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Analyzing Dependence Structure Between Carbon Market and Energy Commodities: Evidence from Copula Approach

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Abstract:

This paper uses copula models to examine the tail dependence behavior of the carbon market and energy commodities. We have taken daily data of the European Union Allowance (EUA) and four energy commodities. The crude oil and coal with more carbon emissions strongly depend on EUA, whereas natural gas and ethanol, which are comparatively cleaner energy sources, are weakly correlated to EUA. Moreover, the results indicate that the dependence and Kendall's tau correlation of EUA increase during the crisis period with all energy commodities except ethanol, which decreases. The relationship of EUA, however, is insignificant with natural gas. The low or weak correlation at the time of market downturns provides diversification benefits. The findings are helpful for investors in risk management and policymakers for devising regulations for the emission trading market for energy markets diversified by the carbon market.

Keywords: European Union Allowance (EUA), Energy Commodities, Copula Method, Portfolio Diversification

I. Introduction

A balance between demand and supply regulates global fossil fuel energy prices. As the market rises, the cost of fuel hikes, whereas a decrease in demand results in a fall in energy prices (such as the period of coronavirus pandemic). Oil is the primary consumable energy source, followed by coal and natural gas. These three sources are responsible for 76% of GHG emissions during 2018 (EIA, 2019). Between 2011-2012, crude oil prices rose dramatically, reaching around 100 US dollars per barrel, with a gradual fall in prices after a few years. However, the consumption of fossil fuels has increased mainly in recent years. This increases carbon emissions, which creates pressure to introduce emission trading schemes (ETS). The primary purpose of these schemes is to reduce CO2 emissions and control the rise in global temperature (Bing, Bloemhof-Ruwaardet, Chaabane & Vorst, 2015).

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In the past decade, coal prices followed the same price trend as crude oil accounted for nearly 40% of the worldwide power generation in 2018 (EIA, 2019). The countries are trying to replace coal power plants with clean energy projects in the coming years. Hence a reduction in the consumption of coal is expected. On the other hand, natural gas prices remain more or less stable in the short term, as it is considered a cleaner alternative to coal.

European Union ETS, the largest capitalization carbon trading market globally, accounts for 43% of European Union (EU) greenhouse gas emissions with 11,000 companies and over thirty-one economies. This EU-ETS is based on a “Cap and Trade” system that limits GHG emissions allowed to the participants. The carbon allowances (EUA) are allocated to the companies against each power plant. However, if the companies are doing fewer emissions than allowed, the surplus EUAs are sold in the market. In contrast, the companies with more carbon emissions buy these allowances from the market – this is how the trading of the European carbon market is carried out (Benz & Trück, 2006).

The EU ETS is divided into phases, and each stage has its compliances. Phase-I was the testing period from January 1, 2005, to December 31, 2005, followed by Phase-II from 2006-2012. Phase-III covers the period of 2013-2020. Currently, the EU ETS is in Phase-IV. The EU cap will be reduced by 1.74% annually. The free and excessive distribution of allowances in Phase-I caused huge prices fluctuations reaching almost zero value. Therefore, free allocation of carbon allowances is slowly replaced with auctions, especially for the power sector. Carbon assets are a factor of production which suggests that changes in carbon prices are closely related to the dynamics of other energy commodity markets.

In recent years, the carbon market has shown sharp variations and leptokurtic distribution in volatility and extreme dependence on conventional energy commodities (Chevallier, 2009; Creti et al., 2012; Hammoudeh et al., 2015; Uddin et al., 2018; Wen et al., 2014). During market downturns, when the production from EUA participants decreases, it will be left with spare allowances, and hence an excessive supply/availability of EUAs will reduce its prices. This way, the carbon prices could be expected to correlate with energy prices negatively. However, during the economic boom period, the increase in consumption and production by EUA participants will increase the cost of energy commodities and CO2 emissions. Hence, a positive relationship is expected to have between EUA and energy prices. These linkages show that diversification benefits can be achieved.

