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Dependence structure between the international crude oil market and the European markets of biodiesel and rapeseed oil

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ABSTRACT

Being an environmentally friendly fuel obtained from rapeseed oil, biodiesel is used extensively in Europe. However, the dependence structure between global crude oil prices and the European prices of biodiesel and rapeseed oil is understudied and unclear. In this paper, we address this gap by utilizing asymmetric copulas and cross-quantilogram approaches on daily data. The results of the DCC-Student-t copula indicate that during bearish periods the conditional connectedness between crude oil prices and biodiesel (rapeseed oil) prices are stronger than during bullish periods, indicating increased co-movement with a decline in crude oil prices. The application of cross-quantilogram indicates that an increase in crude oil price positively influences biodiesel prices reflecting an asymmetric dependence structure among the assets. There is evidence of shifts in the dynamics of quantile dependency during periods of financial and economic turmoil. Overall, the results show a significant dependence between the global crude oil market and the European markets of biodiesel and rapeseed oil in specific periods and under specific market conditions, which have important implications for policymakers and investors.

1. Introduction

Biodiesel is extracted from renewable sources such as vegetable oils and animal fats. In the US biodiesel is generally obtained from soybean oil, whereas in Europe (especially in the European Union (EU)) it is mainly obtained from rapeseed oil [1]. Biodiesel is an appealing substitute for fossil based fuels and poses less threat to human health as it emits less unburned hydrocarbons, carbon monoxide and particulate matter[1] as well as it reduces greenhouse gases due to is short carbon cycle. Even though crop-based biodiesel is heavily regulated, as part of the EU renewable energy directive (REDIII), biodiesel demand will likely double up to 2030 and thus constitute a large share of biofuels used to decarbonise the transport sector.[2] . Crude oil, the most traded energy commodity, has often been found to be closely linked with the agricultural and food markets.[3] Various theories have been proposed in this regard pointing to the roles of food crises [2], US and European legislative policies on biofuels [3,4], demand-supply factors of agricultural products [5], and financialization of commodities [6]. The most noticeable theoretical foundation is that higher oil prices make the production of fertilizers and chemicals more costly and induce higher transportation costs. Furthermore, higher oil prices induce more demand for biofuels, which in turn leads to a higher demand for agricultural commodities (e.g., rapeseed oil), the main source of biodiesel in the EU[OECD-FAO Agricultural Outlook, 2020]. According to Ref. [7], the ongoing controversial debate among investors and policymakers regarding the association between the crude oil market and the agricultural and food markets is far from settled because of the complexity of that relationship. Notably, previous studies linking crude oil to biodiesel

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[1] United States Environmental Protection Agency, A comprehensive analysis of biodiesel impacts on exhaust emissions EPA420-P-02-001, 2002.
[2] This information is sourced from https://www.iea.org/reports/transport-biofuels.
[3] Some studies are still inconclusive regarding the dominance or neutrality of the relationship between energy and agricultural commodities [35].

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and agricultural commodities are generally drawn from US data [2,7,8] and the methods employed are mostly based on standard models such as Granger causality [3,9], VAR and VECM [8], structural VAR [2,5], GARCH processes [10,11], and frequency domains [12–14], which leaves room for enhancement regarding time-variability, asymmetry, and tail dependency. These issues can be addressed by applying a combination of methods involving copulas and quantiles.

Albite not the only important aspect, prices of energy resources and commodities are critical for the development of biodiesel. For example, energy prises has been deemed an important explanatory variable describing the relationship between environmental degradation and economic activities. In 2019, the top five biodiesel producing regions globally where European union, US, Indonesia, Brazil and Argentina. Around 37% of the total produced biodiesel is based on rapeseed oil, 27% soybean oil and 9% palm oil. European biodiesel producers use mainly rapeseed oil and used cooking oil whilst the US, Brazil and Argentina uses mainly soybean oil. Indonesian biodiesel production uses mainly palm oil. The biofuel market in the two major producing regions (EU and the US) is heavily regulated compared to the other producing countries. And even though biodiesel production is expected to decline marginally, the European Union is still expected to be the world's largest biodiesel producer. The complex nature of the global biodiesel market makes delimitations necessary in order for a clear analysis. As the focus of this study is the European biodiesel market, it is essential to also focus on rapeseed as the main production feedstock. Accordingly, in this study we examine the dependence between international crude oil prices (West Texas Intermediate (WTI)) and each of biodiesel and rapeseed oil prices in the EU. In addition to using data from the EU, we employ various approaches to examine the connectedness structure. Firstly, we employ a time-varying DCC-Student-t copula to examine the temporal connectedness structure between crude oil and each of biodiesel and rapeseed oil prices. Secondly, we use the cross-quantilogram approach of [15] to uncover tail connectedness in static and time-varying settings while accounting for the various quantiles of the return distribution.

The contribution of this study is two-fold. Firstly, although the EU biodiesel industry is one of the largest in the world, it remains understudied. The academic literature mostly focuses on the US and Brazilian ethanol markets (e.g., Refs. [16,17]) and there is no consensus on the nature of the association between the prices of crude oil and those of biodiesel and rapeseed oil in the EU. This current study aims to extend such scarce literature. Secondly, we employ a rich set of methods to study the interlinkage between crude oil and each of biodiesel and rapeseed oil markets. Specifically, the time-varying DCC-Student-t copula enables us to examine the temporal dependence structure in a more robust fashion than only the multivariate GARCH or DCC models [10,11]. Furthermore, the application of the cross-quantilogram approach allows us to reveal asymmetric and nonlinear dependence in both the static and time-varying settings across various quantiles of the return distributions. This is important as the imposition of symmetry in the relationship among markets is too restrictive and not realistic, which could lead us to overlook the significant impact of asymmetry. The application of the recursive subsampling analysis helps capture possible shifts in the time-varying cross-quantilograms triggered by periods of financial and economic turmoil and structural breaks in the interdependence structure [18]. Furthermore, the cross-quantilogram approach takes into account a large number of lags. In that sense, our analyses represent an extension to previous studies that apply standard models such as the VAR and VECM models [8], the structural VAR model [2,5], Granger causality [3,9], the nonlinear autoregressive distributed lag (NARDL) [7], the GARCH models [10,11], copula [19,20], and frequency domain or wavelets [12–14].

The rest of the paper is structured as follows. Section 2 reviews the EU biofuel sector and the existing literature. Section 3 provides the dataset and some preliminary analyses. Section 4 describes the methods. Section 5 presents and discusses the findings. Section 6 presents a general discussion over the complex nature of the biodiesel market. The last section, Section 7, concludes.

2. An overview of the EU biofuel sector and the existing literature

2.1. The EU biofuel sector

The use of biofuels in the European Union has risen significantly over the last two decades. EU biofuel production increased from 29.2 PJ in 2000 to 649.8 PJ in 2019. Currently, as shown in Fig. 1, Germany leads the production of biofuels in Europe (143.4 PJ in 2019) followed by France (113 PJ in 2019) and the Netherlands (79.2 PJ in 2019). It is also worth mentioning that Germany holds a nearly 3.5% share of global biofuel production.

While the main purpose of promoting biofuels in the EU region is to reduce the degree of greenhouse gas emissions, diversifying energy supplies and thereby reducing dependence on crude oil have also received huge attention form governments and policymakers. EU policymakers aim to have more than 10% renewable energies in the transportation sector in the near future. Implementing these policies has already led to a substantial rise in biofuel consumption for the EU transport sector over the last few years. In 2019, for example, the total biofuel consumption in this sector amounted to 17.83 million metric tons, which is 3.62 million metric tons more than 2015. Though bioethanol and biodiesel are among the main biofuels, biodiesel appears to be the most consumed biofuel in Europe, with a share of roughly 80%.[4] In 2019, approximately 14.35 million metric tons of oil equivalent were biodiesel, making the EU the largest biodiesel producer in the world.

