Dependence structure among carbon markets around the world: New evidence from GARCH-copula analysis

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Abstract

This paper investigates the dependence structure among carbon markets around the world through the application of different copulas. The analysis provides important insights into the relationship between carbon prices being traded across different exchanges across the world. The novelty of this study rests into assessing carbon allowances for both futures and spot prices across all the key carbon markets, such as the EU, RGGI, California, Quebec, South Korea, as well as the three oldest Chinese pilot carbon markets, Shenzhen, Guangdong and Hubei for the period 2011 to 2019 for future prices and 2015 to 2020 for spot prices. The results demonstrate an asymmetric relationship between most carbon markets. A low tail dependence has been noted between the EU and western carbon markets, while higher tail dependence has been registered with the eastern carbon markets. Further, carbon markets that have linkage agreement, ongoing cooperation or are geographically close tend to have positive and higher tail dependence. The paper points out to regional carbon clubs being formed as per the dependence structure.

Keywords: carbon markets , carbon pricing, copula models, dependence structure

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1 Introduction

Under the Paris Agreement, countries have pledged to reduce their emissions in order to limit the global mean temperature increase to well below 2-degree (Rogelj et al., 2017). The emission trading system (ETS), commonly known as carbon market, is considered as a pivotal tool in the mitigation 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 in place or have been scheduled (Ramstein et al., 2020). Through, carbon markets, the right to emit a given amount of CO2 becomes a tradable commodity and is a factor of production that is subject to stochastic price changes. Academic literature has emphasized the role of pricing in carbon markets by investigating diverse axes of it. Since the beginning of emission trading systems in 2005, a number of studies have analyzed the behavior of emission allowance prices. A strand of literature focuses on co-integration 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 Chinese pilot carbon market risk of spillover), whilst another set of literature focuses on co-integration between two carbon markets and/or between other energy markets (For example Kanamura (2016), Cherubini et al. (2011) and Zeng et al. (2021) for co-integration between EU carbon market and Certified Emission Reductions (CERs), Chun (2018) for spillover between EU and Chinese carbon markets and Balcılar et al. (2016) for cross market correlations between EU carbon market and other energy markets).

This study grounds on existing research on co-integration between carbon markets and contributes to the existing literature by extending the analysis to eight carbon markets: EU ETS, RGGI ETS, California ETS for assessing inter-dependencies amongst future carbon prices and the Quebec ETS, South Korean ETS and three Chinese Pilots ETS (Shenzhen, Guangdong and Hubei) for spot carbon prices. The data ranges from August 2011 to August 2019 and from January 2015 to June 2020 for future and spot prices, respectively. Rather than grounding on traditional co-integration models such as VECM and VAR models, our study measures the dependency across the different trading schemes using tail dependence (see for example (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 since then been extensively adopted in carbon pricing studies (Yu et al., 2020; Uddin et al., 2018; Wu and Hu, 2014). We follow these studies and first estimate, for each pair, the full-range tail dependence copulas through both lower and upper tail and tails asymmetry. Then, we select the best model of copulas over the usual GARCH model based on the goodness of fitness tests by (Kojadinovic et al., 2010).

The aim of this paper is to provide a thorough analysis of the dependence structure between prices in carbon markets around the world. Our main contribution is twofold. First, we apply five different copula models in order to assess the nature of the dependence across the carbon markets globally, which has, to the best of our knowledge, not been done in prior studies. The use of five copula models strengthens the degree and structure of dependence, ensuring that any type of transformation is less likely to change it. Compared with multivariate GARCH, copula-based GARCH can describe the nonlinear risk spillovers between markets. Second, our study is the first to investigate the dependence structure among eight different carbon markets around the world. It also extends to a time horizon which has not been explored by previous studies. This contribution can help reduce price discrepancies across different markets in order to achieve the ultimate objective of a global, worldwide carbon emission trading scheme. Given that the true, that is environmental, cost of emitting one ton of CO2 should be identical everywhere on Earth, price discrepancies between different markets might generate issues, like carbon leakage, that hinder the benefits of the climate actions.

Our study shows that EU carbon market displays a positive tail dependence with uprising carbon markets (South Korea and Chinese Pilot carbon markets) whilst the latter registers zero or weak tail dependence with western carbon markets (RGGI, California and Quebec). In addition, the western carbon markets have a positive dependence amongst themselves which might be due to existing linkage practices. Similarly, the Asian carbon markets are more likely to be dependent on each other. Our results point out to regional dependence structure rather than the uprising of a global carbon market as being lobbied by several stakeholders.

The rest of this study is organized as follows. Section 2 provides an overview of the background of the study by delving into existing literature on methodologies to measure stochastic dependencies in carbon markets. Section 3 presents the methodology to measure tail dependencies and introduces the copula model. Section 4 shows the data sources and empirical settings. Section 5 reports the empirical results along with the robustness checks. The final section concludes.

2 Background

Economic theory has advocated for the use of carbon financial instruments in order to reduce carbon emission since decades through fixed instruments known as carbon taxes or quantity instruments known as emissions trading (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 in 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 a political and economic dimension. The world is witnessing the proliferation of carbon markets globally. The European Union's Emissions Trading System (EU-ETS) is the largest, 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 Tokyo (Japan), South Korea, China, Kazakhstan, and India (Fankhauser, 2011; Jotzo et al., 2013; Wang, 2013). China, the world's largest emerging market, is seen to have great potential for large-scale carbon trading. China has recently set up its national cap-and-trade system in June 2021, comprising of 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. 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 amongst the existing ones, thereby giving rise to this study.

A second motivation for the study rests on the increasing attention on linking carbon markets. Linkages across carbon markets have not escaped the policy makers discussions nor the scholars' attention. To date, existing linkages have been formed, for example EU ETS has agreed to integrate with the Swiss ETS. California's carbon market has an established link with Quebec carbon market. Jotzo and Betz (2009) evaluate a plan to bilaterally integrate the Australian ETS with the EU ETS, which was afterwards aborted in 2012. The impact of linking the EU ETS to the US system was evaluated in Zetterberg et al. (2012). The studies from Marschinski et al. (2012) and Hübler et al. (2014) investigate a proposal for integrating the EU ETS with a Chinese ETS. Similarly, Gavard et al. (2016) modelled a sectoral ETS on electricity and energy-intensive industries in the EU, the US and China, simulating different linkage scenarios. Some empirical evidences also consider a multi-regional integrated ETS in which the EU ETS takes part (Anger, 2008; Dellink et al., 2014; Yu and Xu, 2017).