Initially, Reboredo (2013) examined the dependence between EUA and crude oil by using copulas. In addition, Aatola et al. (2013a) Ji, et al. (2018), and Liu & Chen (2013) investigate the dynamic relationship and volatility spillover between fossil energy (using oil, gas, coal, electricity) and European carbon prices and revealed the significant linkage and spillover effects. This shows that energy prices impact the trading of the CO2 emission market. However, we are partially in line with these studies focusing on the tail dependence behavior of carbon markets and energy commodities.

This study makes the following contributions to the existing literature in three ways. Unlike previous studies that mainly emphasize oil, natural gas, coal, and electricity, this paper considers crude oil and coal dirtier/carbon-emitting fuels and natural gas and ethanol as less carbon-emitting fuels. Differentiation between these two types gives an in-depth understanding of the dependence when markets show upturns and downturns. Copula methods can measure the dependence and tail dependence between markets; hence seven different bivariate copulas are used to model the relationship of EUA with energy variables. Secondly, the appropriate copula is chosen based on the lowest AIC and applied to the crisis period separated from the complete data to see the existence of contagion effect using Kendall's τ values. The findings help the investors in portfolio diversification and asset management, and this study is a source of information for policymakers to design energy policies to control GHG emissions accordingly. Finally, the data period includes the oil price plunge of 2014-2016 and the Covid-19 pandemic, thus providing insight into how sensitively the market dependence responds to such extreme financial oscillations.

The following section presents related literature. Section 3 briefly describes the data and methodology used in the paper. Section 4 elaborates results and discussion, followed by the conclusion, practical implications, and limitations in the final section.

II. Literature Review

European Union ETS is the leading and largest carbon market in the world. As per the Emission Trading Scheme, the firms are given the right to emit CO2 against the issued carbon allowances (carbon credits). One allowance is defined as the right to emit one metric ton of CO2. The ETS Directive further states that these can only be transferred according to provisions of the Directives (EUA 2019). Carbon assets vary in descriptions and functionality (Purdon, 2015). It can be considered the asset provided to firms for generating greenhouse gases (Gomez-Echeverri, 2013), or it can be categorized as public finance, a financial compensation given from rich to developing countries for environmental pollution (Labatt & White, 2011).

Different factors drive carbon prices. A study conducted by (Chevallier, 2009) analyzed the macroeconomic aspects of European Union Allowance prices and found a weak relationship between carbon market and stock-bond variables. However, the other study reveals strong associations between stock prices, EUAs, and the degree of industrial output (Bredin & Muckley, 2011). Moreover, carbon prices are also adversely affected by economic recessions (Chevallier, 2011; Koch et al., 2014). The study conducted by J. Yu & Mallory (2014) shows that exchange rate and carbon prices are significantly correlated, stating that the effect is generated via the energy switching mechanism as carbon, natural gas, and coal prices are all affected by the exchange rate to a varying extent.

Several studies have been dedicated to the association between European allowance price and price of electricity (Aatola et al., 2013b; Bunn & Fezzi, 2007; de Menezes et al., 2016; Jouvet & Solier, 2013; Sijm et al., 2006), founded on the notion that carbon prices influence the electricity industry as it is a significant contributor of the overall EU CO2 emission. For instance, electricity prices depend on fuel prices and EUA (Zachmann, 2013). Besides, electricity prices may also vary because of the fluctuations in the weather condition, thereby leading to variations in the EUA prices (Bredin & Muckley, 2011; Hintermann, 2010; Mansanet-Bataller et al., 2007).

Specifically, for the carbon and energy linkages, Alberola et al. (2008) and Mansanet-Bataller et al. (2007) were the first to empirically investigate the association between the carbon market and energy commodities. These studies find that carbon prices in the EU ETS are linked to crude oil, gas, and coal prices. In continuation to the former researches, Bunn and Fezzi (2008) find the pass-through costs of EUA to electricity prices and the impact of natural gas prices on EUA and electricity prices by using a structural, co-integrated vector-error-correction model. Another researcher finds that coal and natural gas prices Granger-cause the EUA futures (Keppler and Mansanet-Bataller, 2010). Hammoudeh et al. (2015) focused on the nonlinear relationship of carbon and energy markets.

