multivariate joint distribution by first specifying the marginal univariate distributions and then investigating the dependence structure between variables with different copula functions. Moreover, tail dependence can be well described by copulas. Usually, two measurements are applied to evaluate tail dependence: the upper and lower tail dependence coefficients. They function well regardless of whether the markets are crashing or booming. By assuming that X and Y are random variables with marginal distribution functions F and G, it is possible to compute the coefficient of the lower tail dependence, λ_L:

$$\lambda_L = Lim_{t \rightarrow 0+} Pr[Y \leq G^{-1}(t) \mid X \leq F^{-1}(t)] \tag{2}$$

which measures the probability of observing a lower Y if the condition X itself is lower. In contrast, the coefficient of upper tail dependence λ_U can be estimated by:

$$\lambda_U = Lim_{t \rightarrow 1-} Pr[Y > G^{-1}(t) \mid X > F^{-1}(t)] \tag{3}$$

When the value of lower tail dependence is the same as the value of upper tail dependence, we conclude that there is symmetric tail dependence between the two variables. In all other cases, the dependence is considered asymmetric. This approach constitutes an efficient way to order copulas. Moreover, if λ_U of C_2 is greater than λ_U of C_1, it indicates that copula C_2 is more concordant than C_1.

3.2 Marginal Specification

Dependencies in carbon markets can be examined by combining these copula functions with a GARCH-type model including conditional heteroscedasticity, since this model successfully describes the characteristics of volatility clustering in carbon allowance prices. The GARCH family, e.g., EGARCH, MGARCH, GJR-GARCH, TGARCH and ARMA-GARCH models, has been extensively adopted by studies on carbon prices (see, for instance, Wang et al., 2019; Fu and Zheng, 2020; Bulai et al., 2021; Zhang and Wu, 2022). Along with the GJR-GARCH and the TGARCH, the EGARCH model has the very interesting feature of accommodating asymmetric reactions of volatility to positive and negative shocks. One differentiating element in favor of the EGARCH is the log transformation of the conditional variance equation. Most studies use the EGARCH model to capture the leverage effects of financial time series (see previous section).

The conditional variance and autocorrelation of the carbon price returns can be captured through an ARMA-EGARCH model, which can be defined as:

1. For an introduction to copulas see Nelsen et al. (2001), Joe (2006). For applications to various issues in financial economics and econometrics, see Cherubini et al. (2011), Demarta and McNeil (2005), Frey and McNeil (2003) and Hull and White (2006).

$$r_t = \mu + \Sigma_{i=1}^{p} \phi_i r_{t-i} + \Sigma_{j=i}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4}$$

$$\varepsilon_t = \sigma_t z_t \tag{5}$$

$$log(\sigma_t^2) = \omega + \Sigma_{s=1}^{m}[\alpha_s z_{t-s} + (\gamma_s \mid z_{t-s} \mid - E \mid z_{t-s} \mid)] + \Sigma_{s=1}^{m} \beta_s log(\sigma_t^2) \tag{6}$$

Equation (4) is the mean equation, Equation (5) shows the relationship between error and conditional variance of price log-return and Equation (6) is the variance equation. In the mean model in Equation (4), r_t is the log-returns of carbon prices from the different carbon markets. μ is a constant term, ϕ is the *i*th autoregressive coefficient, θ_j is the *i*ith moving average coefficient, and ε_t is the error term at time *t*. *p* and *q* are the orders of autoregressive and moving average terms in the mean model, respectively.

In the distribution model in Equation (5), we refer to Nelsen et al. (2001) and assume that the error term ε_t follows the generalized error distribution (GED). In the variance model in Equation (6), σ_t^2 is the conditional variance prediction at time *t*, ω is the variance intercept parameter, and β_s is the parameter indicating the ARCH effect in volatility. α_s captures the sign effect. γ_s is the size effect. *m* and *n* are the orders of the GARCH equation.

The appropriate *p* and *q* for each of the log-returns of the carbon markets are identified based on the minimum value of the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC).

3.3 Conditional Dependence Structure Specification

In this study, we considered both the symmetric and the asymmetric structure dependence between the variables. For a given set of marginals above, the copula model is used to investigate the conditional dependence structure among carbon markets. We focused on two types of copulas: elliptical copulas (i.e., normal and Student-*t*) and Archimedean copulas (i.e., Gumbel, Frank and Clayton):

For all *u*,*v* in [0,1], the bivariate normal copula is defined by

$$C(u,v) = \int_{-\infty}^{\phi^{-1}(u)} \int_{-\infty}^{\phi^{-1}(v)} \frac{1}{2\pi\sqrt{1-\theta^2}} exp(-\frac{s^2 - 2\theta st + t^2}{2(1-\theta^2)}) dsdt \tag{7}$$

where ϕ represents the univariate standard normal distribution function and θ is the linear correlation coefficient restricted in the interval [–1,1]. The bivariate Student-*t* copula is defined by:

$$C(u,v) = \int_{-\infty}^{t_v^{-1(u)}} \int_{-\infty}^{t_v^{-1(v)}} \frac{1}{2\pi\sqrt{1-\theta^2}} exp(1 + \frac{s^2 - 2\theta st + t^2}{v(1-\theta^2)})^{-(v+2)/2} dsdt \tag{8}$$

where $t_v^{-1}(u)$ denotes the inverse of the cumulative distribution function (CDF) of the standard univariate Student-*t* distribution with *v* degrees of freedom. The Gumbel copula is an asymmetric copula with a higher probability concentrated in the right tail. It can be expressed by:

$$C(u,v) = exp\{-(-ln\, u)^{\theta} + (ln\, v)^{\theta 1/\theta}\},$$
$$\theta \in [1, +\infty] \tag{9}$$

The Frank copula is defined as:

$$C(u,v) = -\frac{1}{\theta} ln\left(1 + \frac{exp(-\theta u)-1)(exp(-\theta v))-1}{exp(-\theta)-1}\right),$$
$$\theta \in [-\infty, +\infty] \tag{10}$$

The Clayton copula is defined as:

$$C(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta},$$
$$\theta \in [0, +\infty] \tag{11}$$

In the finance literature, elliptical copulas are most frequently applied because they have been shown to offer straightforward implications (Nikoloulopoulos et al., 2012; Boako et al., 2019; Wen et al., 2019; Naeem et al., 2020). The normal and student copulas can be classified into this family because they are based on an elliptical contoured distribution. Gaussian copulas are symmetric and do not capture tail dependence, while Student-t copulas can reflect extreme dependence between variables. Archimedean copulas such as the Frank copula also tend to be symmetric and can provide the full range of dependence estimation for marginals exposed to weak tail dependence. However, the Gumbel and Clayton copulas are asymmetric and are not derived from multivariate distributions. Therefore, they are typically used to capture asymmetry between lower and upper tail dependencies. For example, Clayton copulas show greater dependence in the negative tail than in the positive tail, while Gumbel copulas show the opposite. Nevertheless, for both the Clayton and Gumbel copulas, the greater the value of θ is, the greater the dependence between the variables.