There is a growing body of literature on carbon markets integration since 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 with other energy commodities. Different methods have been used in all these studies. Chevallier et al. (2010) employ autoregressive methods to measure the cointegration between EUA futures and spot prices. Rittler (2012) measures spillover effects from futures to the spot market using 10-minute and 30-minute data for the EU carbon market. The relationship between EUA and CERs has also been studied and a positive spillover effect has been identified. Kanamura (2016) adopts a supply and demand correlation model to examine the EUA and CERs returns integration. Trück et al. (2014) add to the empirical analysis of the relationship between EUA future and spot contracts being traded on the EEX and present a convenience yield model for the volatilities between the two assets. Zhu et al. (2020) adopt a vine copula approach to measure the risks and spillovers in Chinese pilot carbon markets and find that the conditional value at risk (CVaR) is a better measure than traditional risk. Wu and Hu (2014) explore the dynamic interdependence between European carbon spot and futures prices using copula-GARCH model. Hu et al. (2015) investigate the dependency characteristics of EU carbon markets using R-vine copula model and find 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 carbon markets literature. Zeng et al. (2021) adopt the copula approach to analyze the dynamic volatility spillover effect between the European Union allowance (EUA) and CERs markets during the second and third phases of trading of the European Emission Trading System, showing that there is a spillover effect across the two carbon markets. Benz and Trück (2009) capture the regime changes in the EU ETS through an AR-GARCH Markov switching price return model. Paolella and Taschini (2008) measure the tails and volatility clustering between the U.S. SO2 permits and EUA price returns through GARCH modelling. Chevallier et al. (2011) use a DCC-MGARCH model to analyze the dynamic correlation between EUAs and CERs and finds that the correlation coefficient between the two markets changes dynamically over time in the range of [0.01; 0.90]. Chun (2018) uses a DCC-MGARCH(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 depict that there are agglomeration effects in the two markets, but the market concentration and price volatility are more significant.

The GARCH-Copula methodology has also been applied in other energy commodities' markets in order to assess tail dependency. For example, Uddin et al. (2018) model 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) use the copula and VAR-BEKK-GARCH models to study the volatility spillovers between the oil and stock markets. Balcılar et al. (2016) rely 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.

From the above literature, it can be deduced that GARCH and Copula models have been the most favored and adopted ones in carbon market integration studies. The widespread finance literature vouch for the two-step copula modeling which involves the marginal estimations prior to deducting the dependence parameters (Embrechts et al., 2002; Meucci, 2011). Copula model encompasses the drawbacks of Pearson correlation coefficient, as it does not require random variables to be elliptically distributed. They are also invariant to increasing and continuous transformations. Thus, for the purpose of this study, we resort to an extensively applied methodology to assess the dependence structure across carbon markets.

Against this backdrop, this study focuses on addressing the gaps in literature. While the above empirical studies focus on carbon price models and the empirical analyses of a single carbon market, they do not seem to pay attention to the characteristics of the price dependency across different carbon markets. With the mushrooming of carbon markets around the world, there is a need to consider in such an analysis a wider range of carbon markets rather than investigating bilateral integration as in previous studies. By studying both spot and future prices across eight carbon markets, we provide a novel insight on the co-integration of carbon markets. Further, given the extensive application of the GARCH-Copula methodology in energy commodities and carbon markets, we rely on the best methodology, to the best of our knowledge, to test the empirical integration of the global carbon market.

3 Methodology

In this study, we employ 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 in the last two decades.[1]

Sklar (1996) shows 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 $C : [0,1]^d \to [0,1]$ 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 according to 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

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

dependence coefficients, which 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:

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

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

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

when the value of lower tail dependence is the same as the value of upper tail dependence, we state that there is symmetric tail dependence between the two variables. In other cases, dependence is 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 is stated that copula C_2 is more concordant than C_1.

Dependencies in carbon markets can be examined by combining these copula functions with a GARCH-type model including conditional heteroscedasticity, since this model not only successfully describes the characteristics of volatility clustering in carbon allowances prices but also eliminates the serial dependence from the component time series. By incorporating asymmetry into the model, the conditional variance of prices of carbon markets is estimated on the basis of an autoregressive (AR) model for the conditional mean and an exponential GARCH (EGARCH) model. The AR(k)-EGARCH (p,q) specification is expressed as follows:

$$x_t = a_0 + \sum_{i=1}^{k} \alpha_i x_{t-i} + \varepsilon_t E_{t-1}(\varepsilon_t) = 0, E_{t-1}(\varepsilon_t^2) = \sigma^2)$$

(4)

and

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{p}(\alpha_i \mid \varepsilon_{t-1}/\sigma_{t-i} \mid +\gamma_i\varepsilon_{t-i}/\sigma_{t-i}) + \sum_{i=1}^{q} \beta_i ln(\sigma_{t-i}^2)$$

(5)

where E_{t-1} is the conditional information operator based on the information at time $t-1$. In Equation 4, the AR(k) model, indicates that the current movement of a variable x_t can be explained by its own past movement $(x_{t-1}, x_{t-2}, ...)$. In this study, the variable x_t is represented by the carbon prices on the different exchanges. In Equation 5, the EGARCH (p, q) model describes the asymmetry of markets. In this study, we follow Nelsen et al. (2001) by assuming that the error term ε_t follows the generalized error distribution (GED). The maximum likelihood method was used to estimate each model, while the Schwarz Bayesian criterion (SBIC) was used to evaluate the AR terms by choosing their smallest value. The Ljung-Box Q-test was then applied to examine the residuals of AR terms. According to the SBIC and residual diagnostics, $k = 1$ and p and q lie in [0,4].