EU biodiesel is produced from edible oils, and rapeseed oil has emerged as the major feedstock for EU biodiesel production, representing almost two thirds of the total feedstock. Other edible oils such as soybean and palm oil are also used as biodiesel feedstock, though in limited amounts. For example, Spain, France, Italy and Portugal produce biodiesel from soybean oil.

The food-water-energy nexus include several aspects such as sustainability, population and economic growth, globalisation and urbanisation and the pressure these factors put on energy, water and food resources. This study investigates the food-fuel nexus from the perspective of biodiesel and rapeseed feedstock price dynamics. Studying such associations is important as the growing demand for alternative fuels could lead to an upsurge in food prices, which in turn can increase the cost of biofuel production. At the same time, crude oil also has a major role to play in the agriculture and biofuel sectors through transportation cost or as a key production input. Hence, this strand of research could be crucial for policymakers deciding whether to raise rapeseed oil stock levels or introduce second-generation biofuels to solve the food versus fuel debate. It is also important for investors making investment and risk management decisions.

2.2. Related studies

The academic literature on the nexus of energy–biofuel/feed crop commodities has increased over the past decade. The biofuel expansion has intensified the relationship between energy prices and food prices, leading to the so-called food crisis (2006–2008). Higher oil prices often lead to a higher demand for biofuel, which in turn leads to a higher demand for agricultural commodities (e.g., rapeseed oil). In fact, higher oil prices make farmers switch from food to energy-related commodity production, which raises food prices [2,12].

In the post food crisis period, some studies point to the presence of a stronger impact of oil-related factors than aggregate demand shocks on the price of agricultural commodities, which highlights the increase of return spillovers in the oil-agriculture nexus after 2006 [13]. However,

[4] The information is sourced from www.ec.europa.eu.

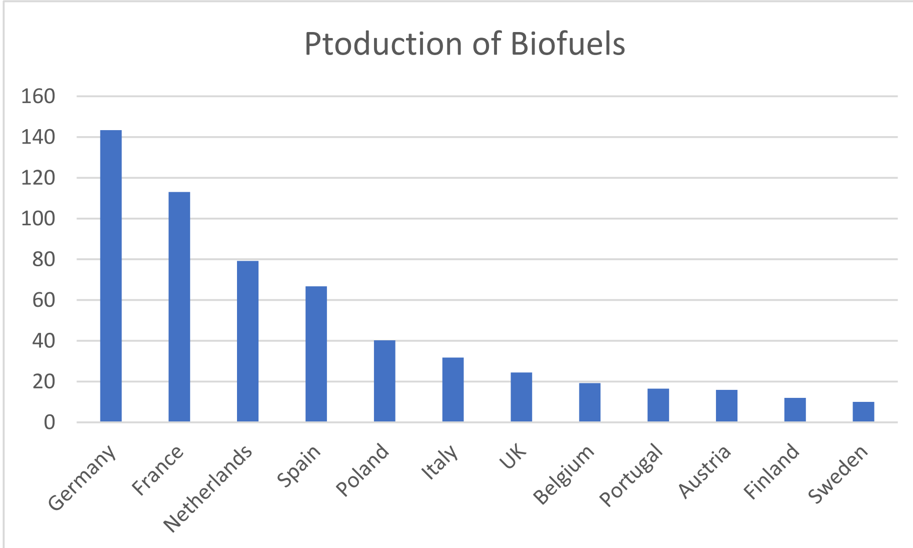

Fig. 1. The production of biofuels in petajoules in the EU during 2019 (source: www.ec.europa.eu).

some studies refute these arguments, claiming that biofuel production and thus agricultural commodity markets are insensitive to energy prices. Advocates of this argument include [21] who show that agricultural commodity prices in the long term are shaped by agricultural supply conditions and not by biofuel demand for agricultural feedstocks. A quite similar argument is put forward by Refs. [6,22]. Furthermore, it is often argued that higher crude oil and agricultural commodity prices are driven by high demand from China and India due to their economic expansion, and not by a direct return spillover from crude oil to agricultural commodities.

On the other hand, biofuel prices depend on legislative policies and regulations [3,4]. For example, the EU Biofuels Directive, especially in regard to the transport sector, has pushed up prices of agricultural products [23]. Higher oil prices may provide an incentive to switch from gasoline to biodiesel, which tends to make biodiesel a suitable substitute, conforming with the new EU Biofuels Directive. Given that biodiesel is the leading biofuel used in the EU transport sector and is mainly obtained from rapeseed oil [1], there are stronger links between agricultural prices and the path of crude oil prices. The financialization of energy and agricultural commodities [24] is also a relevant factor. For example [6], point to the importance of speculation in agricultural crop markets but indicate that agricultural commodity prices reflect shifts in global demand.

The above literature review provides conflicting arguments and inconclusive empirical results on the nexus of energy–biofuel/feed crop commodities. Furthermore, it mainly focuses on US data and makes inferences regarding the impact of crude oil and agricultural commodities or biofuels separately. In this paper, we consider the effect of global crude oil prices on the prices of biodiesel and rapeseed oil in the EU by utilizing the DCC-Student-t copula and cross-quantilogram approaches, which allows us to uncover asymmetric dependence and directional predictability during bearish, normal, and bullish periods.

3. Data and summary statistics

We use daily spot price data over the period July 17, 2008 to April 17, 2020, a total of 3038 daily observations. The sample is selected based on the availability of the data. For example, data for the fatty acid methyl ester (FAME) biodiesel are only available from July 2008. Price data are extracted from DataStream and include WTI[5] crude oil spot prices, FAME[6] biodiesel, and rapeseed oil. The sample covers several unstable periods of economic and financial turmoil, allowing for a detailed overview of tail-based dependences.

Fig. 2 plots daily prices and logarithmic returns. Interestingly, the price series of biodiesel and rapeseed oil follow a similar price trend to instantaneous periods of increasing and decreasing trends. We observe a swift decline in the prices of these assets following the emergence of the global financial crisis (GFC) of 2008. Over the period 2009 to 2012, an upward trend is apparent in crude oil prices. The price of crude oil remains persistently high from 2012 to 2014, which may be considered a boom period. However, during mid-2014, crude oil experiences another price shock due to the gap in supply and demand [25], which results in a sharp decline in crude oil prices. For biodiesel and rapeseed oil, both assets exhibit a similar trend. The price of these assets remains persistently low following the outbreak of the GFC till mid-2010. From mid-2010, the price of these assets increases rapidly till 2011, followed by a persistent decline in the price of both assets. Towards the end of the sample, the prices of biodiesel and rapeseed oil remain at around $800 and $750, respectively.

Based on Table 1, crude oil prices provide the lowest return of −0.39% for investment while exhibiting an annualized standard deviation of 40.5%.[7] The mean annualized returns of biodiesel and rapeseed oil are −3.90% and 5.8%, respectively, and their standard deviations are 28.6% and 22.2%, respectively. In terms of the risk-to-reward measure, the [2] ratio, crude oil provides the lowest reward proportional to risk of −0.873, while the Sharpe ratios of biodiesel and rapeseed oil are −0.373 and −0.674, respectively. All three assets are negatively skewed with values of kurtosis exceeding 3, indicating that the return distributions are asymmetric and exhibit fat tails. The Jarque-Bera normality test confirms this deviation from the Gaussian pattern. The Ljung-Box

[5] Unreported results indicate that the main results remain qualitatively the same if Brent oil prices are used instead of WTI prices; if anything, the results are slightly weaker. These results are available upon request from the authors.

