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The dependence between European Union carbon market and crude oil market: A copula analysis

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Abstract. The current literature analyzed the dependence between EU carbon market and the crude oil market from the perspectives of linear regression and Granger causality test. In this paper, we examine the dependence between carbon market and crude oil market using a particular class of copula model. By using different constant copula models, our findings suggest that the dependence between the two markets is symmetric, and the dependence structure has changed during different phases. Meanwhile, the dependence in the third phase is weaker than the dependence in the second phase. By analyzing the time-varying copula, we come to the conclusion that the time-varying dependence coefficient fluctuates greatly, and there is greater dependence in the period of crisis and instability.

1. Introduction

The European Union has established the first carbon market—European Union Emissions Trading System by a market-oriented method to control the excessive emission of greenhouse gas and to solve the global warming problem. Its development is affected by multiple markets, especially crude oil market, which is a dominant energy resource that plays a more important role in the development of the EU carbon market. Therefore, the study of the dependence between EU carbon market and crude oil market is of great significance both in the stable development of carbon market and in investment portfolio and risk management.

Some literatures have been studied on the dependence between carbon market and international crude oil market. Mansanet-bataler et al. (2007)^[1] using the empirical method came to conclusion that EUA prices responded to changes in crude oil and natural gas prices. Bredin and Muckley (2011)^[2] examined the correlation between EUA and crude oil by using the constant and recursive Johansen multivariate co-integration likelihood ratio, and found that there was a long-term correlation between them. Reboredo(2013)^[3] analyzed the dependence between EUA prices and crude oil prices in the phase II using the constant copula model, it indicated positive dependence and extreme symmetric independence that was consistent with independence and no financial contagion effect between the two markets. Thereafter, Zhenxin Wu (2015)^[4] concluded that there was a significant two-way nonlinear Granger causal relationship between EUA and crude oil market by using the Granger causality test. Marimoutou and Soury (2015)^[5] have found that the correlation between the carbon market and the oil market was nonlinear and time-varying, and the correlation coefficients were significantly different before and after the European debt crisis.

Many empirical results showed that the dependence between two markets was time-varying,



especially when the financial crisis occurred, the dependence fluctuated sharply. The non-linear and time-varying characteristics of two markets' correlations have not been studied in the existing literatures. Therefore, this paper uses a class of more advantageous copula models to analyze the correlation between the carbon market and the crude oil market.

2. Theoretical model

2.1. GARCH model

Volatility is an important measure of risk in finance. One popular way of modeling volatility is the GARCH model. In order to capture the characteristics of EUA and crude oil returns, such as thick tail, leverage effect, variance effect (Bens and Truck,2009)^[6], the GJR-GARCH model (Glosten et al.,1993)^[7] and EGARCH model (Nelson,1991)^[8] will be selected. Concrete models can be written as

$$\text{Mean equation: } r_t = c + \sum_{i=1}^p \phi_i r_{t-i} + \varepsilon_t \quad (1)$$

Where $\varepsilon_t \sim \text{i.i.d}(0, 1)$.

$$\text{Variance equation of GJR-GARCH: } h_t = w + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} + \sum_{i=1}^q \xi_i I[\varepsilon_{t-i} < 0] \varepsilon_{t-i}^2 \quad (2)$$

Where $\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j + \frac{1}{2} \sum_{i=1}^q \xi_i < 1$; When $\varepsilon_{t-i} < 0$, $I[\varepsilon_{t-i} < 0] = 1$, or it will be zero.

Variance equation of EGARCH:

$$\log h_t = w + \sum_{i=1}^q \alpha_i \left[\frac{|\varepsilon_{t-i}|}{\sqrt{h_{t-i}}} - E \left\{ \frac{|\varepsilon_{t-i}|}{\sqrt{h_{t-i}}} \right\} \right] + \sum_{j=1}^p \beta_j \log h_{t-j} + \sum_{i=1}^q \gamma_i \left(\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}} \right) \quad (3)$$

Where $E \left\{ \frac{|\varepsilon_{t-i}|}{\sqrt{h_{t-i}}} \right\} = E \left\{ |z_{t-j}| \right\} = \left(\frac{2}{\pi} \right)^{1/2}$, γ test the existence of leverage effect.