In this study, we consider both the symmetric and the asymmetric structure dependence between the variables. For a given set of marginals above, we adopt the copula model in order to investigate the conditional dependence structure among carbon markets. For this study, we focus 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

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

(6)

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 :

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

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

$$C(u,v) = exp\{-[(-ln\ u)^\theta + (ln\ v)^\theta]^{1/\theta}\}$$
$$\theta\epsilon(1,+\infty) \tag{8}$$

The Frank copula is defined as:

$$C(u,v) = -\tfrac{1}{\theta} ln(1 + \tfrac{exp(-\theta u)-1)(exp(-\theta v))-1}{exp(-\theta)-1})$$
$$\theta\epsilon(-\infty,+\infty) \tag{9}$$

The Clayton copula is defined as:

$$C(u,v) = (u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}, \theta\epsilon(0,+\infty) \tag{10}$$

In the finance literature, elliptical copulas are most frequently applied because they have 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's-t copulas can be classified into this family because they are based on an elliptical contoured distribution. Gaussian copulas are symmetric and show no tail dependence, while Student's-t copulas can exhibit extreme dependence between variables. Archimedean copulas such as Frank copula also tend to be symmetric and able to provide the full range of dependence estimation for marginals exposed to weak tail dependence. However, the Gumbel and Clayton copulas are asymmetric and 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, while Gumbel copulas show the exact opposite. Nevertheless, for both the Clayton and Gumbel copulas, the greater the value of θ, the greater the dependence between the variables.

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

$$\hat{F}_x = \frac{1}{n}\sum_{j=1}^{n} 1\{X_i < x\} \text{ and } \hat{G}_y = \frac{1}{n}\sum_{j=1}^{n} 1\{Y_i < y\} \tag{11}$$

In the implementation, $\hat{F}_x$ and $\hat{G}_y$ are replaced by $n/(n+1)$ uniform variates using the ECDFs of each marginal distribution in order 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 ECDF of each marginal distribution and estimate the unknown parameter θ of the copula.

4 Data

Despite the fact that there are more and more carbon markets implemented all around the world, the trading of future contracts is still at an infancy stage for most of them, except for the EU, RGGI and California ETS. For example, the Chinese carbon markets will only offer future contracts as from 2021. As such, this study could only assess the dependence structure for future contracts for EUA, RGGI and Californian allowances. We however collected data from seven different exchanges. The future contract prices have been retrieved from Refinitiv for EUA being traded on four platforms: EEX, ICE, Nordpool and NYMEX. RGGI emission contracts are traded on Argus and NYMEX platforms. California allowances future contracts are traded on NYMEX. Data for RGGI Argus has been provided by Argus and data for RGGI and California NYMEX have been retrieved from Refinitiv. For the future contracts, a 1-month rolling approach is adopted to obtain the price time series. Our study gathers future contracts prices for the period ranging from August 2011 to August 2019, amounting to around 2048 observations. For all future contracts, we only focused on the December maturity for each year given that there is a large consensus in the literature about the fact that it dominates all other maturities in terms of trading activity (See Mizrach (2012) for a thorough discussion).

Regarding spot prices, our study includes additional carbon markets since there are more widely available. However, most of them are very recent and as such do not offer as much data points as future contracts. For the EUA spot prices, data has been gathered from the MAREX and EEX platforms. Additionally, we have been able to include spot prices from California, Quebec and RGGI since data has been provided by Argus. From the Chinese pilot carbon markets, only the three oldest ones, i.e., Guangdong, Hubei and Shenzhen, are included in our study. These pilot markets are also associated with the largest market activity and provide sufficient and high-quality data for our analysis. Since Sichuan and Fujian markets have begun to operate on December 16, 2016 and December 22, 2016, respectively, we did not include them because of too few data points. The data for the Chinese and South Korean carbon allowances have been gathered through the IETA platform. For spot prices, data were analyzed for the period ranging from January 2015 to June 2020, including 1048 observations.

In all cases, the price returns are 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 $\triangle S_t = S_t - S_{t-1}$ the corresponding log return. Similarly, F_t is the log of the future price and $\triangle F_t = F_t - F_{t-1}$ is the corresponding log-return.

The descriptive statistics of the futures and spot price series are reported in Table 4 and Table 4, respectively. The results of the Jarque-Bera test show that the null hypothesis of a normal distribution is rejected in all cases. The results of the Ljung-Box Q statistics also demonstrate serial correlation in the time series for all variables.

Table 1: Descriptive Statistics (Futures)

	EUA EEX	EUA ICE	EUA Nordpool	EUA NYMEX	RGGI Argus	RGGI NYMEX	California NYMEX
Mean	0.00004	0.0003	0.0002	0.0002	0.0004	0.0016	2.48E-05
Median	0.0008	0	0.0007	0	0	0.0003	0
Maximum	0.2347	0.2382	0.0642	0.4111	0.02323	1.942	0.2323
Minimum	-0.4223	-0.4320	-0.4523	-0.4167	-0.3471	-0.0798	-0.1729
SD	0.0337	0.0341	0.0365	0.0361	0.0178	0.0461	0.0145
Skewness	-0.9072	-0.9454	1.7885	0.1584	-0.3059	36.3340	1.165
Kurtosis	15.736	16.259	60.1742	22.031	136.002	1526.917	72.111
Jarque-Bera	21513***	22972***	309959***	41619***	1583879***	20028039***	446181
Q	92.602***	115.25***	45.486***	62.79***	84.143***	3.4636***	90.573***

This table shows the descriptive statistics for each future contract in our sample. The table depicts 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)