[6] There are two major biodiesels produced from locally grown rapeseed, (1) FAME and (2) rapeseed methyl ester (RME). FAME is the predominant biodiesel blend across the continent and therefore our analysis is based on FAME. We are thankful to an anonymous referee for highlighting this.

[7] We present the annualized values of mean and standard deviation by multiplying each by 250 and $\sqrt{250}$, respectively.

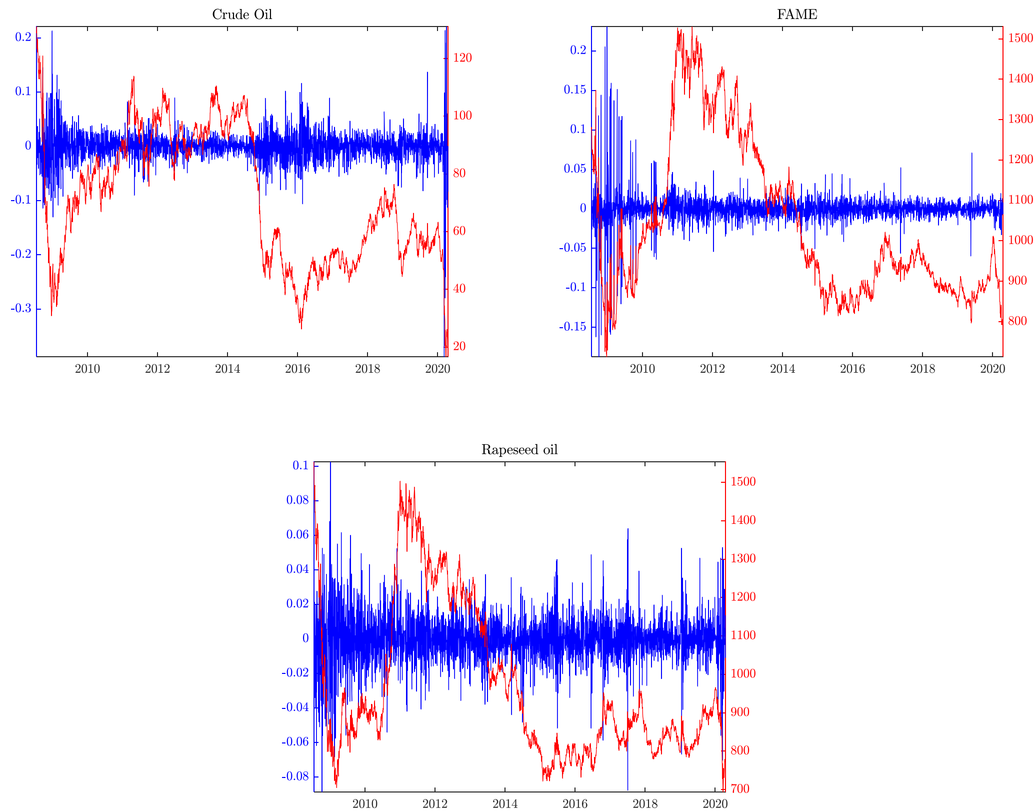

Fig. 2. Price and return series. Right side show daily prices and left side logarithmic returns. Worth noticing is the co-movement between FAME and Rapeseed oil pries, indicating a close relationship.

Table 1
Descriptive statistics.

	Crude oil	Biodiesel	Rapeseed oil
Mean	−0.162	−0.039	−0.058
Standard Deviation	0.435	0.286	0.222
Max.	0.220	0.231	0.103
Min.	−0.388	−0.187	−0.089
SR	−0.873	−0.373	−0.674
Skewness	−0.948	0.395	−0.200
Kurtosis	28.168	48.513	7.879
J-B	80582.5***	262120.9***	3031.7***
Q(10)	133.9***	446.8***	84.9***
$Q^2(10)$	1585.0***	851.9***	961.8***
ARCH(10)	773.6***	482.4***	339.9***
PP	−59.0***	−72.3***	−62.0***
Pearson correlation			
Crude oil	1.000		
Biodiesel	0.114	1.000	
Rapeseed oil	0.226	0.269	1.000

Notes. The sample period is July 17, 2008 to April 17, 2020. The mean and volatility numbers are annualized. SR denotes the Sharpe ratio. J-B corresponds to the Jarque-Bera normality test. Q(10) and $Q^2(10)$ represent the test statistics for serial correlation from the Ljung-Box test with 10 lags of returns and squared returns. ARCH(10) presents the test statistics of conditional heteroscedasticity with 10 lags. PP is the Phillips–Perron statistic that is used to test the null hypothesis that the return series has a unit root. The notation *** suggests the rejection of the null-hypothesis of normality, no serial correlation, and conditional homoscedasticity at the 1% threshold level.

test-statistics are significant for both returns and squared returns. The ARCH test with 10 lags rejects the homoscedasticity null-hypothesis, which points to the necessity of using a GARCH-type framework to capture the embedded stylized facts in the returns series such as volatility clustering and time-varying volatility. The test statistics for the Phillips–Perron test are significant, rejecting the null-hypothesis of unit root against the alternative autoregressive hypothesis. The unconditional correlations of crude oil with biodiesel and rapeseed oil of 11.4% and 22.6%, respectively, indicate a weak linear dependence.

4. Methodology

The methodological setup is structured as follows. We first examine the temporal nonlinear tail connectedness between the global crude oil market and the biodiesel (rapeseed oil) market employing the DCC-Student-t copula. Secondly, we examine the directionality, duration, and magnitude of the dependence structure across various quantiles by utilizing the cross-quantilogram approach.

4.1. Time-varying copula

It is recognized that copula models are adaptable in modeling and characterizing dependence [26]. Accordingly, we employ a time-varying DCC-Student-t copula to examine the temporal connectedness among the markets under study as it takes account of the extreme co-movements which commonly characterize the commodity markets.

We follow a two-stage procedure as proposed by Refs. [27,28] to estimate copula parameters. In the first stage, the parameters corresponding to marginal distributional frameworks (ARMA(1,1)-EGARCH (1,1)) are estimated as:

$$\log \sigma_t^2 = \kappa + \sum_{i=1}^{P}\beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^{Q}\alpha_j\left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right\}\right] + \sum_{j=1}^{Q}\xi_j\left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}}\right) \quad (1)$$

where κ, α_j, β_i and ξ_i correspond to the intercept, ARCH, GARCH, and leverage effects, respectively, of the variance equation. For $\xi_j < 0$, the future conditional uncertainty increases asymmetrically following a negative and positive shock. The EGARCH framework is suitable when the positive and negative shocks have an asymmetric impact on the conditional volatility.