3.4 Estimation

In a second step, we estimate the parameters of the copulas based on the quasi-maximum likelihood (QML) or pseudomaximum likelihood (PML) methods and filter the returns. Following Aloui et al. (2013), we estimate the marginals F_x and G_y using their empirical CDF ^ and $\hat{G}_y$ defined as:

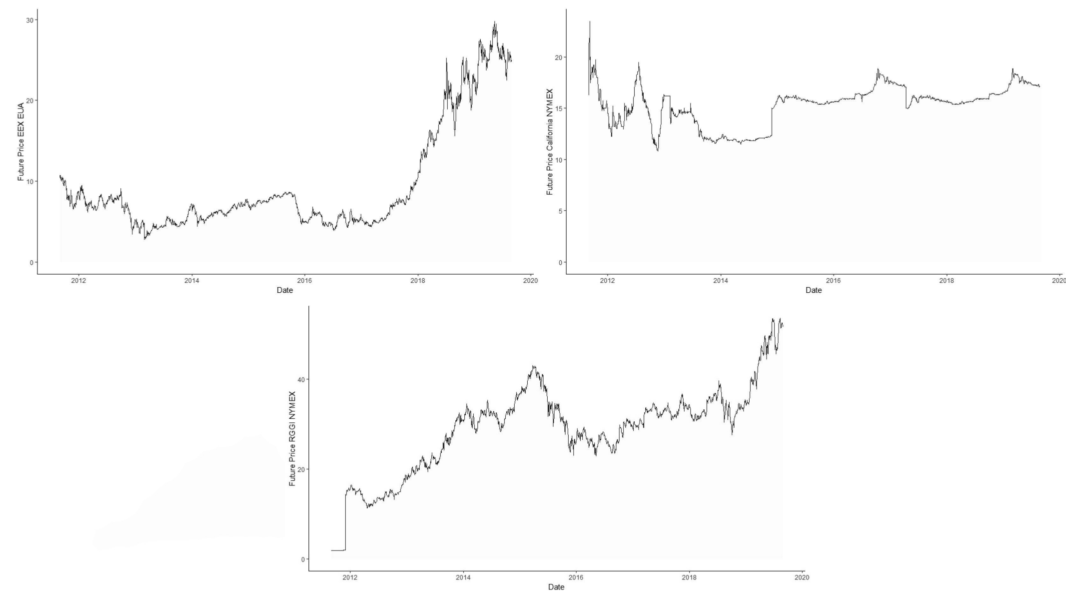
$$\hat{F}_x = \frac{1}{n}\sum_{j=1}^{n} 1\{X_i < x\} \text{ and } \hat{G}_y = \frac{1}{n}\sum_{j=1}^{n} 1\{Y_i < y\} \tag{12}$$

In the implementation, $\hat{F}_x$ and $\hat{G}_y$ are replaced by $n/(n+1)$ uniform variates using the empirical CDF of each marginal distribution to ensure that the first-order condition of the log-likelihood function of the joint distribution is well defined for all finite n. Here, X_i and Y_i are the standardized residuals estimated from the first step. Then, we transform the observations into uniform variates using the empirical CDF of each marginal distribution and estimate the unknown parameter θ of the copula.

4. DATA

In this study, we evaluated the dependence structure among both future and spot contracts of carbon allowances around the world. Although an increasing number of carbon markets have been established around the world, the trading of future contracts is still at an early stage for most of them, except for the EU, RGGI and California ETSs. For example, the Chinese carbon markets only started offering future contracts in 2021. For this reason, we could only assess the dependence structure for future contracts for EUA, RGGI and Californian allowances. The future contract prices were retrieved from Refinitiv for future contracts, with EUA being traded on the European Energy Exchange (EEX). RGGI emission contracts are traded on the New York Mercantile Exchange (NYMEX) platform. California allowances future contracts are traded on NYMEX. For future contracts, a 1-month rolling approach was adopted to obtain the price time series. We obtained future contract prices for the period ranging from August 2011 to August 2019, amounting to approximately 2048 observations. For all future contracts, we only focused on December maturity for each year; there is a clear consensus in the literature that December maturity dominates all other maturities in terms of trading activity (see Mizrach, 2012)

Figure 1: Daily Future Prices of Carbon Allowances.

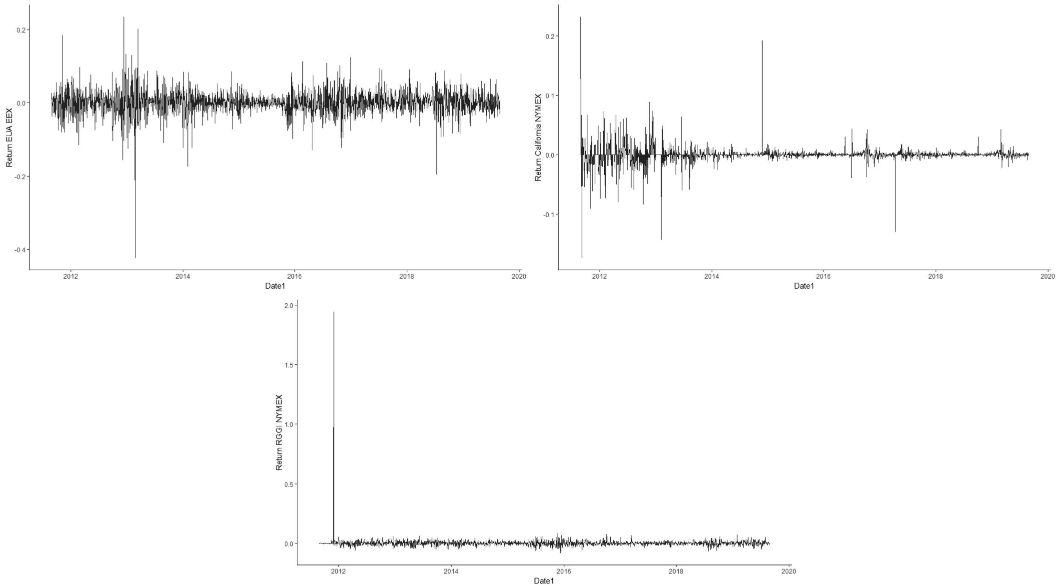


The figures show the daily future prices for EU, California and RGGI , from left to right and top to bottom, respectively.

Regarding spot prices, we included additional carbon markets since they were more widely available. However, most of them were very recent and, thus, did not include as many data points as future contracts. For the EUA spot prices, data were obtained from the EEX platform. Additionally, we included spot prices from California, Quebec and RGGI; the data were provided by Argus. Only the three oldest Chinese pilot carbon markets (Guangdong, Hubei and Shenzhen) were included in our study. These pilot markets were also associated with the largest market activity and provided sufficient and high-quality data for our analysis. Since the Sichuan and Fujian markets began to operate on December 16, 2016 and December 22, 2016, respectively, we did not include them due to the lack of available data points. The data for the Chinese and South Korean carbon allowances were obtained from the International Emissions Trading Association (IETA) platform. For spot prices, data were analyzed for the period ranging from January 2015 to June 2020, including 1048 observations. Overall and to the best of our knowledge, thanks to these different data sources, this was the most comprehensive analysis both in terms of the number of markets and the length of the time period.

In all cases, the price returns were calculated as the first differences of the log of the price indices. Let S_t denote the log of the spot price at time *t* and $\Delta S_t = S_t - S_{t-1}$ denote the corresponding

Figure 2: Daily Returns of Future Contracts of Carbon Allowances.