	EUA EEX	EUA MAREX	Cal Argus	Quebec Argus	RGGI Argus	South Korea	Shenzhen	Guangdong	Hubei
Mean	0.0008	0.0008	0.0002	0.0001	0.0001	0.0007	0.0015	0.0006	0.0002
Median	0	0	0	0	0	0	-0.000005	0.0006	-0.0004
Maximum	0.1282	0.1278	0.1036	0.1158	0.3322	0.0953	1.9637	0.4405	0.4124
Minimum	-0.1945	-0.1942	-0.1714	-0.1840	-0.3677	-0.1165	-1.7062	-0.4653	-0.4155
SD	0.02891	0.02918	0.0083	0.0097	0.0207	0.0189	0.2415	0.0543	0.0414
Skewness	-0.3150	-0.3235	-6.1774	-4.6813	-1.4833	-1.1799	0.4103	-0.0375	0.1105
Kurtosis	4.3965	4.4667	173.6253	122.3088	127.5131	16.4305	13.1370	15.9623	17.4204
Jarque Bera	1135.637***	1172.6693***	1740985.656***	864643.0067***	934823.67***	15839.6414***	7990.6963***	11569.6667***	16424.1238***
Q	0.014826	0.014826	44.196***	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 depicts statistics on moments, median, maximum and minimum, as well as the test statistics associated with the Jarque-Bera and Ljung-Box Q tests.

5 Empirical Results

As carbon price time series exhibit peaks, thick tails, autocorrelation and conditional heteroscedasticity property, the residual sequence of (0, 1) uniform distribution is obtained from carbon price returns before application of copula model, as proposed by Zhu et al. (2020). In the first step, we choose the most appropriate specifications for modelling conditional heteroscedasticity according to the usual information criteria such as the AIC, SBIC and Loglik statistics by employing univariate EGARCH models. Table 5 and Table **??** report the estimation results. As indicated in these tables, all coefficients of the EGARCH term (β) with values close to 1 are statistically significant at the 1% level. Moreover, the coefficients of the asymmetric effect (γ) are statistically significant at the 1% level with negative values. The shape parameters are also statistically significant at the 1% level with values less than 2, suggesting that the tails of the error terms are heavier compared with the normal distribution. These results also present the $Q(S)$ and $Q^2(s)$ statistics in order to validate the empirical results of the EGARCH models. 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 number of auto-correlations less than the number of parameters. Its null hypothesis assumes that there is no auto-correlation up to lag s for standardized residuals. In a second step, we transform the standardized residuals obtained from the EGARCH model into uniform variates based on the empirical CDFs. By applying this step, we obtain the vector of filtered returns in order to estimate the copula functions for carbon markets.

Then, we check the rank correlation coefficients for carbon markets dependence. Table 5 and Table 5 summarize the Kendall's tau and Spearman's rho statistics for the sample. The unconditional correlation shows that there is a positive correlation between EUA and Californian future prices. The EUA and RGGI future price series are negatively correlated while RGGI and Californian future price series have a positive correlation. As for spot prices, EUA future prices are tested from two exchanges namely EEX and MAREX and the results differ. Correlations for EUA EEX with western carbon markets (RGGI, California and Quebec) shows positive but weak correlations while that of EUA MAREX and western carbon markets indicates negative relationship. EUA spot prices points out to positive correlation with eastern carbon markets (Chinese Pilot Carbon markets and South Korea). The three western carbon markets have a negative correlation with the eastern carbon markets. It can also be noted that the western carbon markets have a positive correlation among themselves.

Table 3: Estimations of EGARCH Models (Future)

	EUA EEX	EUA ICE	EUA Nordpool	EUA NYMEX	RGGI Argus	RGGI NYMEX	California NYMEX
Mean Equation							
MU	0.00852***	0.000774***	0.001035***	0.000991***	0	0.001978***	-0.000013***
	(0.000306)	(0.000378)	(0.00055)	(0.000406)	(0)	(0.000003)	(0.000001)
AR1	-0.418334***	-0.228129***	1.889989***	0.093614***	-0.148422***	0.010443***	0.220032***
	(0.133124)	(0.027996)	(0.000752)	(0.006888)	(0.000427)	(0.000206)	(0.000457)
AR2	-0.755928***	-0.740363***	-0.890644***	-0.90191***	-0.067292***	-0.001676***	0.002091***
	(0.031895)	(0.043791)	(0.00025)	(0.01164)	(0.001188)	(0.000018)	(0.000039)
MA1	0.40907***	0.208846***	-1.912334***	-0.123028***	0.14948***	0.010314***	-0.21987***
	(0.146431)	(0.029232)	(0.001726)	(.007545)	(0.000426)	(0.000203)	(0.000459)
MA2	0.701447***	0.688139***	0.913205***	0.898715***	0.05047***	-0.001561***	
	(0.33714)	(0.047122)	(0.000978)	(0.01224)	(0.00119)	(0.000017)	
Variance Equation							
Omega	-0.115884***	-0.127134***	0.15177*	-0.137357***	-0.024596***	-0.699095***	-0.986279***
	(0.031423)	(0.032609)	(0.09146)	(0.033222)	(0.000869)	(0.000212)	(0.046612)
Alpha	-0.01994	-0.024133	-0.038304	-0.037107**	-0.071185***	0.046876***	0.047481
	(0.014884)	(0.015103)	(0.046901)	(0.016113)	(0.00899)	(0.000916)	(0.029981)
Beta	0.983765***	0.982156***	0.978538***	0.980475***	0.998688***	0.901004***	0.907733***
	(0.004418)	(0.004585)	(0.013182)	(0.004722)	(0.000055)	(0.0002)	(0.004241)
Gamma	0.20082***	0.206717***	0.221933***	0.205761***	0.109385***	-0.14001***	0.27447***
	(0.027151)	(0.027326)	(0.026134)	(0.027006)	(0.004548)	(0.00001)	(0.022304)
Shape	1.263821***	1.285036***	1.202046***	1.133495***	0.30088***	1.977216***	0.344461***
	(0.050028)	(0.050626)	(0.042965)	(0.043096)	(0.008731)	(0.000406)	(0.010005)
Diagnostic							
Q	2.028	3.211	0.0272	0.1841	14.87	0.6214	0.06469
	[0.1544]	[0.07312]	[0.869]	[0.6678]	[0.0115]	[0.4305]	[0.7992]
Q-Square	0.8119	0.6191	0.0272	0.3892	0.365	0.0006615	0.01287
	[0.3675]	[0.4314]	[0.869]	[0.5327]	[0.5457]	[0.9795]	[0.9097]