In the second stage, the time-varying copula estimates are computed based on the standardized residuals from the marginal distribution framework. The multivariate specification of the Student-t copula is given by:

$$C_{d,\rho}(u_1, \dots, u_n) = t_{d,R}\left(t_d^{-1}(u_1), \dots, t_d^{-1}(u_n)\right) \quad (2)$$

$$\int_{-\infty}^{t_d^{-1}(u_1)}, \dots, \int_{-\infty}^{t_d^{-1}(u_n)} \frac{\Gamma\left(\frac{d+n}{2}\right)|\rho|^{-\frac{1}{2}}}{\Gamma\left(\frac{d}{2}\right)(\pi v)^{\frac{n}{2}}}\left(1 + \frac{1}{d}z^T\rho^{-1}z\right)^{-\frac{d+n}{2}} dz_1, \dots, dz_n, \quad (3)$$

where d, t_d^{-1} and $t_{d,\rho}$ represent the degrees of freedom, the inverse of the univariate t distribution, and multivariate t distribution, respectively. We replace the linear dependence estimates ρ, with the DCC coefficient, R_t of [29] to estimate the time-varying connectedness structure, which is specified as:

$$R_t = diag(\widetilde{Q}_t)^{-1} Q_t\, diag(\widetilde{Q}_t)^{-1}, \quad (4)$$

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha\, \varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta Q_{t-1}, \quad (5)$$

where $\overline{Q}$ corresponds the covariance of sample of ε_t, $\widetilde{Q}_t$ is the square root of Q_t as diagonal elements and zeros as off-diagonal elements.[8]

4.2. Cross-quantilogram (CQ)

While the copula framework is preferable to the conventional dependence and multivariate GARCH-type frameworks due to its ability to account for dependence during calm and stress periods, it is incapable of including lags and fails to provide a complete picture of the dependence across all quantiles of the distribution of returns in a time-varying setting. Therefore, we use the cross-quantilogram CQ approach [15] which is model-free and does not rely on any specific distribution. In addition, the CQ framework allows us to incorporate arbitrary quantiles and very large lags, which enable us to simultaneously distinguish the directionality, duration, and magnitude of the connectedness among the assets [30].

Let x_t and y_t be the two stochastic stationary series. Based on an assumption that $x_t = (x_{1t}, x_{2t})^T \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$ and $y_t = (y_{1t}, y_{2t})^T \in \mathbb{R}^2$, we can define the conditional distribution and a quintile function as $q_{i,t}(\tau_i) = inf\{v : F_{(y_i|x_i)}(v|x_{it}) \geq \tau_i\}$ and $F_{(y_i|x_i)}(\cdot|x_{it})\ \forall\ \tau_i \in (0,1)$. The cross-quantilograms that reflect the cross-connectedness of various quantiles are given by:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}\left(y_{1,t} - q_{1,t}(\tau_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}{\sqrt{E\left[\psi_{\tau_1}^2\left(y_{1,t} - q_{1,t}(\tau_1)\right)\right]}\sqrt{E\left[\psi_{\tau_2}^2\left(y_{2,t-k} - q_{2,t-k}(\tau_2)\right)\right]}} \quad (6)$$

where k corresponds the lag/lead to time t, and $\psi_a = 1[u < 0] - a$ corresponds to the quantile hit process. Following [15], we examine the null-hypothesis of conditional independence $(H_0 : \rho_\tau(1) = \dots = \rho_\tau(p) = 0)$ against an alternative hypothesis $(H_1\ \rho_\tau(k) \neq 0)$ by utilizing a Ljung-Box test for statistical inference such as:

$$\widehat{Q}_\tau(p) = T(T+2)\sum_{k=1}^{p}\frac{\widehat{\rho}^2(k)}{T-k}. \quad (7)$$

5. Empirical results

We first present the dependence estimates of crude oil with biodiesel and rapeseed oil by employing time-varying copulas. We then show the results of the CQ approach to encapsulate the connectedness in the extreme quantiles of the returns in static and time-varying settings.

Our results based on the DCC-Student-t copula indicate that the conditional interconnectedness between crude oil prices and biodiesel (rapeseed oil) prices are stronger during bearish periods than during bullish periods, which suggests a tendency for positive co-movement to persist with a decline in crude oil prices. Our results from the cross-quantilograms show that an increase in crude oil prices positively influences biodiesel prices and indicates evidence of asymmetric dependence. For example, an extreme decline in crude oil price tends to exhibit more spillover on the returns of rapeseed oil than an upward trend of equal magnitude. Further results from the recursive cross-quantilograms reveal evidence of shifts in the dynamics of quantile dependency mostly driven by economic and financial crises.

5.1. Time-varying DCC-copulas

The univariate marginal models are estimated and the best-fitted framework from several marginal distributional models (EGARCH, GJR-GARCH, and GARCH) are selected. We selected the best fitted GARCH-model based on log-likelihood and information criteria. We checked the residual with Q(10), Q^2(10) and ARCH to confirm that there is no serial correlation and ARCH that any effect is removed. The results show that the model is robust and statistically well fitted for GARCH modeling. Table 2 provides the estimates of the marginal model (ARMA (1,0)-EGARCH(1,1)) specification, which is determined to be the best-suited model based on the AIC values.[9] The coefficients of AR(1) are strongly significant, suggesting that the current returns instantaneously embody the past information. Both the ARCH (α) and GARCH (β) are statistically significant at 1% level, except for ARCH term in crude oil which is statistically significant at the 5% level. The leverage parameter is significant only for crude oil, demonstrating the asymmetric impact of positive and negative news on the conditional variance of crude oil. The parameter capturing the tail connectedness behaviour (Student-df) is significant with values exceeding 3 for the three underlying assets, which indicates a potential for joint extreme movement. These estimates clearly reflect the relevance and importance of using the Student-t error distribution in capturing the dynamic aspects of returns. The results from diagnostics suggest that there is no significant autocorrelation and ARCH effects in the residuals, indicating that the employed marginal model is stable.

Based on the EGARCH filtered returns, we evaluate the connectedness pattern of crude oil with FAME biodiesel and rapeseed oil by employing various time-varying copula frameworks. Table 3 presents the parameters for the copula frameworks employed[10]. The time-varying connectedness coefficient is low and strongly significant for all the copula frameworks. The Student-t copula, based on AIC values, is better able to encapsulate the connectedness structure in our sample. The parameter β is high and strongly significant for both biodiesel and

[8] For detailed information about the copula frameworks, we refer interested readers to Ref. [36].

[9] See Table A1 in the Appendix. In addition, we use various specifications of the mean and variance equations to select the best-suited marginal distribution framework. For the sake of brevity, we chose not to report these estimates. However, these are available from the corresponding author upon request.

[10] For brevity, we discuss the parameters of the lowest AIC copula framework.

Table 2
Marginal distribution models.

	Crude oil	Biodiesel	Rapeseed oil
Constant	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
AR(1)	−0.034**	−0.114***	−0.108***
	(0.017)	(0.019)	(0.018)
κ	0.000*	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
β	0.955***	0.408***	0.877***
	(0.006)	(0.047)	(0.016)
α	0.011**	0.338***	0.090***
	(0.005)	(0.066)	(0.015)
ξ	0.061***	−0.114	0.015
	(0.011)	(0.074)	(0.021)
Student-df	5.925***	3.075***	5.087***
	(0.471)	(0.151)	(0.525)
LogL	7555.2	9537.6	9130.5
AIC	−15096.5	−19061.2	−18252.1
BIC	−15054.4	−19019.1	−18209.9
Skewness	−1.713	3.204	0.013
Kurtosis	30.635	39.263	5.131
J—B	98093.5***	171543.3***	574.4***
Q(10)	2.929	16.797	10.742
$Q^2(10)$	1.532	8.469	14.180
ARCH(10)	1.519	8.349	14.251

Notes. The sample period is July 17, 2008 to April 17, 2020. This table presents estimates from the univariate marginal distribution model with standard errors in parenthesis. Q(10), $Q^2(10)$, and ARCH(10) show the test-statistics from the Ljung-Box test for autocorrelation in residuals, squared residuals, and the ARCH test with 10 lags, respectively. ***, ***, and * indicate significance at the 1%, 5%, and 10% threshold levels, respectively, while the notation ***, **, and * on the diagnostic tests indicate the rejection of the null hypothesis of normality, no autocorrelation, and conditional homoscedasticity in the residuals at the 1%, 5%, and 10% threshold level, respectively.

rapeseed oil, implying the time-varying nature of connectedness. The parameter α, which captures the asymmetric influence of shocks on the conditional dependence, is insignificant for both series. The degrees of freedom (DoF) capturing the extreme movements is significant for FAME biodiesel suggesting a tendency for joint extreme movement with crude oil.