2.2. Copula model

Copula theory was first proposed by Sklar(1959)^[9], it states that the joint distribution of two continuous random variable X and Y, $F_{XY}(x,y)$, with marginal functions $F_X(x)$ and $F_Y(y)$, is characterized by a copula function C such that:

$$F_{XY}(x,y) = C(F_X(x), F_Y(y)) = C(u,v) \quad (4)$$

Where $u = F_X(x)$, $v = F_Y(y)$, u and v have a uniform distribution (0,1).

We use several copula specifications to capture different patterns of dependence. For all these copulas, Table 1 provides the functional form, dependence parameters and upper and lower tail dependence.

Table 1. Distribution and characteristic of several copula models.

Copula	Distribution	Parameter	Lower tail	Upper tail
Gaussian	$C_N(u,v,\rho) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v))$	$\rho \in (-1,1)$	—	—
Student-T	$C_{ST}(u,v,\rho,v) = T_{v,\rho}(t_v^{-1}(u), t_v^{-1}(v))$	$\rho \in (-1,1)$	\checkmark	\checkmark
Clayton	$C_{CL}(u,v,\alpha) = \max \left\{ \left(u^{-\alpha} + v^{-\alpha} - 1 \right)^{\frac{1}{\alpha}}, 0 \right\}$	$\alpha \in [-1, \infty) \setminus \{0\}$	\checkmark	—
Gumbel	$C_G(u,v,\delta) = \exp \left(- \left((-\log u)^\delta + (-\log v)^\delta \right)^{1/\delta} \right)$	$\delta \in [1, \infty)$	—	\checkmark
TVP Student-T	$C_{ST}(u,v,\rho,\rho_t) = T_{v,\rho_t}(t_v^{-1}(u), t_v^{-1}(v))$	$\rho_t \in (-1,1)$	\checkmark	\checkmark

Note. $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$ are standard normal quantile functions, Φ_ρ is the bivariate standard normal cumulative distribution function with correlation ρ , $t_v^{-1}(u)$ and $t_v^{-1}(v)$ are the quantile functions of the univariate Student-t distribution with v degree-of-freedom parameter, $T_{v,\rho}$ is the bivariate Student-t cumulative distribution function with v degree-of-freedom parameter and correlation ρ , TVP indicates time varying parameter, and, ρ_t , as in Patton (2006)^[10], is

given by $\rho_{T,t} = \Lambda \left(w_T + \beta_T \rho_{t-1} + \alpha_T \cdot \frac{1}{10} \cdot \sum_{j=1}^{10} t^{-1}(u_{t-j}) \cdot t^{-1}(v_{t-j}) \right)$, where $\Lambda(x) = (1 - e^{-x}) \cdot (1 + e^{-x})^{-1/2}$ is the logistic transformation modified to maintain the value of ρ_t in $(-1, 1)$.

3. Data

Our database consists of daily continuous futures prices for EUA and Brent crude oil from 2008/01/02 to 2018/03/16. Data obtained from the Quandl database traded in the Intercontinental Exchange. EUA future prices were converted to USD using the EUR/USD exchange rate, and the exchange rate came from Yahoo Finance website. The final actual valid data is 2564 groups. In order to reduce the volatility of the futures price series, they were transformed into a logarithmic return series. The logarithmic return series of the asset is expressed as $R_t = \ln(P_t / P_{t-1})$, Where P_t is the closing price for EUA or Brent crude oil.

Table 2. Descriptive statistics for EUA and oil price returns.

	Mean	Std.dev.	Skewness	Kurtosis	JB test	Q test	ARCH-LM	ADF
EUA	-0.00035	0.033	-0.708	17.313	22091 (0.000)	34.901 (0.000)	94.652 (0.000)	-14.470 (0.000)
oil	-0.00015	0.022	0.064	6.632	1410.6 (0.000)	29.050 (0.001)	427.325 (0.000)	-14.677 (0.000)

Note. The value in () indicates the probability value p of the null hypothesis at the 5% level, The results of ADF test, Q test and ARCH test are calculated with 10 lags.