Table 4: Estimations of EGARCH Models (Spot)

	EUA EEX	EUA MAREX	Cal Argus	Quebec Argus	RGGI Argus	South Korea	Shenzhen	Guangdong	Hubei
Mean Equation									
MU	0.000635	0.000412	0	0.000004	0	0	-0.00007	0.000478***	-0.000308***
	(0.000593)	(0.001156)	(0)	(0)	(0)	(0)	(0.001114)	(0.00011)	(0.000051)
AR 1		-0.255489***	0.89279***	1.179101***		-0.095726***	-0.285307***	0.620814***	-0.28763***
		(0.018832)	(0.000321)	(0.000456)		(0.000288)	(0.046138)	(0.0244)	(0.032787)
AR 2		-0.501079***	-0.64716***	-0.754293***		0.07299***	0.088536***	0.087613***	0.127359***
		(0.008041)	(0.000266)	(0.000331)		(0.001316)	(0.045979)	(0.025634)	(0.008074)
AR 3			0.29032***	0.496832***					
			(0.00016)	(0.000247)					
AR 4			-0.28833***	0.072014***					
			(0.000151)	(0.000047)					
MA 1		0.229272***	-0.89328***	1.179705***		0.094297***	0.225996***	-0.877505***	0.078987**
		(0.022477)	(0.000321)	(0.000356)		(0.000284)	(0.036423)	(0.02056)	(0.026726)
MA 2		0.450232***	0.64721***	0.754701***		0.008312***	-0.272002***	0.056002***	-0.194464***
		(0.010933)	(0.000266)	(0.000327)		(0.000052)	(0.053085)	(0.01116)	(0.009402)
Variance Equation									
Omega	-0.188063***	-0.169048***	-0.99281***	-0.386914***	-0.821347***	-1.320085***	-0.109263***	-0.49468***	-1.884205***
	(0.05666)	(0.005605)	(0.280959)	(0.149316)	(0.192002)	(0.012117)	(0.039291)	(0.116537)	(0.284501)
Alpha	-0.027111	-0.019453	-0.13171	0.0245	0.060627	-0.0924***	-0.070469**	0.014249	-0.106504**
	(0.020933)	(0.020698)	(0.095104)	(0.086974)	(0.078691)	(0.001394)	(0.030299)	(0.040192)	(0.049529)
Beta	0.974158***	0.976625***	0.90319***	0.953789***	0.901176***	0.91154***	0.971533***	0.92369***	0.726004***
	(0.007712)	(0.000267)	(0.026917)	(0.014053)	(0.02671)	(0.000549)	(0.009836)	(0.017753)7	(0.040947)
Gamma	0.243744***	0.212389***	0.82584***	0.414835***	0.721787***	0.289436***	0.418205***	0.717498***	0.960298***
	(0.034664)	(0.030593)	(0.136795)	(0.076666)	(0.12156)	(0.026655)	(0.054912)	(0.079742)	(0.086014)
Shape	1.276318***	1.056421***	0.28156***	0.330698***	0.118011***	0.143065***	1.253877***	1.053713***	0.872769***
	(0.064743)	(0.00683)	(0.029316)	(0.026514)	(0.002422)	(0.005108)	(0.06627)	(0.057793)	(0.042647)
Diagnostic									
Q	1.2	1.985	0.007563	8.586	9.629	0.1665	0.05534	0.0592	0.5656
	[0.2733]	[0.15888]	[0.9307]	[0.003388]	[0.0019156h]	[0.6832]	[0.814]	[0.8078]	[0.452]
Q Square	0.3382	1.647	0.007563	25.789	0.2612	0.006061	1.594	0.5329	2.227
	[0.56086]	[0.1993]	[0.9307]	[0.049029]	[0.6093]	[0.9379]	[0.2068]	[0.4654]	[0.1357]

Table 5: Correlation of estimates of the dependence of the exchanges (Future)

Exchanges	Kendall Tau	Spearman Rho	Exchanges	Kendall Tau	Spearman Rho
EUA EEX - California NYMEX	0.005811123	0.008511106	EUA NYMEX - RGGI Argus	0.02401744	0.03238464
EUA ICE - California NYMEX	0.02504631	0.03587103	EUA EEX - RGGI NYMEX	0.00324931	0.004654155
EUA Nordpool - California NYMEX	0.0818	0.1117	EUA ICE - RGGI NYMEX	-0.02540384	-0.03772394
EUA NYMEX - California NYMEX	0.008234846	0.01175061	EUA Nordpool - RGGI NYMEX	0.009832285	-0.000665622
EUA EEX - RGGI Argus	0.0100244	0.01360517	EUA NYMEX - RGGI NYMEX	-0.00189362	-0.002571995
EUA ICE - RGGI Argus	0.01032653	0.01434559	California NYMEX - RGGI Argus	0.0240639	0.031536
EUA Nordpool - RGGI Argus	0.02187084	0.02964945	California NYMEX - RGGI NYMEX	0.01644667	0.02413451

Table 6: Correlation of estimates of the dependence of the exchanges (Spot)