Various studies have used copula models to measure the dependency of EUA and oil prices (Reboredo, 2013; Reboredo et al., 2019). The copula approach helps measure the marginal distributions, whereas simple correlation coefficients give the level of dependence. This paper uses simple bivariate copulas as high dimensional copulas are complicated and challenging to mature (Aas et al., 2009; Mohti et al., 2019). Multiple copulas are used to select the best fit among them as markets show different dependence patterns with each other (Trivedi and Zimmer, 2005). Therefore we chose seven copulas in this paper.

III. Data and Methods

A. Data

We consider the future prices of EUA (European Union Allowance) and crude Brent oil (OIL), coal (COAL), natural gas (NGAS), and ethanol (EtOH). EUA futures are traded on the European Climate Exchange (ECX) and measured in Euro per ton. All energy commodities pollute the environment; however, oil and coal produce more carbon, and natural gas and ethanol comparatively emit less carbon. The data is obtained from Datastream, a global database of Thomson Reuters. The sample period starts from January 5, 2009, to May 31, 2021. This period is chosen when the markets returned to stability after GFC (global financial crisis), as several researchers have covered this crisis in their studies. However, this study mainly focuses on the recent energy crisis and outbreak of the Covid-19 pandemic.

Figure 1 shows the price trends of the carbon market and energy commodities. EUA shows a steady decrease from mid-2011, possibly due to the European debt crisis. However, a sharp rise after 2017 and 2022 is observed; the reason could be the economic recovery from the oil price crisis and the Covid-19 pandemic. Energy prices soared, production and consumption tend to rise globally. The crude oil and coal prices follow a similar pattern, whereas natural gas and ethanol correlate in the same direction except during 2016-2019.

Table 1 presents the summary stats of the log return series of EUA and energy commodities. The standard deviation is highest for EUA, followed by NGAS, OIL, EtOH, and COAL, whereas the mean value is negative for NGAS and positive for all other return series. The kurtosis values are higher, indicating leptokurtic distribution and significant Jarque-Bera values asymmetry in the data series.