Table 2 reports descriptive statistics for the EUA and oil price returns series. Mean returns were negative and very small relative to the standard deviations. The skewness of EUA returns was negative, suggesting a greater probability of large decrease, while oil's was positive. Both series showed high values for the kurtosis statistic, consistent with fat tail in the returns distributions. The JB test significantly indicated that the non-conditional distributions of two series were not subject to normal distribution. Moreover, the Q test showed the presence of serial correlation in the returns series, and the ARCH-LM test indicated that ARCH effect were likely to be found in both the returns series. ADF test suggested that both returns series were stable. In general, the EUA and crude oil returns series were suitable for modeling by using AR-GARCH models.

4. Empirical results

4.1. Results for the marginal models

The marginal distribution model described in Eqs.(1)-(3) for EUA and oil returns. The most suitable model is selected according to AIC values. Results are displayed in Table 3. The leverage effect was significant for both EUA and oil returns. Evidence regarding leverage effects implied that news in the EUA and oil markets had an asymmetric impact on volatility: bad news caused high volatility in the subsequent periods than good news. Consistent with the descriptive evidence reported in Table 2 on no-normality and fat tails, the estimated values for the degrees of freedom for the Student-t distribution suggested that the error terms were not normal. The last rows of Table 3 also showed that neither autocorrelation nor ARCH effects remained in the residuals, and the residuals series are i.i.d. uniform (0,1) by K-S test. Therefore, the copula models could correctly capture co-movement between the EUA and oil markets.

Table 3. Parameter estimates for the marginal distribution EUA and oil returns models.

	Phase II		Phase III		Phase II-III	
	EUAII	BrentII	EUAIII	Brent III	EUA	Brent
c	-0.0003 (-0.488)	0.0007 (1.428)	0.0009 (1.428)	-0.0005 (-1.294)	0.0003 (0.717)	0.0000 (0.088)
AR(1)	0.057 (2.033)			-0.057 (-2.204)		-0.044 (-2.274)
AR(2)			-0.073 (-2.812)		-0.049 (-2.534)	
ω	0.000 (1.578)	0.000 (1.484)	-0.115 (-2.724)	-0.029 (-1.554)	-0.103 (-3.660)	0.000 (1.143)

α_1	0.024 (1.523)	0.025 (1.541)	0.177 (5.682)	0.089 (4.254)	0.149 (7.284)	0.021 (2.513)
β_1	0.937 (71.743)	0.944 (68.438)	0.984 (164.480)	0.996 (422.625)	0.986 (250.558)	0.952 (132.164)
ξ	0.060 (2.991)	0.049 (2.349)				0.054 (4.544)
γ			-0.028 (-1.515)	-0.066 (-5.452)	-0.042 (-3.623)	
DoF	9.401 (4.377)	6.738 (5.146)	5.117 (7.780)	7.266 (4.787)	6.161 (9.369)	7.011 (7.379)
LL	2724.6	3046.0	2864.4	3584.3	5582.3	6631.3
Q(10)	3.114 (0.979)	8.946 (0.537)	5.534 (0.853)	0.545 (8.861)	8.548 (0.575)	12.195 (0.272)
Q(10)2	9.048 (0.528)	9.414 (0.493)	3.238 (0.975)	12.323 (0.264)	8.047 (0.624)	10.958 (0.361)
K-S	0.015 (0.946)	0.019 (0.781)	0.015 (0.922)	0.017 (0.829)	0.011 (0.936)	0.012 (0.864)

Note. The value in the () corresponding to the parameter value represents the t statistic. The value in the () corresponding to statistic test result indicates the probability value at the 5% level.

4.2. Results for the constant copula models

Table 4. Constant copula model estimates.