Exchanges	Kendall Tau	Spearman Rho	Exchanges	Kendall Tau	Spearman Rho
EUA EEX - California Argus	0.05019401	0.07221525	California Argus - South Korea	-0.006670378	-0.008840761
EUA EEX - RGGI Argus	0.003536191	0.004907739	California Argus - China Shenzhen	-0.003148573	-0.005181906
EUA EEX - Quebec Argus	0.02763463	0.04055479	California Argus - China Guangdong	0.0254011	0.03699499
EUA EEX - South Korea	0.02605428	0.03562104	California Argus - China Hubei	-0.007287602	-0.01053764
EUA EEX - China Shenzhen	0.0250959	0.03766576	RGGI Argus - Quebec Argus	0.3466266	0.4644963
EUA EEX - China Guangdong	-0.02595083	-0.03838255	RGGI Argus - South Korea	-0.006670378	-0.008840761
EUA EEX - China Hubei	-0.02761391	-0.04022077	RGGI Argus - China Shenzhen	-0.003148573	-0.005181906
EUA Marex - California Argus	-0.03734339	-0.0539622	RGGI Argus - China Guangdong	0.0254011	0.03699499
EUA Marex - RGGI Argus	-0.001479225	-0.001778546	RGGI Argus - China Hubei	-0.007287602	-0.01053764
EUA Marex - Quebec Argus	-0.02348151	-0.03345438	Quebec Argus - South Korea	-0.01220411	-0.01572005
EUA Marex - South Korea	0.004897054	0.006944378	Quebec Argus - China Shenzhen	0.01407236	0.02249627
EUA Marex - China Shenzhen	0.008207407	0.01119979	Quebec Argus - China Guangdong	-0.008977605	-0.0137067
EUA Marex - China Guangdong	0.000672106	0.001099924	Quebec Argus - China Hubei	-0.02588069	-0.03840586
EUA Marex - China Hubei	0.02187673	0.03251539	South Korea - China Shenzhen	-0.02725326	-0.03585316
California Argus - RGGI Argus	0.02879062	0.03952292	South Korea - China Guangdong	0.01198828	0.01637785
California Argus - Quebec Argus	0.3466266	0.4644963	South Korea - China Hubei	0.04213532	0.05706218

By applying the vector filtered returns, we incorporate five copula functions (Normal, Student's-t, Frank, Gumbel and Clayton) in order to estimate the dependence parameters θ for the sample. The results are reported in Table 7 and 8.

The results show that for future return series, all outcomes are significant at the 1% level for all the copulas. The dependence parameters for EUA and California allowances are mostly negative and also very low. Similar results can be deduced for the dependence structure between EUA and RGGI as well. The dependence parameters between California and RGGI are negative despite that there are linkages among both markets and their mechanism structure are similar. The results differ from Paolella and Taschini (2008) who find contagion between EUA future prices and SO2 permits.

As for the spot return series, a higher dependency has been noted throughout the markets. All the copulas have generated significant results at the 1% level. The EU ETS has registered a positive dependence with California and Quebec while it depicts a negative dependence with RGGI. In turn, it shows that spot prices in the two oldest markets are still not converging in the longer run.

Mixed relationship between the EU ETS and Asian carbon markets has been noted. Notably, positive dependence parameters with Chinese Shenzhen and Hubei ETS and negative parameters with South Korea and Chinese Guangdong ETS. The results show that despite that EU carbon market is one of the largest in the world, it is not highly correlated with the uprising markets notably in the Asian regions. These results are in line with the findings of Chun (2018) about EU and Chinese markets spillover between 2014 to 2017.

The dependence parameters between U.S. and Asian carbon markets are also mostly negative for the different copulas. Only, RGGI and South Korea registered some positive relationship. California and RGGI has generated negative parameters as in the case for future return series. California and Quebec carbon markets however have positive parameters which might be due to their existing linkages. Quebec and RGGI registered negative parameters as well. The Asian carbon markets have positive dependence parameters across the different copulas.

Table 7: Correlation of estimates of the dependence of the exchanges(Future)

Exchanges	Normal	student's t	Frank	Gumbel	Clayton
EUA EEX - California NYMEX	-0.005217(0.023)***	-0.009409(0.027)***	-0.06562(0.146)***	1.008(0.014)***	-0.0143(0.034)***
EUA ICE - California NYMEX	0.03864(0.025)***	0.03831(0.026)***	0.2231(0.149)***	1.015(0.014)***	0.05068(0.035)***
EUA Nordpool- California NYMEX	-0.03999(0.024)***	-0.03903(0.026)***	-0.2067(0.147)***	1.033 (0.015)***	-0.02119(0.025)***
EUA NYMEX - California NYMEX	0.01127(0.024)***	0.005152(0.027)***	-0.01348(0.146)***	1(0.014)***	0.0283 (0.026)***
EUA EEX - RGGI Argus	0.04625(0.023)***	0.04722 (0.023)***	0.322(0.138)***	1.017 (0.014)***	0.07428 (0.032)***
EUA ICE - RGGI Argus	-0.01473(0.023)***	-0.01393(0.024)***	-0.01417(0.14)***	1.002(0.015)***	-0.003918(0.029)***
EUA Nordpool - RGGI Argus	-0.001888(0.022)***	-0.001807(0.024)***	-0.0004723(0.134)***	1.006 (0.012)***	-0.0009146(0.031)***
EUA NYMEX - RGGI Argus	0.003951(0.024)***	0.00446(0.024)***	0.06161 (0.139)***	1.007(0.015)***	0.01379(0.029)***
EUA EEX - RGGI NYMEX	-0.01238(0.021)***	-0.01183(0.023)***	-0.04584(0.132)***	1.005(0.015)***	-0.0102(0.03)***
EUA ICE - RGGI NYMEX	0.02096(0.022)***	0.02119(0.025)***	0.1172(0.134)***	1.013(0.015)***	0.02665(0.03)***
EUA Nordpool - RGGI NYMEX	0.04531(0.022)***	0.04461(0.023)***	0.2335(0.131)***	1.021(0.013)***	0.05217(0.032)***
EUA NYMEX - RGGI NYMEX	0.01476(0.022)***	0.01475 (0.023)***	0.08434 (0.135)***	1.008(0.011)***	0.01926 (0.03)***
California NYMEX - RGGI Argus	-0.03371(0.027)***	-0.03346(0.027)***	-0.1971(0.154)***	1.022 (0.017)***	-0.03745(0.025)***
California NYMEX - RGGI NYMEX	-0.02121(0.025)***	-0.02155(0.026)***	-0.1217(0.149)***	1.013 (0.017)***	-0.02597(0.035)***

Table 8: Correlation of estimates of the dependence of the exchanges (Spot)