Figure 1: Price movements of EUA and Energy Commodities

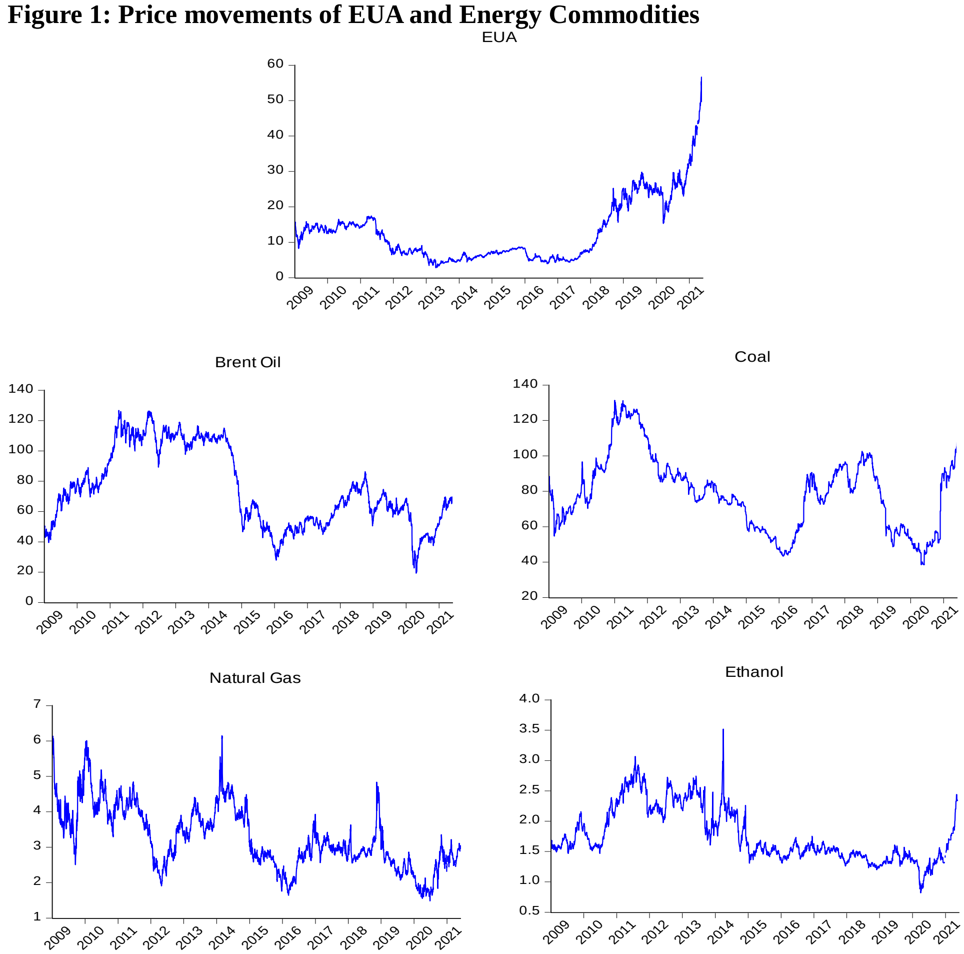

Table 1: Descriptive Statistics

	EUA	OIL	COAL	NGAS	EtOH
Mean	0.000672	0.000083	0.000113	-0.000081	0.000360
Maximum	0.238234	0.190774	0.263090	0.267712	0.097525
Minimum	-0.432077	-0.279761	-0.228593	-0.180545	-0.309978
Std. Dev.	0.031620	0.022912	0.016328	0.031379	0.021566
Skewness	-0.816162	-0.839485	2.830534	0.593560	-2.444197
Kurtosis	17.743593	21.170341	78.929097	8.003571	33.221210
Jarque-Bera	29640.96***	44855.21***	780941.32***	3562.36***	126251.07***
Observations	3233	3233	3233	3233	3233

Note: EUA is European Union Allowance, representing the carbon market, OIL representing Brent oil, NGAS and EtOH denote natural gas and ethanol.

Table 2 presents the Pearson correlation results of the carbon asset and energy prices. EUA is significantly positively correlated to energy commodities except natural gas, which has little relation with EUA and ethanol. A positive relationship shows that the markets move in the same direction. Table 3 presents the unit root diagnostic tests of all variables. The results show the stationarity of data with significant PP (Phillips and Perron) and ADF (Augmented Dickey-Fuller) and insignificant KPSS (Kwiatkowski–Phillips–Schmidt–Shin).

Table 2: Correlation Matrix

	EUA	OIL	COAL	NGAS	EtOH
EUA	1				
OIL	0.190148***	1			
COAL	0.098078***	0.112656***	1		
NGAS	0.022124	0.040342**	0.042112**	1	
EtOH	0.045150**	0.176826***	0.046861***	0.019698	1

Notes: ***,**,* represent significance at 1%, 5%, and 10% levels respectively.

Table 3: Unit Root Diagnostics Test

Variables	PP	ADF	KPSS
EUA	-54.6872***	-20.0822***	0.0477
Brent Oil (OIL)	-55.5879***	-21.4178***	0.1612
Coal	-40.1624***	-20.1919***	0.0904
Natural Gas (NGAS)	-57.8035***	-21.628***	0.1895
Ethanol (EtOH)	-51.1012***	-22.563***	0.0653

Notes: PP, ADF, and KPSS are unit root tests. *** represents the rejection of the null hypothesis of unit root and non-stationarity at the 1% level.