The figures show the returns for future contracts for EU, California and RGGI, from left to right and top to bottom, respectively.

log return. Similarly, F_t is the log of the future price, and $\Delta F_t = F_t - F_{t-1}$ is the corresponding log-return.

The descriptive statistics of the futures and spot price series are reported in Tables 1 and 2, respectively. We observed kurtosis > 3 for all the variables, indicating that none of the distributions could be considered normal, as suggested by the fourth moment. In addition, the returns distributions were negatively skewed for two EU ETS contracts and RGGI and positively skewed for the remainder. Skewness for spot contracts was negative for all variables. The results of the Jarque-Bera test led us to reject the null hypothesis of normality in all cases. The results of the Ljung-Box Q statistics also indicated serial correlation in the time series for all variables.

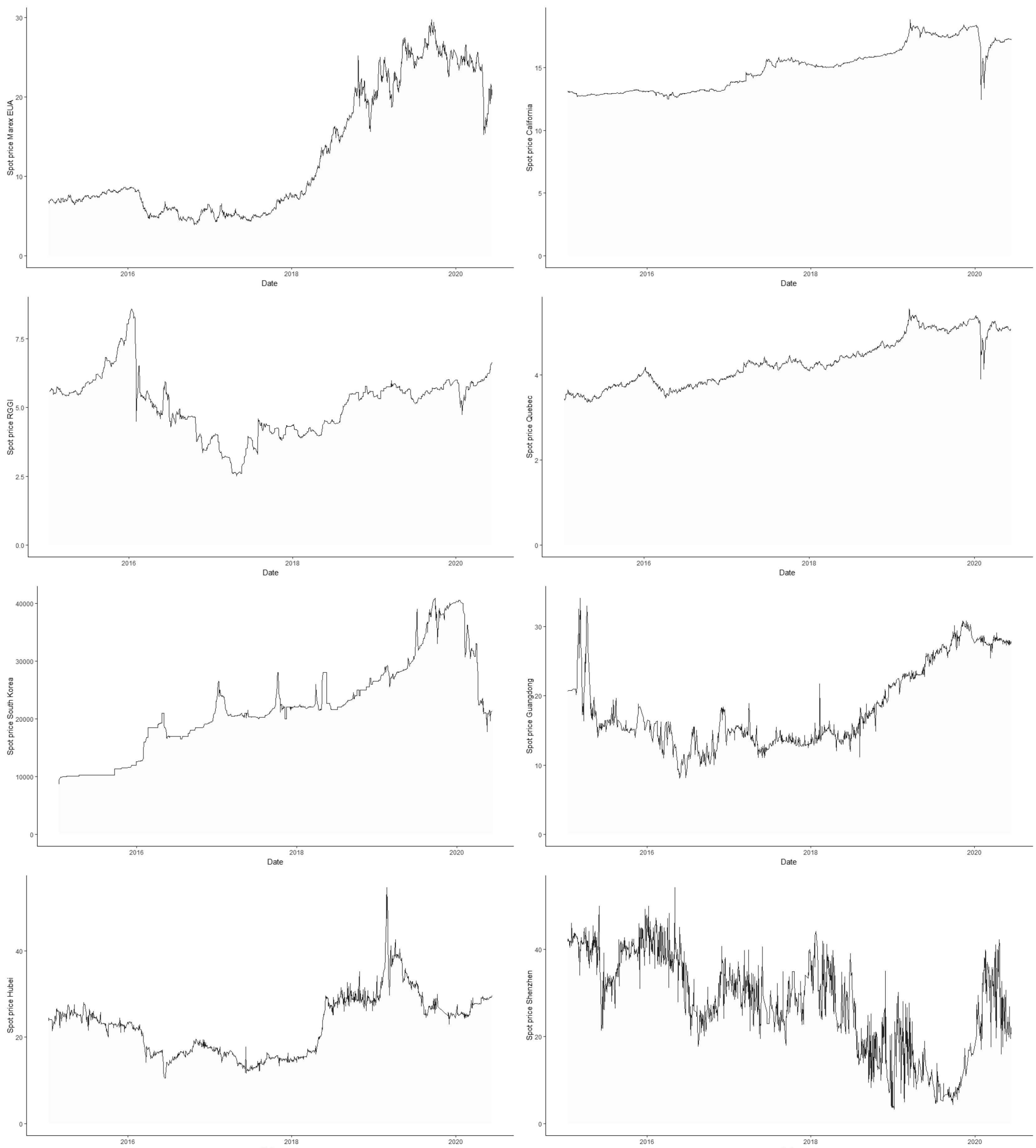
5. EMPIRICAL RESULTS

5.1 Main Results

Since the carbon price time series exhibited peaks, fat tails, autocorrelation and the property of conditional heteroscedasticity, the residual sequence of the [0, 1] uniform distribution was obtained from carbon price returns before application of the copula model, as proposed by Zhu et al. (2020).[2] Based on the parameter estimation of the mean equation, the return μ on carbon emissions for future contracts in the EU, RGGI and California was positive, which indicates that the carbon price is relatively stable during the sample period. In contrast, the return on carbon emissions for spot contracts was near zero or negative, indicating a lack of trading activity. From the mean equation, the different combinations with lags from 0 to 4 were taken, and the ARMA (p,

2. The price returns series were tested for stationarity using the Augmented Dickey-Fuller test (ADF). The resulting p-values led to the rejection of the null hypothesis assuming the presence of a unit root in the returns series, meaning that the returns series were, as expected, stationary. The results are available upon request.