Exchanges	Normal	student's t	Frank	Gumbel	Clayton
EUA EEX - California Argus	0.05256 (0.029)***	0.05239 (0.029)***	0.2516 (0.172)***	1.024 (0.017)***	0.05923 (0.04)***
EUA EEX - RGGI Argus	-0.06731 (0.04)***	-0.06632 (0.042)***	-0.2485 (0.238)***	1.016 (0.026)***	-0.0519 (0.05)***
EUA EEX - Quebec Argus	0.06918 (0.03)***	0.06912 (0.03)***	0.3723 (0.173)***	1.019 (0.019)***	0.0845 (0.041)***
EUA EEX - South Korea	0.005239 (0.03)***	0.004236 (0.029)***	-0.02986 (0.169)***	1 (0.016)***	-0.005118 (0.039)***
EUA EEX - China Shenzhen	-0.03579 (0.03)***	-0.03499 (0.032)***	-0.184 (0.177)***	1.029 (0.018)***	-0.03837 (0.04)***
EUA EEX - China Guangdong	-0.03705 (0.03)***	-0.03718 (0.034)***	-0.237 (0.193)***	1 (0.018)***	-0.05316 (0.035)***
EUA EEX - China Hubei	0.01842 (0.03)***	0.01937 (0.03)***	0.1054 (0.168)***	1.009 (0.014)***	0.04213 (0.032)***
EUA Marex - California Argus	-0.01793 (0.03)***	-0.01777 (0.028)***	-0.06671 (0.16)***	1.009 (0.014)***	-0.01243 (0.036)***
EUA Marex - RGGI Argus	-0.01246 (0.04)***	-0.01182 (0.043)***	-0.03084 (0.243)***	1.023 (0.022)***	-0.005964 (0.051)***
EUA Marex - Quebec Argus	-0.01183 (0.03)***	-0.01157 (0.028)***	-0.02341 (0.165)***	1 (0.014)***	-0.005108 (0.035)***
EUA Marex - South Korea	-0.008663 (0.03)***	-0.01073 (0.03)***	-0.06004 (0.167)***	1.017 (0.015)***	0.00574 (0.029)***
EUA Marex - China Shenzhen	0.01208 (0.03)***	0.01166 (0.031)***	0.08796 (0.178)***	1.005 (0.014)***	0.02086 (0.042)***
EUA Marex - China Guangdong	-0.01288 (0.03)***	-0.01202 (0.031)***	0.04072 (0.186)***	1 (0.016)***	0.008498 (0.04)***
EUA Marex - China Hubei	0.05128 (0.03)***	0.0489 (0.029)***	0.2645 (0.163)***	1.026 (0.017)***	0.05976 (0.041)***
California Argus - RGGI Argus	-0.01939 (0.04)***	-0.01916 (0.042)***	-0.08596 (0.239)***	1.008 (0.02)***	-0.01946 (0.052)***
California Argus - Quebec Argus	0.09906 (0.02)***	0.09722 (0.032)***	0.5861 (0.154)***	1.086 (0.018)***	0.1354 (0.044)***
California Argus - 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 Argus - China Guangdong	-0.02875 (0.03)***	-0.006216 (0.041)***	-0.1952 (0.184)***	1.021 (0.021)***	-0.04105 (0.039)***
California Argus - China Hubei	0.01413 (0.03)***	0.04192 (0.042)***	0.06635 (0.172)***	1.008 (0.018)***	0.01543 (0.036)***
RGGI Argus - Quebec Argus	-0.005927 (0.04)***	-0.002926 (0.042)***	-0.04782 (0.237)***	1.006 (0.027)***	-0.01262 (0.053)***
RGGI Argus - South Korea	0.03829 (0.04)***	-0.005644 (0.042)***	0.2955 (0.231)***	1.006 (0.025)***	0.07129 (0.046)***
RGGI Argus - China Shenzhen	-0.006798 (0.04)***	-0.001988 (0.044)***	0.07998 (0.733)***	1.009 (0.028)***	0.01892 (0.056)***
RGGI Argus - China Guangdong	-0.005597 (0.04)***	0.01848 (0.03)***	-0.04602 (0.237)***	1.004 (0.027)***	-0.008462 (0.053)***
RGGI Argus - China Hubei	-0.001311 (0.04)***	-0.00362 (0.035)***	-0.05518 (0)***	1.006 (0.026)***	-0.01219(0.05)***
Quebec Argus - South Korea	0.01849 (0.03)***	-0.001396 (0.033)***	0.1084 (0.176)***	1.012 (0.018)***	0.02384 (0.037)***
Quebec Argus - China Shenzhen	-0.003571 (0.03)***	-0.00362 (0.035)***	-0.03147 (0.191)***	1.004 (0.019)***	-0.00723 (0.037)***
Quebec Argus - 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)***

To validate which copula offers the best results, we employ the goodness-of-fit test which compares the distance between the estimated and empirical copulas. The larger the values of the statistics, the higher the probability that the null hypothesis that copula C belongs to the class C_0 is rejected. Kojadinovic et al. (2010) propose a multiplier approach to find the p-values related to the test statistics, which overcomes the problem of dependence of the unknown parameter θ when estimating the distribution. As such, the highest p-value indicates that the distance between the estimated and empirical copulas is the smallest, in turn, suggesting that the copula under scrutiny best fits the data.

The results of the goodness-of-fit tests and tail dependence are summarized in Table 9 and Table 10. It can be deduced that the magnitudes of the tail dependencies in either direction vary significantly across the carbon market pairs. This suggests that the strength of market linkages under extreme conditions is quite different among the pairs.

For EU and California carbon markets, the Frank copula provides the best fit. For EU and RGGI, the asymmetric copulas (Gumbel and Clayton) provide the best fit suggesting asymmetric comovements in the carbon allowance prices. However, the tail dependence between the two carbon markets is very low. For California and RGGI, the Normal and Gumbel copula provide the best fit. The tail dependence is very low in this case.

The goodness-of-fit tests for spot returns indicate presence of asymmetry since most of the pairs are best fitted to the Frank, Gumbel and Clayton copulas. The EU tail dependence with the Asian carbon markets is higher than that with the western carbon markets. The EUA has a zero tail dependence with California, RGGI and Quebec carbon markets. The western carbon markets also register higher tail dependence with the Asian carbon markets. The strongest tail dependence has been noted for California and Quebec carbon markets which might be due to their existing linkages. The Californian and RGGI tail dependence is almost zero for both future and spot prices.