Table 4: Diagnostics tests of Autocorrelation and conditional-heteroscedasticity

Variables	Q(20)	Q^2(20)	ARCH-LM (20)
EUA	63.9541***	408.006***	11.913***
OIL	41.7643***	1218.67***	30.882***
COAL	411.906***	1228.43***	61.317***
NGAS	36.5173**	558.092***	13.057***
EtOH	70.5941***	79.501***	3.014***

Note: Ljung-Box Q-statistics and squared Q statistics tests to check autocorrelation up to 20th order. ARCH Engle LM test (1982) captures the ARCH effect in the estimated residuals up to 20th order. *** represents the rejection of the null hypothesis of no autocorrelation and conditional homoscedasticity at a 1% significance level.

ARCH-LM test is used to capture the Arch effects in the return series, and Table 4 result confirms the existence of autocorrelation and heteroscedasticity. Hence, a GARCH model is applied to overcome these problems in the time-series data.

B. Methodology

Marginal Model

The log return series are modeled by using an ARMA(m, n)-GARCH(p, q)-Student-t model to describe the marginal densities (Patton, 2006), considering the autocorrelation and volatility persistence. To construct the marginal distribution, the marginal model is expressed as:

$$g_{i,t} = \alpha_0 + \sum_{j=1}^{m} \alpha_j \; g_{i,t-j} + \varepsilon_{i,t} + \sum_{j=1}^{n} \Phi_j \, \varepsilon_{i,t-j,} \; i = 1,2 \qquad (1)$$
$$\varepsilon_{i,t} = \omega_{i,t} d_{i,t} , d_{i,t} \sim i.i.d.st_{v_i} \qquad (2)$$
$$\omega_{i,t}^2 = \beta_0 + \sum_{j=1}^{p} \beta_j \, \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q} \gamma_j \omega_{i,t-j}^2 \qquad (3)$$

where g_1 and g_2 are energy indices returns, $\varepsilon_{i,t}$ is the error term, $\omega_{i,t}^2$ is the conditional variance of returns, $d_{i,t}$is the standardized residual following the Student-t distribution with v_i degrees of freedom.

Copula Model

We have taken the copula method to measure the dependence between carbon asset and energy commodities. The copula helps in capturing the dependence structure of a multivariate distribution. As per Sklar's(1959) theorem, a bivariate joint cumulative distribution function (F) of carbon market ($g_{1,t}$) and energy market ($g_{2,t}$) can be divided into two marginal distribution functions (F1 and F2) and a copula cumulative distribution function (C) which denotes the dependence structure between the two series:

$$F\left(g_{1,t}, g_{2,t}; \delta_{1,} \delta_2, \theta_c\right) = C(F_1(g_1; \delta_1), F_2(g_2; \delta_2); \theta_c \qquad (4)$$

where $F_k\left(g_{k,t};\, \delta_k\right),\; k = 1, 2\ldots$ etc. is the combined marginal distribution function of $g_{k,t}$. *C* is copula dependence; F_1 and F_2 represent marginal distribution functions of carbon and energy market returns g_1 and g_2 and $(\delta_{1,} \delta_2, \theta_c)$ represents parameter sets of $F\left(g_{k,t}; \delta_k\right)$ and *C*. The bivariate joint density function can be represented as:

$$f\left(g_1, g_2; \delta_{1,} \delta_2, \theta_c \middle| F_{t-1}\right) = C_t(F_1(g_1; \delta_1), F_2(g_2; \delta_2); \theta_c) \cdot f_1(g_1; \delta_1) \cdot f_2(g_2; \delta_2) \qquad (5)$$

where C_t is the copula density, and f_1, f_2 are the marginal densities of g_1, g_2 respectively. This study follows seven bivariate copulas: Normal copula, Student-t copula, Clayton copula, Gumbel copula, Frank copula, Joe copula, and Survival Gumbel copula. Gaussian, Student-t, and Frank copulas are suitable for analyzing symmetric dependence; Clayton and Survival Gumbel copulas measure left/lower tail dependence, whereas Gumbel and Joe copulas measure the right/upper tail dependence.