Fig. 3 presents the development of the time-varying connectedness from the DCC-Student-t copula.[11] Notably, the connectedness between assets significantly increases with the outbreak of GFC in 2008. However, the connectedness among the assets gradually declines during 2009. We see significant fluctuations in the connectedness structure with episodes of increasing and decreasing trends. The interconnectedness significantly increases in 2011 and peaks during the European debt crisis. This indicates that bearish periods increase the conditional connectedness among the underlying assets, while bullish periods result in lower dependence. The linkage structure gradually declines over the period 2012 to 2014, which may be considered a boom period. The connectedness between crude oil and FAME hit a trough during 2015. This is primarily due to the significant decline in crude oil prices during 2015. The decline in crude oil prices results in a significant increase in the connectedness structure of both assets in 2015, which gradually decline to pre-2015 levels. From 2016 to the end of the sample, the connectedness parameter remains persistently low, which is due to bearish market expectations of oil prices over the period. These results reflect the tendency for positive co-movement which persists with lower

[11] We present only the figures for the DCC-Student-t copula parameters. The development of connectedness parameters for the Gaussian copula are available from the authors upon request.

Table 3
Time-varying copula estimates between crude oil and biodiesel (rapeseed oil).

	Student-t			Gaussian	
	Biodiesel	Rapeseed oil		Biodiesel	Rapeseed oil
ρ	0.174***	0.223***	ρ	0.174***	0.224***
	(0.001)	(0.002)		(0.001)	(0.002)
DoF	30.336**	32.113			
	(15.422)	(32.499)			
α	0.007	0.008	α	0.006	0.005
	(0.008)	(0.011)		(0.007)	(0.004)
β	0.986***	0.990***	β	0.986***	0.993***
	(0.023)	(0.018)		(0.023)	(0.005)
Log(L)	53.442	94.285	Log(L)	52.069	93.060
AIC	−100.884	−182.569	AIC	−100.138	−182.120

	Clayton			SJC	
	Biodiesel	Rapeseed oil		Biodiesel	Rapeseed oil
ρ	0.089***	0.108***	$\rho(U)$	0.019***	0.056***
	(0.000)	(0.001)		(0.000)	(0.001)
Ω	−3.011***	−3.675***	$\rho(L)$	0.061***	0.088***
	(0.426)	(0.249)		(0.000)	(0.001)
α	−0.175	0.041	$\Omega(U)$	0.128	−0.514
	(0.475)	(0.240)		(5.292)	(2.391)
β	−0.527***	−0.995***	$\alpha(U)$	−9.999	−10.000
	(0.180)	(0.012)		(138.143)	(7.986)
Log(L)	41.993	70.494	$\beta(U)$	0.319	−0.279
AIC	−77.986	−134.988		(8.424)	(0.280)
			$\Omega(L)$	−1.268	1.182
				(4.266)	(0.703)
			$\alpha(L)$	−10.000	−10.000***
				(14.657)	(4.128)
			$\beta(L)$	−0.676***	0.273
				(0.251)	(0.318)
			Log(L)	51.815	91.966
			AIC	−91.630	−171.932

Notes. The sample period is July 17, 2008 to April 17, 2020. This table presents the time-varying DCC-copula parameters for biodiesel and rapeseed oil using various copula frameworks. Standard errors are presented in parentheses. The notation ***, **, and * show significance at the 1%, 5%, and 10% threshold level, respectively.

crude oil prices.

The increased co-movement during stress periods, as shown in the above results, indicates the potential for increased dependence in the extreme quantiles of the return distribution, which can be better captured by the cross-quantilogram approach applied in the next section.

5.2. Cross-quantilograms

We examine the cross-quantile correlation (CQC) structure among the underlying assets via the CQ approach of [15]. The CQC estimates are presented for various lag lengths in the form of heatmaps, which are graphical representations of the unconditional bivariate dependence. Panel A of Fig. 4 and Fig. 5 presents the results for mutual directional predictability, that is, the CQC of crude oil returns to the returns of FAME biodiesel and rapeseed oil, respectively, for all quantiles of the return distribution. We use the Ljung-Box test to evaluate the statistical significance of directional predictability, and all the insignificant dependence parameters are set to zero. In each heatmap in Panel A, the quantiles of crude oil are displayed on the horizontal axis, while the vertical axis shows quantiles of biodiesel and rapeseed oil. In Panel B, the quantiles of crude oil are presented on the vertical axis. The magnitude of positive and negative causal spillovers is represented by the colour scheme from red (strong positive), green (no correlation) to blue (strong negative).

From Panel A of Fig. 4, for lag 1, we observe a significant positive directional predictability from crude oil to the biodiesel market when

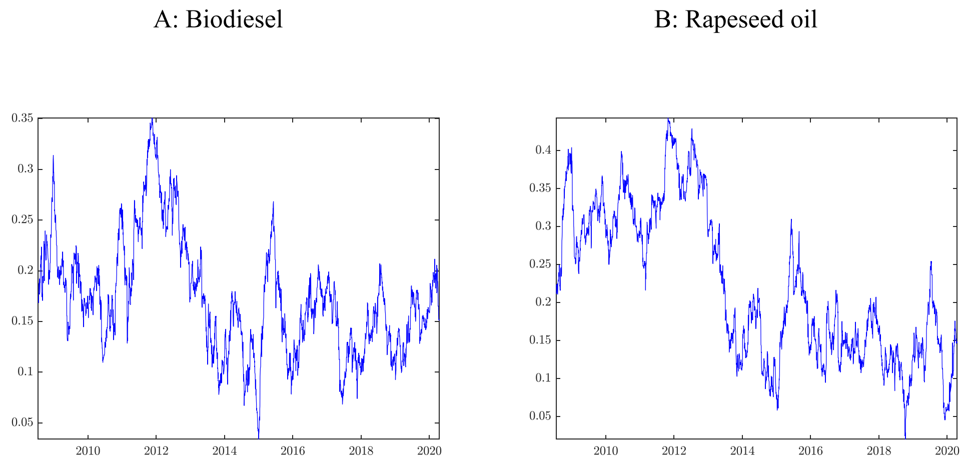

Fig. 3. Time-varying DCC parameters based on the Student-t copula. Vertical axis show correlation magnitude between respective variable and crude oil. The horizontal axis show timeline. For biodiesel the correlation parameter ranges from 0.05 to 0.35 and for Rapeseed oil 0.05 to 0.4. Higher parameter value means stronger correlation relationship between variable and crude oil.

both return series are around the extreme quantiles of the return distribution. Specifically, our findings indicate that crude oil positively influences the lower quantiles of biodiesel when the return distribution of crude oil is at the lower to median quantile. This suggests that the downward movement (extreme lower quantiles) in crude oil prices have a positive impact on biodiesel prices. Similarly, we find a positive directional predictability in the upper quantiles of crude oil to the upper quantile of biodiesel. This result indicates that higher crude oil prices positively influence biodiesel prices, which may be attributed to the substitution effect between biodiesel and crude oil. However, the positive influence of crude oil on biodiesel weakens, but persists, in the case of lag 5. In the case of lag 22, the positive influence of crude oil dissipates, indicating a lack of directional predictability. For lag 66, we observe a weak connectedness in the extreme lower quantiles of distribution, implying a deterioration of the directionality over time. The results raises questions regarding what factors lies behind the positive price correlations in the lower end of crude oil prices and biodiesel prices and the time dependent dynamics. These results can be an indication of that blending policies influence biodiesel prices positively at lower levels of crude oil and biodiesel prise. This could mean that lower oil and fuel prices increases demand and in turn an increase of biodiesel blending share, which raises the price of biodiesel. However, this needs to be studied further in order to verify. From Panel B of Fig. 4, we find a lack of directional spillover from biodiesel to crude oil at all lags. This may be attributed to the fact that biodiesel is mainly restricted to the transportation sector as a fuel blended with conventional diesel. Therefore, it may not directly serve the needs of institutions that are highly reliant on energy consumption.