Table 9: 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
EUA EEX - California NYMEX	0.866	0.658	**0.802**	0.71	0.781	0	0.011
EUA ICE - California NYMEX	0.134	0.0025	0.0944	**0.0385**	0.21	1.15E-06	0
EUA Nordpool- California NYMEX	0.196	0.0564	**0.125**	0.395	0.0794	0	0.0438
EUA NYMEX - California NYMEX	0.152	0.137	**0.151**	0.724	0.169	0	0
EUA EEX - RGGI Argus	0.0764	5.00E-04	**0.13**	0.0355	0.0115	0	0
EUA ICE - RGGI Argus	0.0814	5.00E-04	0.148	**0.418**	0.184	0	0.00277
EUA Nordpool - RGGI Argus	0.253	0.00549	0.2	**0.392**	0.248	0	0.00825
EUA NYMEX - RGGI Argus	0.265	0.0015	0.279	**0.359**	0.267	0	0.00961
EUA EEX - RGGI NYMEX	0.688	0.0195	0.69	**0.748**	0.649	0	0.00689
EUA ICE - RGGI NYMEX	0.75	0.0045	0.625	0.68	**0.761**	5.06E-12	0
EUA Nordpool - RGGI NYMEX	**0.729**	0.0266	0.575	0.727	0.718	0	0
EUA NYMEX - RGGI NYMEX	**0.653**	0.0015	0.595	0.77	0.586	0	0
California NYMEX - RGGI Argus	**0.149**	5.00E-04	0.0794	0.114	0.0674	0	0
California NYMEX - RGGI NYMEX	0.0405	0.0045	0.0215	**0.1**	0.0594	0	0.0177

Table 10: 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
EUA EEX - California Argus	**0.308**	0.0195	0.172	0.228	0.242	0	0
EUA EEX - RGGI Argus	0.0944	0.167	0.284	0.0135	**0.294**	0	0
EUA EEX - Quebec Argus	0.0574	5.00E-04	0.0215	0.153	**0.167**	0.000273851	0
EUA EEX - South Korea	0.168	0.112	0.103	**0.257**	0.137	0	0
EUA EEX - China Shenzhen	00.0684	0.0804	0.0465	**0.107**	0.0984	0	0.03869
EUA EEX - China Guangdong	**0.0984**	5.00E-04	0.0495	0.0335	0.0614	0	0
EUA EEX - China Hubei	0.0924	0.0504	0.0594	**0.147**	0.124	0	0.01232721
EUA Marex - California Argus	0.175	0.0485	0.188	**0.244**	0.191	0	0.01232721
EUA Marex - RGGI Argus	0.262	0.0375	**0.229**	0.292	0.269	0	0.03092631
EUA Marex - Quebec Argus	0.168	5.00E-04	0.13	**0.257**	0.154	0	0
EUA Marex - South Korea	0.0228	0.15	0.188	**0.25**	0.196	0	0.02303933
EUA Marex - China Shenzhen	0.198	0.133	**0.407**	0.298	0.435	0	0
EUA Marex - China Guangdong	0.266	0.0225	0.611	0.453	**0.704**	9.18E-06	0
EUA Marex - China Hubei	0.0664	0.0355	0.0365	**0.666**	0.0325	0	0.03482353
California Argus - RGGI Argus	**0.44**	0.206	0.374	0.0634	0.41	0	0
California Argus - Quebec Argus	0.257	**0.777**	0.282	0.423	0.0864	0.1041575	0.1041575
California Argus - South Korea	0.0564	0.101	0.0425	**0.186**	0.0704	0	0.01232721
California Argus - China Shenzhen	0.237	0.151	**0.295**	0.0864	0.271	0	0
California Argus - China Guangdong	0.239	0.155	0.171	**0.482**	0.177	0	0.02831111
California Argus - China Hubei	0.73	0.00549	0.588	0.113	**0.603**	3.09E-20	0
RGGI Argus - Quebec Argus	0.881	0.477	0.063	0.31	**0.892**	0	0
RGGI Argus - South Korea	0.105	0.187	0.112	**0.82**	0.0233	0	0.00825109
RGGI Argus - China Shenzhen	0.181	0.362	0.469	**0.875**	0.458	0	0.01232721
RGGI Argus - China Guangdong	**0.117**	0.0265	0.0704	0.0874	0.0984	0	0
RGGI Argus - China Hubei	**0.565**	0.0435	0.493	0.544	0.509	0	0
Quebec Argus - South Korea	**0.473**	0.0025	0.375	0.151	0.46	0	0
Quebec Argus - China Shenzhen	0.414	5.00E-04	0.33	**0.485**	0.398	0	0.005515466
Quebec Argus - China Guangdong	0.0425	0.294	0.0135	**0.325**	0.0335	0	0.0136787
Quebec Argus - 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

6 Conclusion

Tail dependence characterizes the cross carbon markets linkages and is of interest to investors as it is used as an economic barometer in carbon financing. The study of the dependence structure of carbon markets is also crucial if one aims to design a unique global carbon market to reach the global climate goals. However, the literature on dependence structure on multiple carbon markets is very thin. We aim to shed light on the dependence structure among carbon markets through GARCH-Copula models which have been extensively adopted in literature.

We employ three carbon markets namely, EU, RGGI and California for the future price analysis and expanded 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 find the following. First, there is more asymmetric dependence relationship in the spot returns among carbon markets. The EU ETS being one of the largest carbon market around the world, registered very low and negative dependence with both the oldest carbon markets from the western region (RGGI, California and Quebec) and with the uprising ones from the eastern regions (South Korea and Chinese carbon markets). The western carbon markets are also more likely to be dependent amongst each other and similar results has been registered for eastern carbon markets. In turn, this highlights more potential for regional carbon clubs rather than an uprising global carbon market.

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

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