		Phase II	Phase III	Phase II—III
Gaussian copula	ρ_N	0.319	0.158	0.232
	AIC	-131.730	-33.554	-141.661
T-copula	ρ_T	0.337	0.164	0.240
	ν	14.257	99.983	31.253
	AIC	-138.662	-33.262	-144.216
Clayton copula	α	0.420	0.158	0.270
	AIC	-115.087	-22.800	-116.205
Gumbel copula	δ	1.238	1.090	1.148
	AIC	-111.065	-23.745	-109.385

Table 4 reports the results for the constant copula models. To find out the copula that offered the best performance, we compared different copula models through the AIC values. By analyzing Table 4, we could conclude that: Firstly, the Student-t copula in Phase II had the best fitting effect. The normal copula offered the best performance in Phase III, because the degree of freedom of the Student-t copula was very large, so Student-t copula converged to normal copula. But the optimal model of the whole stage was Student-t copula. According to the properties of normal copula and Student-t copula, the dependence between the two markets was symmetrical, and the optimal fitting function changed, so did the dependence structure. Secondly, all the correlation parameters of different copulas in different phases were greater than 0, which indicated that the carbon market and the crude oil market were positive dependence. Finally, the dependence parameter in the Phase III was smaller than the corresponding value in phase II, which indicated that the dependence for carbon market and the oil market was weakening. That's because European Union had formulated stricter distribution standards in phase III. At the same time, the carbon allowance was distributed uniformly by the European Commission, and the auction ratio was changed from a maximum of 10% in phase II to a minimum of 30%, with a 10% reduction in total. All of the above reasons made the dependence decreased.

4.3. Analysis of time-varying t copula

Table 5 represents the dependence time dynamics captured by time-varying Student-t copula (TVP t copula). AIC values of copula models indicated that the fitting effect of TVP t copula is better than any constant copulas'. The dependence parameters of the first-order lag of was -2.124, which indicated that the correlation of the current phase was negatively correlated with the previous one, and made the correlation coefficients fluctuate more frequently.

Table 5. Time varying copula model estimates.

	ω	β	α	AIC
TVP t copula	0.945	-2.124	0.269	-151.509

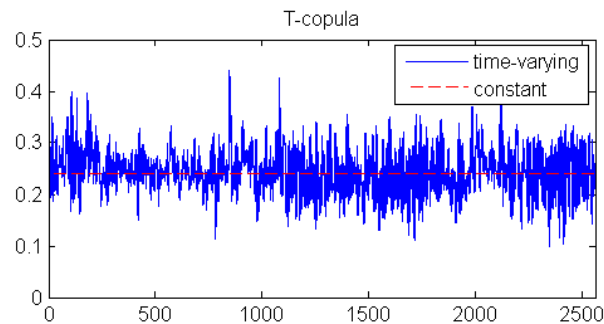


Figure 1. Time varying dependence path of the EUA and oil returns

Figure 1 represents the dependence time dynamics captured by t-copula. The horizontal axis of Figure 1 is the data in 2563 data position: 500, 1000, 1500, 2000, 2500 correspond to the timing of the 2010/01/25, 2012/02/06, 2014/01/29, 2016/01/07, 2017/12/14.

In the study phase, there were three large fluctuations in the dependence. They confirmed that greater dependence in the period of financial crisis and instability. Firstly, there was sharp fluctuation during January 2008 to December 2008. It was mainly affected by the financial crisis, the world economy and oil consumption reduced simultaneously that resulted in a sharp fall in prices; at the same time, the EU market was severely affected by the financial crisis, too. During June 2011 to June 2012, there was sharply fluctuating due to the European debt crisis and instability caused by the wars and revolutions in the Middle East and North Africa. The third period between August 2015 and October 2016 fluctuated significantly because countries were hoping for the Paris climate conference to raise the EU's target of a 30% reduction, so EUA prices went higher. But as the Paris climate agreement failed to agree on target for emissions reductions, the EUA prices began to fall that resulted in the change in dependence.

5. Conclusion

The market dynamics of EUA prices have important policy implication. In this paper we studied the dependence between EU carbon market and Brent crude oil market through different copulas. The returns were modeled by TGARCH or EGARCH model, which could deal with the fat tails and negative skewness. It did have a significant impact of oil prices on the EUA prices. Constant copula models indicated that the dependence for two markets was positive and symmetric as well as decreased. The time-varying correlation between carbon market and oil market did vary over time and was not constant. It rose considerably when facing a period of turmoil and instability. Our results highlight that oil price volatility has a significant impact on EUA prices. However, one should not disregard the fact that other factors should be taken into account in this matter. In fact, other fossil energy and renewable resource as well as low intensive energy sources can affect EUA prices.

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