Fig. 5 presents the CQC between crude oil and rapeseed oil. For lag 1 (Panel A), we find a positive CQC across various quantiles of the return distribution, signifying a strong positive spillover from crude oil to rapeseed oil. The results are economically viable as rapeseed oil is largely used as an input for biodiesel production which is strongly becoming a substitute for crude oil. Notably, we observe a significant spillover in the lower quantiles of rapeseed oil even when crude oil is in the upper quantile (0.65). We observe weak or no dependence when both crude oil and rapeseed oil are in the extreme upper quantiles of the return distributions. This result indicates an asymmetric dependence as an extreme decline in crude oil price tends to exhibit more spillover on the returns of rapeseed oil than an upward trend of equal magnitude. However, only weak evidence of spillover is shown from crude oil to rapeseed oil over lag 5 and lag 22, while the spillover deteriorates but persists over lag 66. These findings are in-line with [31,32] who report an asymmetric impact from crude oil on agricultural commodities that strengthens over periods of turmoil. However, they are in contrast to Refs. [19,33] who support a neutrality hypothesis from oil to agricultural commodities. This discrepancy may be attributed to the framework employed, as [19,33] use copulas and Granger causality to evaluate overall dependence and causation, respectively, while we rely on CQC to provide a more detailed estimation of directional connectedness across various quantiles. In Panel B of Fig. 5, we see weak evidence of directional predictability from rapeseed oil to crude oil. The directionality is only apparent in the lower tail of the distribution that tends to deteriorate over longer lag lengths. These findings concord with the evidence reported by Refs. [31,34], which confirms low directional spillover from agricultural commodities to crude oil.

5.3. Recursive cross-quantile correlation

The time-static quantile-hit process presented in the previous subsection would not be applicable for capturing dynamic connectedness. Hence, we use a recursive subsampling estimation to evaluate the variation in interdependence in a time-varying setting. The recursive subsampling analysis is suitable for capturing possible shifts in time-varying CQC triggered by periods of financial and economic turmoil and structural breaks in the interdependence structure. We set the window period to 252 days to estimate the first CQC. We then re-estimate the CQC by increasing the window-length by one day and this process is carried out till the end of sample period. Figure presents the results from recursive CQC for crude oil with biodiesel and rapeseed oil when both distributions are at the 5%, 50%, and 95% quantiles. In each graph, the blue line represents the dynamic CQCs estimated in the recursive subsample, while the red lines present the 95% confidence level for the null-hypothesis of non-predictability. We use a 1000 bootstrap iteration procedure to derive confidence interval.

Panel A of Fig. 6 presents the recursive CQCs between crude oil and biodiesel. For the lower quantile of return distribution, we observe an upward shift in CQC during the mid-2009 and in the start of 2010, which may be attributed to the outbreak of the GFC and Eurozone debt crisis, respectively. This further signifies that the shocks from crude oil are of an asymmetric nature to biodiesel which tends to strengthen during periods of turmoil and weaken or remain stable during periods of

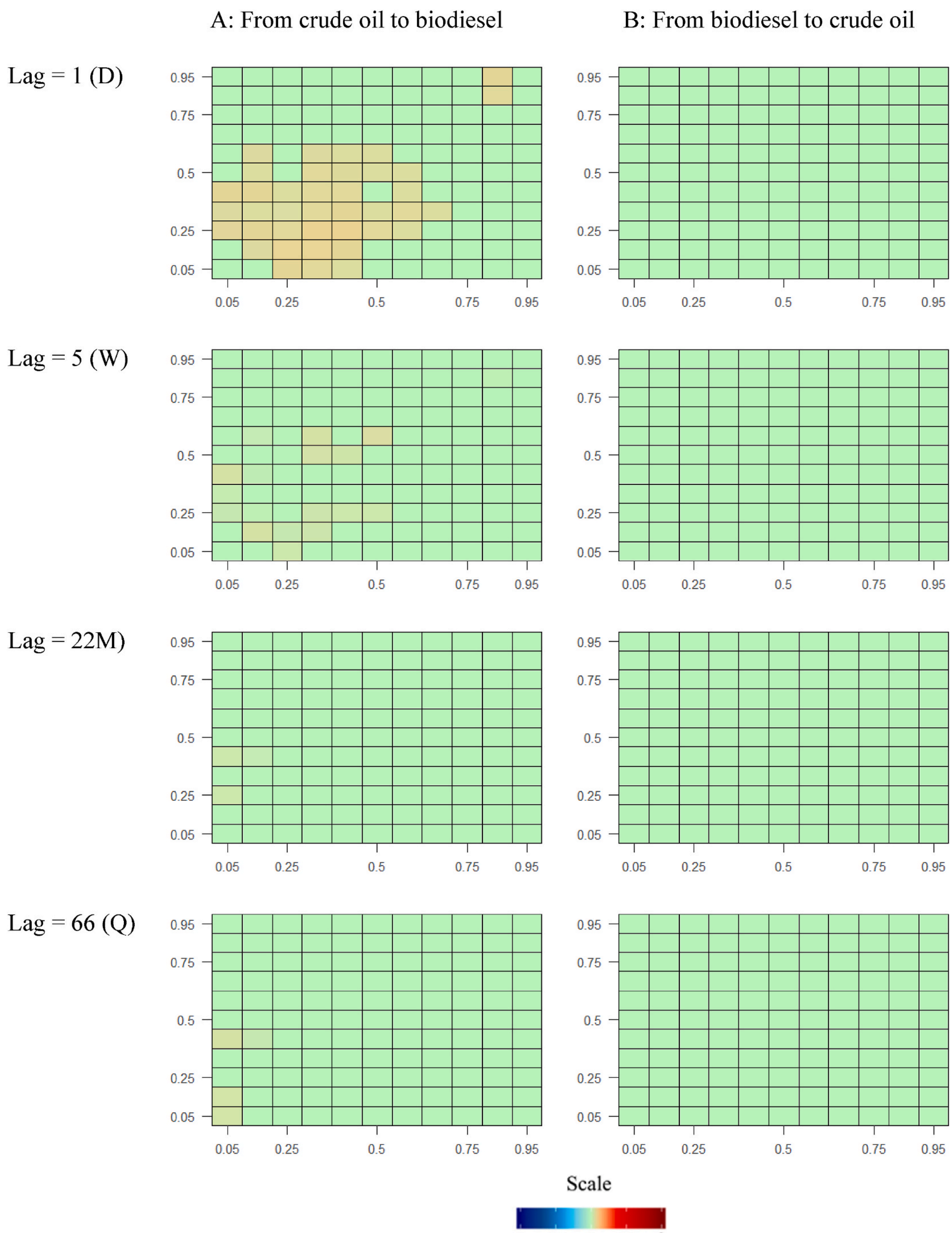

Fig. 4. Cross-quantilogram correlation between crude oil and biodiesel. Panel A: Crude oil price on horizontal axis and biodiesel on vertical axis. Panel B: Biodiesel price on horizontal axis and crude oil on vertical axis. Panel A lag = 1 (daily returns) indicate a positive correlation in the area of normal to lower market situations and some positive correlation in the upper extreme market situations.

economic prosperity. Similar results are obtained for recursive CQCs between crude oil and rapeseed oil. The CQC increases significantly during the Eurozone debt crisis and tends to decline gradually towards the end of the sample. In terms of median quantiles, the CQC between crude oil and biodiesel decreases at the beginning of the sample and flattens out in 2013 at around zero. Similar findings are reported for crude oil and rapeseed oil. In terms of the extreme upper quantile between crude oil and biodiesel, there is significant variations in the recursive CQC. The CQC exhibits a significant upward trend between 2009 and 2012. However, the CQC stabilizes around a mean value of 0.10 and exhibits a decline towards the end of the sample. Similarly, the CQC between crude oil and rapeseed oil increases significantly between 2009 and 2014. It is noteworthy that the linkage between crude oil and rapeseed oil is negative between 2009 and 2011, indicating an asymmetric relationship among these variables. However, the connectedness among the assets gradually declines during 2014 and stabilizes around a mean value of zero.