IV. Results and Discussion

A. Marginal Model results

A marginal model is a prerequisite for copula estimations. This paper takes ARMA-GARCH Student-t model, and results are reported by taking lags from zero to one. The best-fitted model is chosen based on the lowest AIC (Akaike information criterion). We take multiple bivariate copulas to capture the tail dependence structure of the carbon market and traditional energy commodities.

Table 5 shows that the mean and variance coefficients are mostly significant with a maximum 10% level. The Ljung-Box values fail to reject the null hypothesis of no ARCH effects and homoscedasticity. Hence, these tests show the model's fitness and specification.

Table 5: Marginal model estimations

	EUA	OIL	COAL	NGAS	EtOH
ARMA-GARCH (m, n), (p, q)	(1,0), (2,1)	(1, 1), (2, 1)	(1,0), (2,2)	(1,0), (2,2)	(1, 1), (2, 1)
Mean Equation Results					
Constant	0.001089***	0.00055	-0.00024**	-0.00051	0.000559*
	(0.000375)	(0.000351)	(0.000119)	(0.000431)	(0.000311)
AR(1)	0.006937	0.987231***	0.199775***	-0.00693	-0.00568
	(0.018489)	(0.016469)	(0.019205)	(0.017188)	(0.1092)
AR(2)		-	-	-	-
		-	-	-	-
MA(1)		-0.98295***			0.169465
		(0.018407)			(0.10716)
MA(2)		-	-	-	-
		-	-	-	-
Variance Equation Results					
Constant	0.109962***	0.059485***	0.051054	0.248349***	0.406133**
	(0.039611)	(0.020377)	(0.10733)	(0.070102)	(0.14396)
ARCH(α_1)	0.120042***	0.114939***	3.231683	0.046998**	0.225804***
	(0.01849)	(0.01972)	(3.5636)	(0.021304)	(0.057324)
ARCH(α_2)		-	-2.98917	0.074897***	-
		-	(3.1331)	(0.021434)	-
GARCH(β_1)	0.729143***	0.59113***	1.387404***	0.261293***	0.413355**
	(0.12128)	(0.1667)	(0.15495)	(0.16175)	(0.19102)
GARCH(β_2)	0.145775	0.287124*	-0.42447***	0.591502	0.270296
	(0.1175)	(0.15363)	(0.1126)	(0.1476)	(0.19618)
Diagnostic Tests					
Log Likelihood	7187.044	8381.191	10659.25	6998.45	8613.57
Akaike	-4.441722	-5.17983	-6.58908	-4.32443	-5.32358
Bayes	-4.42856	-5.16478	-6.57403	-4.30939	-5.30853
		Q-Statistics on Standardized Residuals			
Q(20)	23.2379	16.3039	36.0109	19.7242	21.535
		Q-Statistics on Squared Standardized Residuals			
Q(20)	16.7581	16.8451	30.7691	20.6508	9.92488
ARCH LM-test					
ARCH (10)	1.162	0.88784	0.25284	1.0562	0.6847

Notes: The different combinations with lags from 0 to 2 are taken, and the ARMA (m, n), GARCH (p, q) are selected with the lowest AIC. Ljung-Box Q-statistics and Q^2 tests are used to check autocorrelation up to 20th lag. ARCH Engle LM test (1982) measures the ARCH effect in the estimated residuals up to 10 lags. ***, **, and * represent the rejection of the null hypothesis at 1%, 5%, and 10% significance levels respectively. Numbers in parenthesis are standard errors.

B. Bivariate Copula model results for the complete sample

Table 6 presents the estimation results of seven copulas for the whole sample period, and the best-fitted copula for each pair is selected based on the lowest AIC. The dependence is highest for the EUA-OIL pair for the majority of copulas and lowest in the case of EUA-NGAS. Among all copulas and pairs of variables, Gaussian (Normal) copula is best-fitted as it has the lowest AICs for EUA-OIL and EUA-EtOH, whereas Student-t and Clayton copulas are fit for EUA-COAL and EUA-NGAS, respectively. The Kendall's tau correlation is significant for all other pairs except EUA-NGAS. This confirms that the carbon market has no significant relation with natural gas.