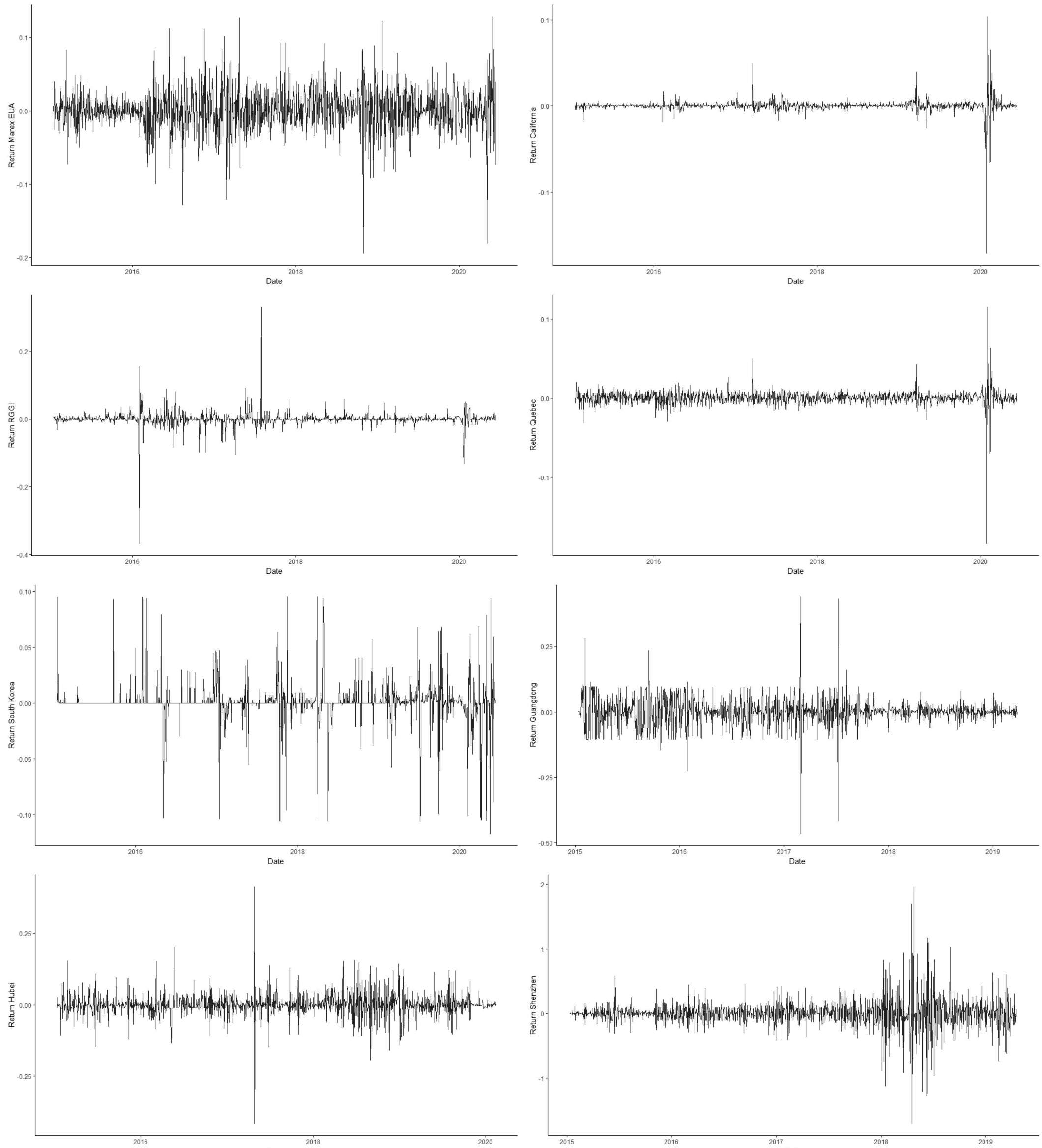
Figure 3: Daily Spot Prices of Carbon Allowances.



The figures show the daily spot prices for EU, California, RGGI, Quebec, South Korea, Guandong, Hubei and Shenzhen, from left to right and top to bottom.

q) with the lowest AIC was selected. Based on the mean equation, the EU, RGGI and California future returns for carbon emissions were subject to ARMA (2,2), (2,2) and (2,1), respectively. For spot returns, the EU ETS had ARMA (0,0), California ETS (4,2), Quebec ETS (4,2), RGGI ETS (0,0), South Korea, Shenzhen, Guangdong and Hubei with ARMA (2,2). Tables 3 and 4 report the estimation results. As seen in these tables, all the coefficients of the EGARCH term (β) with values close to 1 were statistically significant at the 1% level. Moreover, the coefficients of the asymmetric effect (γ) were statistically significant at the 1% level with negative values. The shape parameters were also statistically significant at the 1% level with values less than 2, suggesting that the tails of the error terms were heavier compared to the normal distribution. The $Q(s)$ and $Q^2(s)$ statistics were

Figure 4: Daily Returns of Spot Contracts of Carbon Allowance.



The figures show the returns of spot contracts for EU, California, RGGI, Quebec, South Korea, Guandong, Hubei and Shenzhen, from left to right and top to bottom.

used to validate the empirical results of the EGARCH models.[3] In a second step, we transformed the standardized residuals obtained from the EGARCH model into uniform variates based on the empirical CDFs. By applying this step, we obtained a vector of filtered returns to estimate the copula functions for carbon markets. Then, we checked the rank correlation coefficients for carbon market dependence. Figures 5 and 6 summarize Kendall's tau and Spearman's rho statistics for the sample.

3. The $Q(s)$ statistic at lag s is a test statistic that has an asymptotic Chi-square distribution with degrees of freedom equal to the difference in the number of autocorrelations and the number of parameters. The null hypothesis of the corresponding test is that there is no autocorrelation up to lag s for standardized residuals.

Table 1: Descriptive statistics (Futures).

	EU	RGGI	California
Mean	0.00004	0.0016	2.48E-05
Median	0.0008	0.0003	0
Maximum	0.2347	1.9420	0.2323
Minimum	–0.4223	–0.0798	–0.1729
SD	0.0337	0.0461	0.0145
Skewness	–0.9072	36.3340	1.165
Kurtosis	15.736	1526.917	72.111
Jarque-Bera	21513***	20028039***	446181
Q	92.602***	3.4636***	90.573***

This table shows the descriptive statistics for each future contract in our sample. The table includes statistics on moments, median, maximum and minimum, as well as the test statistics associated with the Jarque-Bera and Ljung-Box Q tests.

Table 2: Descriptive Statistics (Spot)

	EU	California	Quebec	RGGI	South Korea	Shenzhen	Guangdong	Hubei
Mean	0.0008	0.0002	0.0001	0.0001	0.0007	0.0015	0.0006	0.0002
Median	0	0	0	0	0	–0.000005	0.0006	–0.0004
Maximum	0.1282	0.1036	0.1158	0.3322	0.0953	1.9637	0.4405	0.4124
Minimum	–0.1945	–0.1714	–0.1840	–0.3677	–0.1165	–1.7062	–0.4653	–0.4155
SD	0.02891	0.0083	0.0097	0.0207	0.0189	0.2415	0.0543	0.0414
Skewness	–0.3150	–6.1774	–4.6813	–1.4833	–1.1799	0.4103	–0.0375	0.1105
Kurtosis	4.3965	173.6253	122.3088	127.5131	16.4305	13.1370	15.9623	17.4204
JarqueBera	1135.637***	1740985.656***	864643.0067***	934823.67***	15839.6414***	7990.6963***	11569.6667***	16424.1238***
Q	0.014826	0.014826	6.3623***	9.7216***	21.17***	249.96***	37.786***	89.007***

This table shows the descriptive statistics for each spot contract in our sample. The table includes statistics on moments, median, maximum and minimum, as well as the test statistics associated with the Jarque-Bera and Ljung-Box Q tests.

Table 3: Estimations of EGARCH Models (Future)

	EU	RGGI	California
Mean Equation			
μ	0.0085***	0.0019***	–0.0000***
	(0.0003)	(0.0000)	(0.0000)
AR_1	–0.4183***	0.0104***	0.2200***
	(0.1331)	(0.0002)	(0.0004)
AR_2	–0.7559***	–0.0016***	0.0020***
	(0.0318)	(0.0000)	(0.0000)
MA_1	0.4090***	0.0103***	–0.2198***
	(0.1464)	(0.0002)	(0.0004)
MA_2	0.7014***	–0.0015***	
	(0.3371)	(0.00001)	
Variance Equation			
ω	–0.1158***	–0.6990***	–0.9862***
	(0.0314)	(0.0002)	(0.0466)
α	–0.0199	0.0468***	0.0474
	(0.0148)	(0.0009)	(0.0299)
β	0.9837***	0.9010***	0.9077**
	(0.0044)	(0.0002)	(0.0042)
γ	0.2008***	–0.1400***	0.2744***
	(0.0271)	(0.0000)	(0.0223)
GED Parameter	1.2638***	1.9772***	0.3444***
	(0.0500)	(0.0004)	(0.0100)
Diagnostic			
Q	2.0280	0.6214	0.0646
	[0.15440]	[0.4305]	[0.7992]
$Q^2(10)$	0.8119	0.0006	0.0128
	[0.3675]	[0.9795]	[0.9097]

This table presents the results of the estimations of the EGARCH models for each future contract. All the standard parameter estimates are reported.