5.4. Summarising analysis

The results imply that the relationship between biodiesel and crude oil has stabilised after an initial period (years up to around 2016) of

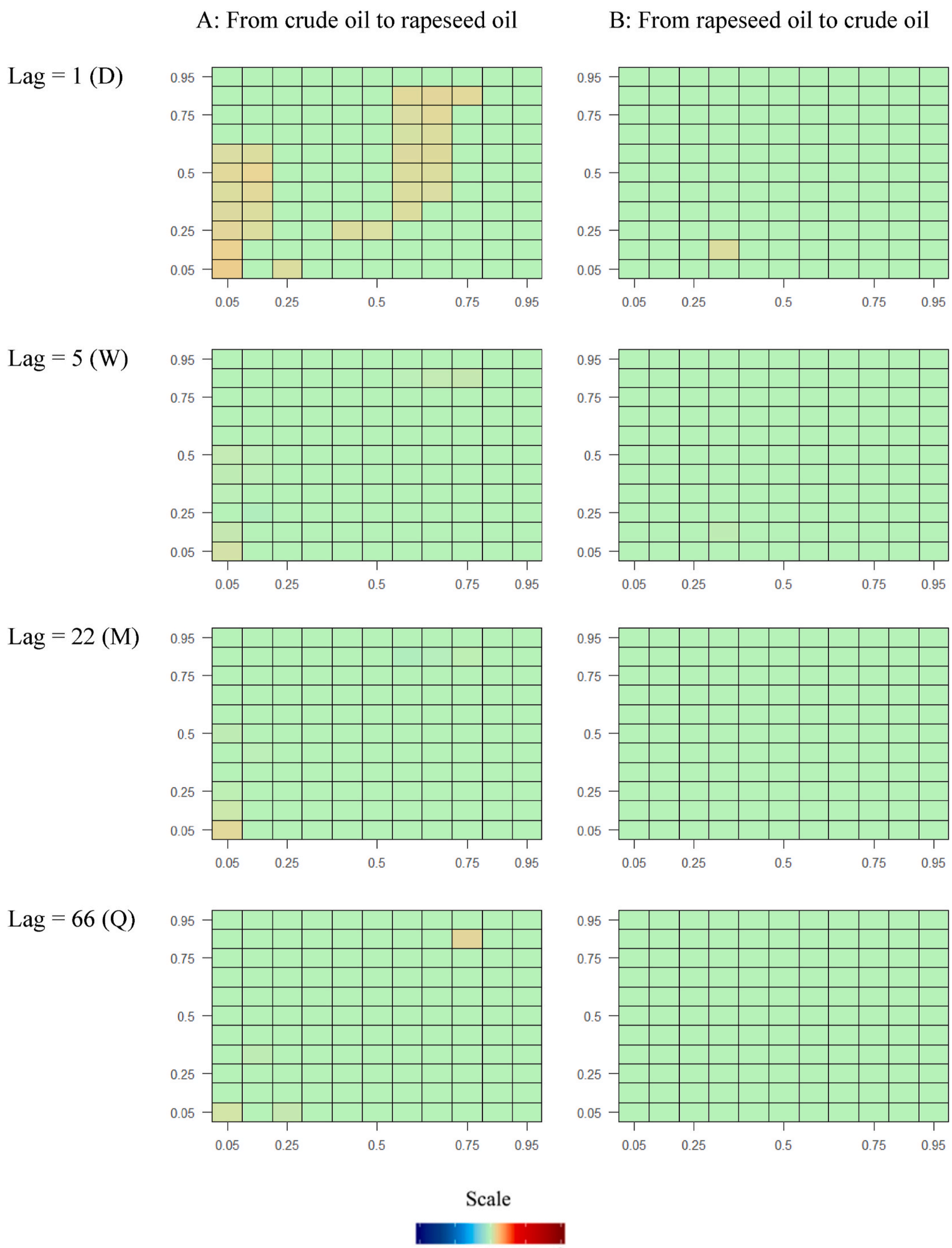

Fig. 5. Cross-quantilogram correlation between crude oil and rapeseed oil. Panel A: Crude oil price on horizontal axis and Rapeseed oil on vertical axis. Panel B: Rapeseed oil price on horizontal axis and crude oil price on vertical axis. Panel A Lag = 1 (daily returns) indicate that extreme negative crude oil returns have a positive correlation with rapeseed in normal to extreme negative returns, and also positive correlation in normal to high returns in both crude oil and Rapeseed oil.

volatility with varying levels of increasing and decreasing correlation strengths. The correlation effects are mostly short run effects, and the directionality run exclusively from crude oil to both biodiesel and rapeseed. Biodiesel seem to be more sensitive to crude oil prices (sensitive to normal and negative crude oil price returns) whilst rapeseed oil is sensitive to extreme negative crude oil price returns. Rapeseed oil is also sensitive to high crude oil returns. The cross-quantilogram results show that biodiesel and rapeseed oil has historically been more linked in extreme market conditions and highly volatile. Meaning varying linkages at extreme high and low prices. However, the link between crude oil and biodiesel (rapeseed oil) has stabilised from around 2015.

6. Discussion

The choice of methods and studied variables in this study does have some consequences. While being able to study specific binary relations with precision, the methodological approach doesn't capture all influencing factors. It should be noted that factors such as taxes and policies, alternate feedstocks, substitution effects between biodiesel and fossil based diesel all have some effects on biodiesel price. The bioenergy