The data is divided into regime 1, which includes complete data (from January 2009 to May 2021), and regime 2 includes the crisis period (starting from June 2014 to May 2021). The collapse in oil prices since 2014 and Covid-19 pandemic are the main events that denote it the crisis period. The best-fitted copulas of the complete sample are further used to check the change in dependence and correlation strength in crisis time. The results are reported in Table 7 and indicate that the dependence and Kendall's tau correlation increases from regime 1 to regime 2 for all pairs except EUA-EtOH in which it decreases. Hence, it shows that in crisis situations, different commodities react differently.

Table 6: Estimates of Copula models

		EUA/OIL	EUA/COAL	EUA/NGAS	EUA/EtOH
Normal copula	ρ	0.195***	0.17***	0.009	0.14***
	S.E	0.016	0.017	0.02	0.02
	LL	62.55	48.79	0.33	31.44
	AIC	**-123.11**	-95.59	1.35	**-60.87**
	BIC	-117.02	-89.51	7.43	-54.79
	Kendal τ	0.13***	0.11***	0.01	0.09***
	Tail λ_U	0	0	0	0
	Tail λ_L	0	0	0	0
Student -t copula	ρ	0.196***	0.18***	0.008	0.14***
	S.E	0.017	0.018	0.02	0.018
	DoF	44.26***	16.63***	99.98	33.64*
	S.E	36.73	5.51	553.85	22.15
	LL	62.79	53.94	-0.85	29.03
	AIC	-121.58	**-103.87**	5.7	-54.06
	BIC	-109.42	-91.71	17.86	-41.89
	Kendal τ	0.12***	0.12***	0.01	0.09***
	Tail λ_U	0	0	0	0
	Tail λ_L	0	0	0	0
Clayton	α	0.225***	0.17***	0.03*	0.14***
	S.E	0.023	0.02	0.018	0.02
	LL	54.09	32.22	1.12	22.15
	AIC	-106.19	-62.44	**-0.25**	-42.3
	BIC	-100.11	-56.36	5.83	-36.21
	Kendal τ	0.10***	0.08***	0.01	0.06***
	Tail λ_U	0	0	0	0
	Tail λ_L	0.04	0.02	0	0.01
Gumbel	α	1.11***	1.11***	1.01***	1.07***
	S.E	0.01	0.01	0.01	0.01
	LL	45.11	47.85	0.29	17.7
	AIC	-88.22	-93.7	1.42	-33.39
	BIC	-82.14	-87.62	7.5	-27.31
	Kendal τ	0.10***	0.10***	0.01	0.07***
	Tail λ_U	0.13	0.14	0.01	0.09
	Tail λ_L	0	0	0	0
Frank	α	1.13***	1.13***	-0.01	0.89***
	S.E	0.11	0.11	0.11	0.11
	LL	56.15	55.37	0	35.2
	AIC	-110.30	-101.74	1.99	-59.40
	BIC	-104.22	-90.66	8.07	-52.32
	Kendal τ	0.12***	0.12***	0	0.10***
	Tail λ_U	0	0	0	0
	Tail λ_L	0	0	0	0
Joe	α	1.12***	1.14***	1.01***	1.07***
	S.E	0.02	0.017	0.01	0.02
	LL	27.36	35.01	0.27	8.24
	AIC	-52.73	-68.03	1.46	-14.48
	BIC	-46.65	-61.95	7.54	-8.39
	Kendal τ	0.06***	0.07***	0	0.04***
	Tail λ_U	0.14	0.16	0.01	0.08