Table 4: Estimations of EGARCH Models (Spot)

	EU	California	Quebec	RGGI	South Korea	Shenzhen	Guangdong	Hubei
Mean Equation								
μ	0.0006	0	0	0	0	0	0.0004***	–0.0003***
	(0.0005)	(0)	(0)	(0)	(0)	(0.0011)	(0.0001)	(0.00005
AR_1		0.8927***	1.1791***		–0.0957***	–0.2853***	0.6208**	–0.2876***
		(0.0188)	(0.0004)		(0.0002)	(0.0461)	(0.0244)	(0.0327)
AR_2		–0.6471***	–0.7542***		0.0729***	0.0885***	0.0876***	0.1273***
		(0.0002)	(0.0003)		(0.0013)	(0.0459)	(0.0256)	(0.0080)
AR_3			0.4968***					
		(0.0001)	(0.0002)					
AR_4		–0.2883***	0.0720***					
		(0.0001)	(0.0000)					
MA_1		–0.8932***	1.1797***		0.0942***	0.2259***	–0.8775***	0.0789**
		(0.0003)	(0.0003)		(0.0002)	(0.0364)	(0.0205)	(0.0267)
MA_2		0.6472***	0.7547***		0.0083***	–0.2720***	0.0560***	–0.1944***
		(0.0002	(0.0003)		(0.0000)	(0.0530)	(0.0111)	(0.0094)
Variance Equation								
ω	–0.1880***	–0.9928***	–0.3869***	–0.8213***	–1.3200***	–0.1092***	–0.4946***	–1.8842***
	(0.0566)	(0.2809)	(0.1493)	(0.1920)	(0.0121)	(0.0392)	(0.1165)	(0.2845)
α	–0.0271	–0.1317	0.0245	0.0606	–0.0924***	–0.0704**	0.01424	–0.1065**
	(0.0209)	(0.0951)	(0.0869)	(0.0786)	(0.0013)	(0.0302)	(0.0401)	(0.0495)
β	0.9741***	0.9031***	0.9537***	0.9011***	0.9115***	0.9715***	0.9236***	0.7260***
	(0.0077)	(0.0269)	(0.0140)	(0.0267)	(0.0005)	(0.0098)	(0.0177)7	(0.0409)
γ	0.2437***	0.8258***	0.4148***	0.7217***	0.2894***	0.41825***	0.7174***	0.9602***
	(0.0346)	(0.1367)	(0.0766)	(0.1215)	(0.0266)	(0.0549)	(0.0797)	(0.0860)
GED Parameters	1.2763***	0.2815***	0.3306***	0.1180***	0.1430***	1.2538***	1.0537***	0.8727***
	(0.0647)	(0.0068)	(0.0265)	(0.0024)	(0.0051)	(0.0662)	(0.0577)	(0.0426)
Diagnostic								
Q	1.2000	0.00756	8.5860	9.6290	0.1665	0.0553	0.0592	0.5656
	[0.2733]	[0.9307]	[0.0033]	[0.0019]	[0.6832]	[0.8140]	[0.8078]	[0.4520]
$Q^2(10)$	0.3382	0.0075	25.789	0.2612	0.0060	1.5940	0.5329	2.2270
	[0.5608]	[0.9307]	[0.0490]	[0.6093]	[0.9379]	[0.2068]	[0.4654]	[0.1357]

This table presents the results of the estimations of the EGARCH models for each spot contract. All the standard parameter estimates are reported.

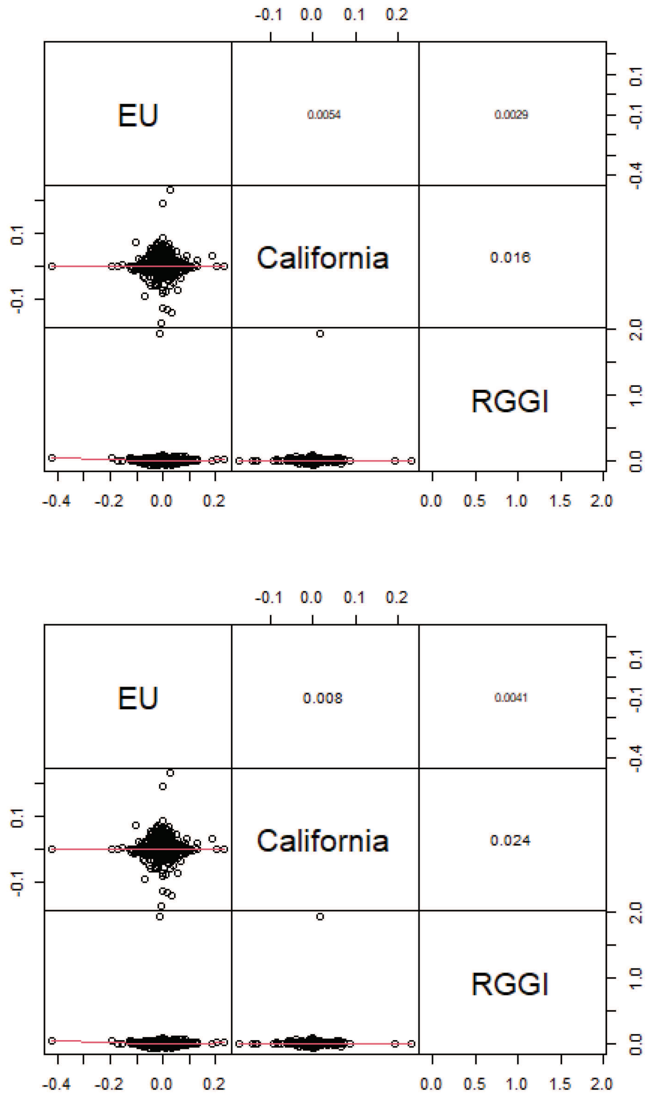
There was a significant negative correlation between EUA and RGGI for future contracts. For spot prices, greater significant correlations were observed. The greatest positive correlation was between Quebec and Californian carbon allowances, which might be due to the existing link between these two markets. California and Quebec also exhibited a positive but weak correlation with the EU ETS. RGGI did not have any significant link with the western markets; rather, weak correlation was observed between South Korea and Guangdong. The South Korean ETS was weakly correlated with those of Hubei and Shenzhen.

By applying the vector filtered returns, we incorporated five copula functions (normal, Student-t, Frank, Gumbel and Clayton) to estimate the dependence parameters θ for the sample. The results are reported in Tables 5 and 6.

The results showed that for future return series, all outcomes were significant at the 1% level for all copulas. The dependence parameters for EU and Californian allowances were mostly negative and very low. Similar results were found for the dependence structure between EU and RGGI as well. The dependence parameters between California and RGGI were negative, despite the fact that there is a link between markets and their mechanism structure is similar. The results differed from those of Paolella and Taschini (2008) who found a correlation between EUA future prices and SO_2 permits.

For the spot return series, a higher dependency was noted throughout the markets. All the copulas had significant results at the 1% level. The EU ETS exhibited a positive dependence with California and Quebec and a negative dependence with RGGI. This indicated that spot prices in the two oldest markets have still not converged after a period of time.