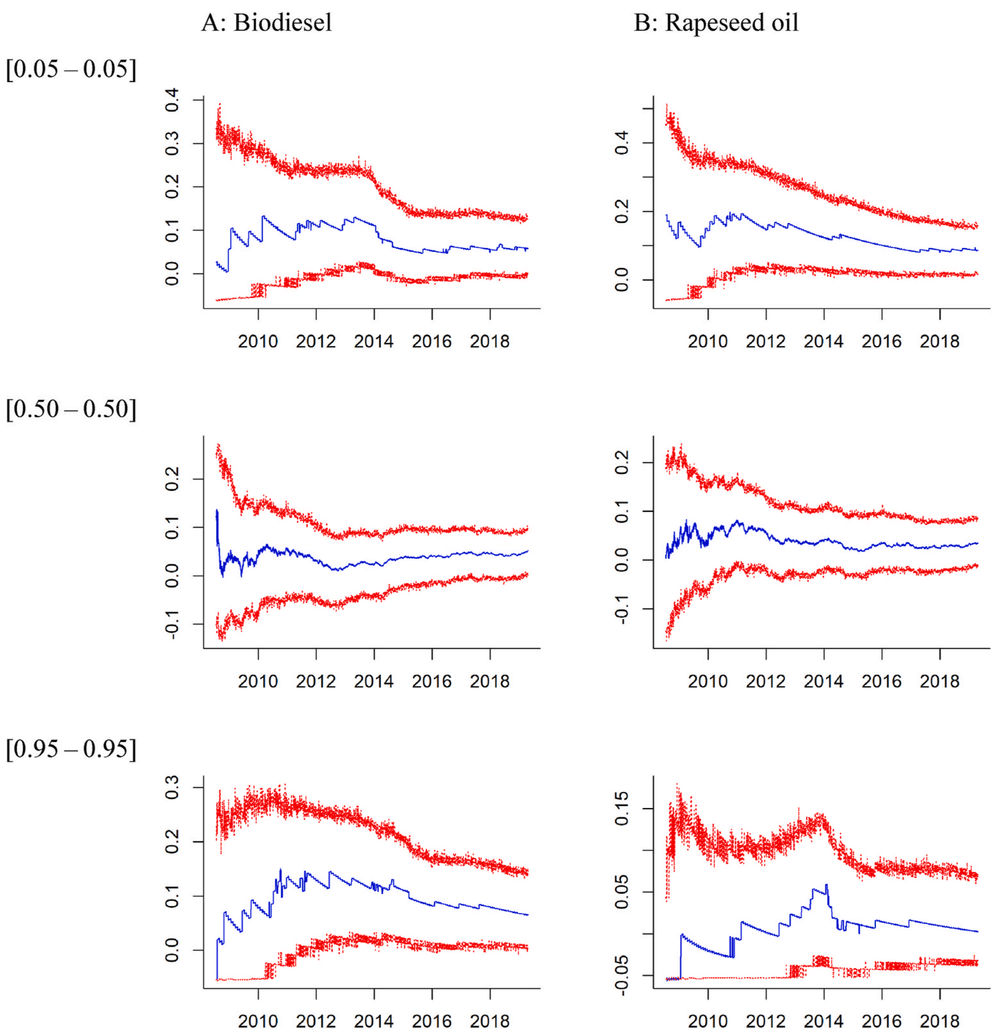

Fig. 6. Cross-quantilogram correlation show the changes in correlation through between crude oil and biodiesel (rapeseed oil) in recursive subsamples. For extreme negative returns [0.05–0.05], both biodiesel and Rapeseed display a (positive) higher and more volatile initial correlation structure and a diminishing correlation from 2014. At normal returns conditions [0.50–0.50], the correlations structure lies stable nearer zero. And for extreme returns [0.95–0.95] a (positive) and volatile correlation structure can be seen in the time leading up to 2014–2016, then a more stable structure.

sector is a large and complex sector and there are many aspects governing the market and numerous links and relations influencing the behaviour of the global energy system. This study does not claim be exhaustive when it comes to all relational aspects concerning biodiesel or the related feedstock markets. This calls for further studies of the complex relationships between feedstock markets and biodiesel. A potentially fruitful research area that warrants further study is for example the topic of crop rotation and the relationship to biofuel price formation.

7. Conclusion

In this paper, we shed light on the energy-biodiesel/food debate by examining the interdependence between the market of crude oil and the markets of biodiesel and rapeseed oil in Europe. Using daily data from July 17, 2008 to April 17, 2020, we apply the DCC-Student-t copula and show that during bearish periods the conditional connectedness between crude oil prices and biodiesel (rapeseed oil) prices are stronger than during bullish periods, which indicates a tendency for positive comovement to persist with a decline in crude oil prices. We examine the quantile-based dependency by applying cross-quantilograms and the results indicate that increases in crude oil prices positively influence biodiesel prices and show the existence of an asymmetric dependence. For example, an extreme decline in crude oil prices tends to exhibit more spillover on the returns of rapeseed oil than an upward trend of equal magnitude. Further results from the recursive cross-quantilograms reveal evidence of some shifts in the dynamics of quantile dependency mostly driven by economic and financial crises. Overall, our results reveal evidence of some significant links between the international crude oil market and the European markets of biodiesel and rapeseed oil in particular periods and under specific market conditions.

Our findings have some implications for institutional investors, hedgers, and specialized commodity investors. They indicate the possibility of refining the prediction of biodiesel and rapeseed oil prices based on crude oil prices under some specific quantiles, while showing that such predictability is time-varying and subject to economic and crisis periods. The markets response dynamics presented in this study indicate that the connectedness between biodiesel and crude oil have certain effects in specific conditions. It is therefore important to construct and evaluate the policy ability to counteract volatile biofuel prices in situations where spillover effects are strongest. The complex nature of the biofuel market and the fact that many factors may influence market behaviour also imply that there may be need for a number of specific policies targeting specific mechanisms. As the correlation structure in normal market conditions seems to have become more stable through time, but still volatile in more extreme market situations, policy should be constructed for long term predictability amongst market participants. Prices for biodiesel and renewable diesel have risen faster than crude oil recently and high biodiesel prices has impacted biofuel blending requirements. Our findings also have implications regarding portfolio allocations and hedging strategies, for European market participants, pointing to the necessity to differentiate between average and tail-based dependence. Our analyses matter to policymakers given their continuous monitoring of the benefits of the EU Biofuels Directive, especially on the EU transport sector where biodiesel is the leading biofuel. Other concerns for policymakers are food price stability and food security given that biodiesel production often competes for land with agricultural production. Future research could consider how diversification benefits vary over time and under various quantiles if crude oil and each of biodiesel and rapeseed oil are combined in the same portfolio.

CRediT authorship contribution statement

Muhammad Yahya: Conceptualization, Formal analysis, Writing – original draft, Final Revision. **Anupam Dutta:** Conceptualization, Validation, Writing – original draft. **Elie Bouri:** Writing – review & editing, Final Revision, Project administration. **Christoffer Wadström:** Writing – original draft, Validation, Final Revision. **Gazi Salah Uddin:** Writing – original draft, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

APPENDIX

Table A.1
GARCH-type model estimates

	Panel A: GARCH model			Panel B: GJR-GARCH model		
	Crude oil	Biodiesel	Rapeseed oil	Crude oil	Biodiesel	Rapeseed oil
Constant	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AR(1)	−0.030*	−0.116***	−0.108***	−0.027	−0.107***	−0.106
	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.018)
Constant	0.000**	0.000***	0.000***	−0.041***	−1.840***	−0.220
	(0.000)	(0.000)	(0.000)	(0.013)	(0.218)	(0.055)
GARCH(1)	0.940***	0.527***	0.878***	0.995***	0.791***	0.975***
	(0.008)	(0.039)	(0.015)	(0.002)	(0.025)	(0.006)
ARCH(1)	0.058***	0.238***	0.097***	0.082***	0.409***	0.201***
	(0.008)	(0.039)	(0.013)	(0.012)	(0.035)	(0.022)
Leverage(1)				−0.069***	0.024	−0.009
				(0.009)	(0.024)	(0.014)
DoF	5.783***	3.108***	5.111***	6.035***	3.126***	5.024***
	(0.426)	(0.156)	(0.529)	(0.502)	(0.156)	(0.520)
LogL	7533.2	9520.9	9132.8	7549.2	9521.8	9133
AIC	−15054.3	−19029.7	−18253.6	−15084.3	−19029.5	−18247.1
BIC	−15018.2	−18993.6	−18217.5	−15042.2	−18987.4	−18204.9
Skewness	−2.399	3.073	0.014	−1.499	3.120	0.019
Kurtosis	46.677	38.362	5.098	24.888	38.010	5.159
J-B	244230.1***	162965.0***	557.1***	61740.2***	159977.8***	589.9***
Q(10)	5.498	15.975	10.765	3.186	15.326	11.008
Q^2 (10)	1.859	2.950	12.630	3.812	5.815	24.244***
ARCH (10)	1.844	2.935	12.686	3.787	5.730	23.803***

Notes. The sample period is July 17, 2008 to April 17, 2020. Standard errors are presented in parentheses. The notation ***, **, and * show significance at the 1%, 5%, and 10% threshold level, respectively.

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