	Tail λ_L	0	0	0	0
Survival Gumbel	α	1.12***	1.11***	1.01***	1.08***
	S.E	0.01	0.01	0.01	0.01
	LL	58.94	40.29	0.57	22.55
	AIC	-115.88	-78.58	0.85	-43.11
	BIC	-109.80	-72.50	6.93	-37.02
	Kendal τ	0.11***	0.10***	0.01	0.07***
	Tail λ_U	0	0	0	0
	Tail λ_L	0.14	0.13	0.01	0.09

Notes: ***, **, and * represent the rejection of the null hypothesis at 1%, 5%, and 10% significance levels respectively. λ_U and λ_L denote the upper tail and lower tail. The values in bold show the lowest AIC values among all copula families.

Table 7: Comparison of dependence and correlation in the whole sample and crisis Period

		EUA/OIL		EUA/EtOH	
		Complete sample	Crisis period	Complete sample	Crisis period
Normal copula	ρ	0.195***	0.22***	0.14***	0.06***
	S.E	0.016	0.02	0.02	0.02
	LL	62.55	46.45	31.44	6.09
	AIC	-123.11	-90.89	-60.87	-10.17
	BIC	-117.02	-85.38	-54.79	-4.09
	Kendal τ	0.13***	0.14***	0.09***	0.04***
	Tail λU	0	0	0	0
	Tail λL	0	0	0	0
		EUA/COAL			
		Complete sample	Crisis period		
Student-t copula	ρ	0.18***	0.21***		
	S.E	0.018	0.02		
	DoF	16.63	12.17		
	S.E	5.51	4.07		
	LL	53.94	44.58		
	AIC	-103.87	-85.16		
	BIC	-91.71	-74.14		
	Kendal τ	0.12***	0.14***		
	Tail λU	0	0		
	Tail λL	0	0		
		EUA/NGAS			
		Complete sample	Crisis period		
Clayton	α	0.03*	0.03*		
	S.E	0.018	0.02		
	LL	1.12	0.98		
	AIC	-0.25	0.05		
	BIC	5.83	5.56		
	Kendal τ	0.01	0.02		
	Tail λU	0	0		
	Tail λL	0	0		

Note: ***, **, and * represent the rejection of the null hypothesis at 1%, 5%, and 10% significance levels respectively.

Emission trading schemes help in decreasing environmental damage (Benz and Trück, 2006). Since most earlier studies have concentrated on simple co-movements between carbon and energy commodities, however, the tail dependence behavior of these markets is understudied. We contribute to the literature by using the seven different bivariate copulas. We focus on the EU-ETS and energy variables. The dependence of the carbon market is strongest with oil and coal as these are more polluting energy sources;

these findings are in line with Chevallier, 2009 and Uddin et al., 2018. However, the dependence of EUA is weaker with natural gas and ethanol, which is consistent with Uddin et al., 2018. The low interdependence of the carbon market with NGAS and EtOH clearly shows that these are comparatively cleaner energy sources from oil and coal.

V. Conclusions

The consumption of fossil energy leads to environmental issues that can create social, economic, and health problems. The increasing demand for fossil fuels has led to the introduction of emission schemes that can help in controlling carbon emissions. With such schemes of pricing carbon, the dependence on traditional sources of energy can be reduced. Hence this study aims at extending the present literature by drawing useful insights related to diversification potentials.

We find that EUA has more dependence with oil and coal compared to ethanol and natural gas, and this dependence increases during the crisis period. Hence, we identify that the carbon market provides diversification benefits of investment in energy variables. The study has important implications for investors, policymakers, and portfolio managers. The results suggest that portfolio managers should formulate the mixed portfolio diversification strategies. Furthermore, the findings are useful for investors in risk management, and policymakers for devising regulations for the emissions' trading market for energy markets diversified by the carbon market.

The scope of present research is limited to the carbon and energy market; however, it can be extended by considering clean energy markets, stock markets, and metal markets. Further, the dependence between the European carbon market and Chinese carbon markets can be checked. The advanced copula methods can also be taken in future studies to give a more comprehensive view of these markets.

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