Figure 5: Correlations between Future Returns.

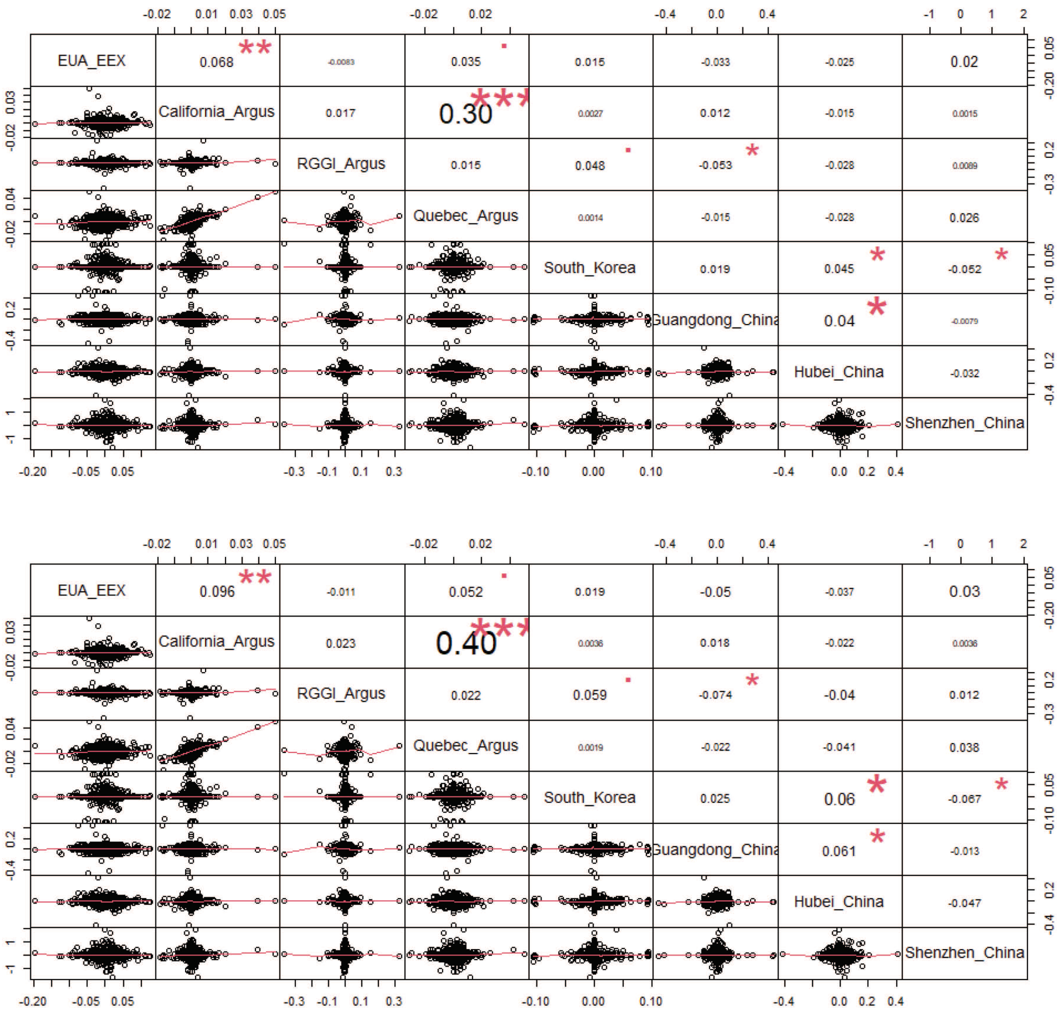


Figures showing the Kendall and Spearman's Correlation respectively for Future Contracts

A mixed relationship between the EU ETS and Asian carbon markets was found. Notably, there were positive dependence parameters for the Chinese Shenzhen and Hubei ETSs and negative parameters for the South Korea and Chinese Guangdong ETSs. The results showed that although the EU ETS was the first and one of the largest in the world, it was not highly correlated with the uprising markets, notably in the Asian regions. These results were in line with the findings of Chun (2018) regarding EU and Chinese markets spillover between 2014 and 2017.

The dependence parameters between the U.S. and Asian carbon markets were also mostly negative for the different copulas. Only RGGI and South Korea exhibited a positive relationship. Negative parameters were obtained for California and RGGI, as was the case for the future return series. However, positive parameters were obtained for the California and Quebec carbon markets, which might be due to the existing link between them. Quebec and RGGI registered negative

Figure 6: Correlations between Spot Returns.



Figures showing the Kendall and Spearman's Correlation for Spot Contracts

parameters as well. The Asian carbon markets exhibited positive dependence parameters across the different copulas. This study provided a first snapshot of the dependence structure among carbon markets globally. The results highlighted the low dependency among the markets. Alexeeva and Anger (2016) discussed the globalization of the international carbon market through the mechanism of the International Carbon Action Partnership (ICAP). The European Commission, a founding member of the ICAP, expressed interest in globalizing transactions. However, thus far, no strong signal regarding a potential link and dependency with the EU ETS has emerged. To date, the EU ETS has only been linked with Norway and Switzerland ETSs. A discussion of a link with the Australian ETS was initiated but rather quickly aborted. Ye et al. (2021) also found that the EU carbon market was strongly influenced by the economic policies in the U.S. However, we found that the EU ETS was unlikely to be dependent on the U.S. carbon markets, most notably the California ETS and RGGI ETS.

We expected a dependence structure given that common carbon price drivers across carbon markets were found in the literature (for example, see Chevallier (2012); Hammoudeh et al. (2015);

Ji et al. (2019) for EU ETS and energy prices). Previous studies described the strong correlation between carbon markets and commodity markets. Since commodity prices are very similar on an international level, it is likely that the dependence structure among carbon markets is strong since they are influenced level by similar drivers. Our results indicated a weak dependency, so there is a need to expand and compare the extent of the spillover of international commodities on carbon markets.

Ranson and Stavins (2016) noted that the single most significant predictor of systems linking may be geographic proximity. Existing linkages are mostly based on geographical criteria. The EU Member States are linked through the EU ETS. Norway and Switzerland are positioned in geographic proximity. Quebec and California are linked, as are the Australian and New Zealand ETSs. The relationship between geography and dependence was reflected in our findings. The Asian carbon markets, South Korean ETS and Chinese ETS were positively dependent. The California ETS and RGGI ETS exhibited stronger dependence (despite being negative) than the other pairs tested. Thus, our results corroborated the findings of Ranson and Stavins (2016).

Table 5: Correlation of Estimates of the Dependence of the Exchanges (Futures)

Exchanges	Normal	Student-t	Frank	Gumbel	Clayton
EU—California	–0.005217(0.023)***	–0.009409(0.027)***	–0.06562(0.146)***	1.008(0.014)***	–0.0143(0.034)***
EU—RGGI	–0.01238(0.021)***	–0.01183(0.023)***	–0.04584(0.132)***	1.005(0.015)***	–0.0102(0.03)***
California—RGGI	–0.02121(0.025)***	–0.02155(0.026)***	–0.1217(0.149)***	1.013 (0.017)***	–0.02597(0.035)***

This table presents the results of the correlation of the estimates of the dependence of the different exchanges for future contracts by pair of exchange. We incorporated five copula functions (normal, Student-t, Frank, Gumbel and Clayton) in order to estimate the dependence parameters θ for the sample.

5.2 Best Copula Model

To determine which copula yielded the best results, we employed the goodness-of-fit test, which compares the distance between the estimated and empirical copulas. The larger the value of the statistics are, the higher the probability that the null hypothesis that copula C belongs to class C_0 is rejected. Kojadinovic et al. (2010) proposed a multiplier approach to find the *p*-values related to the test statistics, overcoming the problem of dependence of the unknown parameter θ when estimating the distribution. Greater *p*-values indicate that the distance between the estimated and empirical copulas is smaller, suggesting that the copula under examination best fits the data.

The results of the goodness-of-fit tests and tail dependence are summarized in Tables 7 and 8. We found that the magnitudes of the tail dependencies in either direction varied significantly across the carbon market pairs. This suggested that the strength of market linkages under extreme conditions were quite different among the pairs.

For the EU and California carbon markets, the Frank copula provided the best fit. The symmetric relationship indicated that the carbon markets moved in the same direction. For the EU and RGGI, the asymmetric copulas (Gumbel and Clayton) provided the best fit, suggesting asymmetric comovements in the carbon allowance prices. However, the tail dependence between the two carbon markets was very low. For California and RGGI, the Normal and Gumbel copulas provided the best fit. The tail dependence was very low in this case.

The goodness-of-fit tests for spot returns indicated the presence of asymmetry since most of the pairs were best fitted by the Frank, Gumbel and Clayton copulas. The EU tail dependence with the Asian carbon markets was higher than that with the North American carbon markets. The EUA had a zero-tail dependence on the California, RGGI and Quebec carbon markets. The North American carbon markets also registered higher tail dependence with the Asian carbon markets. The

Table 6: Correlation of Estimates of the Dependence of the Exchanges (Spot)

Exchanges	Normal	student's t	Frank	Gumbel	Clayton
EU—California	0.05256 (0.029)***	0.05239 (0.029)***	0.2516 (0.172)***	1.024 (0.017)***	0.05923 (0.04)***
EU—RGGI	–0.06731 (0.04)***	–0.06632 (0.042)***	–0.2485 (0.238)***	1.016 (0.026)***	–0.0519 (0.05)***
EU—Quebec	0.06918 (0.03)***	0.06912 (0.03)***	0.3723 (0.173)***	1.019 (0.019)***	0.0845 (0.041)***
EU—South Korea	0.005239 (0.03)***	0.004236 (0.029)***	–0.02986 (0.169)***	1 (0.016)***	–0.005118 (0.039)***
EU—China Shenzhen	–0.03579 (0.03)***	–0.03499 (0.032)***	–0.184 (0.177)***	1.029 (0.018)***	–0.03837 (0.04)***
EU—China Guangdong	–0.03705 (0.03)***	–0.03718 (0.034)***	–0.237 (0.193)***	1 (0.018)***	–0.05316 (0.035)***
EU—China Hubei	0.01842 (0.03)***	0.01937 (0.03)***	0.1054 (0.168)***	1.009 (0.014)***	0.04213 (0.032)***
California—RGGI	–0.01939 (0.04)***	–0.01916 (0.042)***	–0.08596 (0.239)***	1.008 (0.02)***	–0.01946 (0.052)***
California—Quebec	0.09906 (0.02)***	0.09722 (0.032)***	0.5861 (0.154)***	1.086 (0.018)***	0.1354 (0.044)***
California s—South Korea	–0.01086 (0.03)***	–0.01356 (0.029)***	–0.1285 (0.166)***	1.009 (0.016)***	–0.02916 (0.038)***
California Argus—China Shenzhen	–0.03858 (0.03)***	–0.02897 (0.031)***	–0.154 (0.179)***	1.028 (0.018)***	–0.0332 (0.04)***
California—China Guangdong	–0.02875 (0.03)***	–0.006216 (0.041)***	–0.1952 (0.184)***	1.021 (0.021)***	–0.04105 (0.039)***
California—China Hubei	0.01413 (0.03)***	0.04192 (0.042)***	0.06635 (0.172)***	1.008 (0.018)***	0.01543 (0.036)***
RGGI—Quebec	–0.005927 (0.04)***	–0.002926 (0.042)***	–0.04782 (0.237)***	1.006 (0.027)***	–0.01262 (0.053)***
RGGI—South Korea	0.03829 (0.04)***	–0.005644 (0.042)***	0.2955 (0.231)***	1.006 (0.025)***	0.07129 (0.046)***
RGGI—China Shenzhen	–0.006798 (0.04)***	–0.001988 (0.044)***	0.07998 (0.733)***	1.009 (0.028)***	0.01892 (0.056)***
RGGI—China Guangdong	–0.005597 (0.04)***	0.01848 (0.03)***	–0.04602 (0.237)***	1.004 (0.027)***	–0.008462 (0.053)***
RGGI—China Hubei	–0.001311 (0.04)***	–0.00362 (0.035)***	–0.05518 (0)***	1.006 (0.026)***	–0.01219(0.05)***
Quebec—South Korea	0.01849 (0.03)***	–0.001396 (0.033)***	0.1084 (0.176)***	1.012 (0.018)***	0.02384 (0.037)***
Quebec—China Shenzhen	–0.003571 (0.03)***	–0.00362 (0.035)***	–0.03147 (0.191)***	1.004 (0.019)***	–0.00723 (0.037)***
Quebec—China Guangdong	–0.0012 (0.03)***	–0.001396 (0.033)***	–0.001094 (0.173)***	1.01 (0.017)***	0.0009459 (0.044)***
Quebec Argus—China Hubei	0.01628 (0.03)***	0.01608 (0.03)***	0.0126 (0.168)***	1.002 (0.018)***	0.02078 (0.032)***
South Korea—China Shenzhen	–0.02361 (0.03)***	–0.02435 (0.031)***	–0.1673 (0.179)***	1.019 (0.021)***	0.004771 (0.027)***
South Korea—China Guangdong	0.01611 (0.03)***	0.01598 (0.033)***	0.04178 (0.188)***	1.005 (0.02)***	0.02615 (0.036)***
South Korea—China Hubei	0.07537 (0.03)***	0.07399 (0.03)***	0.4302 (0.167)***	1.046 (0.018)***	0.09818 (0.043)***

This table presents the results of the correlation of the estimates of the dependence of the different exchanges for spot contracts by pair of exchange. We incorporated five copula functions (normal, Student-t, Frank, Gumbel and Clayton) in order to estimate the dependence parameters θ for the sample.

strongest tail dependence was noted for the California and Quebec carbon markets, which might be due to their existing link. The Californian and RGGI tail dependence was almost zero for both future and spot prices.

Table 7: Results for the Goodness-of-Fit-Tests and Tail Dependence Coefficients of the Best Copulas (Future)

Exchanges	Normal	student's t	Frank	Gumbel	Clayton	Lower Tail	Upper Tail
EU—California	0.866	0.658	**0.802**	0.71	0.781	0	0.011
EU—RGGI	0.688	0.0195	0.69	**0.748**	0.649	0	0.00689
California—RGGI	0.0405	0.0045	0.0215	**0.1**	0.0594	0	0.0177

This table presents the results of the goodness-of-fit-tests and tail dependence coefficients of the best copulas, for the different exchanges, for future contracts by pair of exchange. We incorporated the five copula functions (normal, Student-t, Frank, Gumbel and Clayton) and add information about lower tail and upper tail values.

Table 8: Results for the Goodness-of-Fit-Tests and Tail Dependence Coefficients of the Best Copulas (Spot)

Exchanges	Normal	student's t	Frank	Gumbel	Clayton	Lower Tail	Upper Tail
EU—California	**0.308**	0.0195	0.172	0.228	0.242	0	0
EU—RGGI	0.0944	0.167	0.284	0.0135	**0.294**	0	0
EU—Quebec	0.0574	5.00E-04	0.0215	0.153	**0.167**	0.000273851	0
EU—South Korea	0.168	0.112	0.103	**0.257**	0.137	0	0
EU—China Shenzhen	00.0684	0.0804	0.0465	**0.107**	0.0984	0	0.03869
EU- China Guangdong	**0.0984**	5.00E-04	0.0495	0.0335	0.0614	0	0
EU—China Hubei	0.0924	0.0504	0.0594	**0.147**	0.124	0	0.01232721
California—RGGI	**0.44**	0.206	0.374	0.0634	0.41	0	0
California—Quebec	0.257	**0.777**	0.282	0.423	0.0864	0.1041575	0.1041575
California—South Korea	0.0564	0.101	0.0425	**0.186**	0.0704	0	0.01232721
California—China Shenzhen	0.237	0.151	**0.295**	0.0864	0.271	0	0
California—China Guangdong	0.239	0.155	0.171	**0.482**	0.177	0	0.02831111
California—China Hubei	0.73	0.00549	0.588	0.113	**0.603**	3.09E-20	0
RGGI—Quebec	0.881	0.477	0.063	0.31	**0.892**	0	0
RGGI—South Korea	0.105	0.187	0.112	**0.82**	0.0233	0	0.00825109
RGGI—China Shenzhen	0.181	0.362	0.469	**0.875**	0.458	0	0.01232721
RGGI—China Guangdong	**0.117**	0.0265	0.0704	0.0874	0.0984	0	0
RGGI—China Hubei	**0.565**	0.0435	0.493	0.544	0.509	0	0
Quebec—South Korea	**0.473**	0.0025	0.375	0.151	0.46	0	0
Quebec—China Shenzhen	0.414	5.00E-04	0.33	**0.485**	0.398	0	0.005515466
Quebec—China Guangdong	0.0425	0.294	0.0135	**0.325**	0.0335	0	0.0136787
Quebec—China Hubei	0.342	0.0125	0.401	0.422	**0.48**	3.26E-15	0
South Korea—China Shenzhen	**0.191**	0.0784	0.186	0.0984	0.156	0	0
South Korea—China Guangdong	0.131	0.0015	0.0844	**0.53**	0.144	0	0.006885108
South Korea—China Hubei	**0.428**	0.291	0.313	0.268	0.109	0	0

This table presents the results of the goodness-of-fit-tests and tail dependence coefficients of the best copulas, for the different exchanges, for spot contracts by pair of exchange. We incorporated the five copula functions (normal, Student-t, Frank, Gumbel and Clayton) and add information about lower tail and upper tail values.

5.3 Discussion

This study shed light on the very important topic of the dependence structure among the different carbon markets. The results clearly highlighted some dependencies, usually at the regional level. This study naturally led to a set of policy recommendations.

If the ultimate goal is truly to have a unique price for carbon emissions throughout the world (see Green et al., 2014) to reflect its true environmental cost, policy makers cannot ignore the regional dependencies. On the one hand, strengthening them can foster the creation of larger carbon clubs that, in turn, could ultimately lead to a unique global market. On the other hand, some local challenges might be preferred above the greater good of a global market. Whether regional carbon clubs should be encouraged remains an open question. In a similar vein, the regional dependence in this study rested on the existing regional networks, i.e., the North American and EU being regional initiatives. Policy makers should pay attention to upcoming carbon markets from emerging countries (such as Ghana, Jordan, Singapore, Vanatu and more) and determine if they are able to converge on a regional level with a similar effectiveness. In this race of converging to the global carbon market, the regional clubs constructed by emerging markets will need to be on a larger scale and will demand more linkages with other regional clubs to ensure liquidity and trading in the market.

This study also raised another interesting point associated with the advent of new carbon markets and the upcoming implementation of Article 6 of the Paris Agreement. With the mushrooming of regional initiatives, paying the (high) cost of carbon contracts is almost unavoidable, which encourages carbon leakage. Strong regulation should be put in place to legally enforce price targets across different markets to ultimately make the prices converge on the different ETSs. Recommendations to strengthen the digital infrastructure as well as the monitoring, reporting and verification processes are prominent.

We also highlighted the interesting fact that newly created schemes tended to be positively linked to the EU ETS, emphasizing the real pioneering role of the EU ETS. One of the solutions for reaching a global market might be the extension of the EU ETS, strengthening its position, which in turn could affect all the new initiatives by installing a natural price correlation between the ETSs. The EU ETS has already started to follow that strategy by encompassing the Swiss ETS, but it may enlarge even more, notably through West Asian ETSs, to eventually make a bridge with Chinese pilot markets. Nevertheless, during the integration of emerging carbon markets with the EU ETS, policy makers should not repeat the CDM process (whereby developing countries were providing the carbon credits) which eventually became irrelevant and had to be cancelled.

Since the compliance markets are very much in the limelight, policy makers should not ignore the presence and impact of voluntary carbon markets on carbon prices. The nexus between compliance and voluntary carbon markets has not yet received the scientific attention it deserves, mainly due to the lack of data and transparency regarding counter trading in voluntary carbon markets. With the implementation of Article 6 of the Paris Agreement, the transfer of international carbon emissions will influence the carbon markets and ultimately price dynamics.

6. CONCLUDING REMARKS

Tail dependence characterizes the linkages of cross carbon markets and is of interest to investors as an economic barometer in carbon financing. The study of the dependence structure of carbon markets is also crucial for designing a unique global carbon market to reach global climate goals. However, the literature regarding the dependence structure of multiple carbon markets is limited. We aimed to shed light on the dependence structure of carbon markets through GARCH-copula models, which have been extensively adopted in the literature.

We used three carbon markets for the future price analysis: EU, RGGI and California. We expanded the sample to include EU, RGGI, California, Quebec, South Korea and three Chinese carbon markets to measure the dependence of spot prices. By implementing the copula model to assess the dependence structure among these carbon markets, we found that there was more asymmetric dependence among carbon markets in the spot returns. The EU ETS, one of the largest carbon markets in the world, exhibited very low and negative dependence on both the oldest carbon markets, RGGI, California and Quebec, and on the upcoming markets in Asia (South Korea and Chinese carbon markets). The RGGI, California and Quebec carbon markets are also more likely depend on each other, and similar results have been obtained for Asian carbon markets. This suggests a greater potential for regional carbon clubs rather than an expanding global carbon market.

This study suggests avenues for future research. More platforms and a longer time period can be investigated, both for spot and future contracts, notably on the most recent eastern carbon markets. Another avenue of research could involve the use of tail dependence to design a unique carbon market or to reduce carbon leakage. All these topics are part of our future research plan.

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