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# Connectedness between energy and nonenergy commodity markets: Evidence from quantile coherency networks

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## Abstract

The worldwide economy has experienced several changes in energy and nonenergy prices. This has motivated academics, investors, and policymakers to analyze the relationships between energy and nonenergy commodity markets. In this study, a novel approach of quantile coherency is used to examine the dependence structure between energy and nonenergy commodity pairs at different frequencies and quantiles in their joint return distribution over the period 1960:M1–2019:M10. Overall, the empirical findings illustrate evidence of low significant dependency between energy and nonenergy commodity markets across different frequencies and quantiles. In addition, our findings show that some nonenergy commodity markets have a neutral relationship with global energy commodity markets.

**Keywords:** Energy; Nonenergy; Quantile coherency; Network analysis; Dependence; Commodity markets

**JEL classification:** Q1; Q4; Q02; P28

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## 1. Introduction

The commodity prices have strong influence on economic indicators (Bhar and Hamori, 2008; Clarida et al. 1998; Holtemöller and Mallick, 2016; Mallick and Sousa, 2013; Stock and Watson, 2003; Zhang et al., 2019), as well as on portfolio formation. Clarida et al. (1998) document the significant impact of commodity prices on inflation, interest rate and economic output. Similar findings are vindicated by (Stock and Watson, 2003). Later, Bhar and Hamori (2008) have reported the significance of commodity prices in monetary policy. Mallick and Sousa (2013) and Holtemöller and Mallick (2016) formed a dynamic model which validated the role of commodity prices shocks, which tends to surge the inflation rate and demand. To keep this in mind, central bank modify the inflation stabilization strategy. Zhang et al. (2019) suggests that liquidity effects can penetrate through and spill over across commodity sector boundaries.

Besides the economic implication of commodity prices, portfolio managers use the recent trends, interconnectedness and spillover of commodity prices while shaping the optimal portfolio strategies which helps to minimize the investment risks. The inception of classic portfolio theory has been associated with an increased interest in the analysis of the interrelationships between assets and financial markets. As lower correlations among asset returns have been shown to reduce overall portfolio risk, several portfolio options, such as international and sectoral diversification, have traditionally been analyzed (Pal and Mitra, 2019). Though, it seems clear that the connection between energy and nonenergy may enhance the discount factor. López Cabrera and Schulz (2016) found a synchronization between energy and commodities over the peak and trough business cycles. However, the synchronization among energy and nonenergy postulates the transmission of shocks are evident in own market and over the markets, which confirms the shock spillover phenomena between energy and nonenergy markets. Portfolio applications aside, the study of connectedness in financial markets has been further explored in the strand of literature on contagion and spillovers between financial markets. In a notable paper on the topic, Forbes and Rigobon (2002) explored the heteroskedasticity bias of correlation coefficients. They provided a distinction between interdependence, that is, general comovement between markets that are increasing, and contagion, which they defined as an increase in comovement following a shock in one country. Hence, contagion refers to an increase in interdependence during market downturns.

In this context, the motivation for our study stems from the interest in capturing comovement relevant to both application areas addressed in previous research and contributes to the literature on comovement in financial markets by examining the interrelationships of commodities while exploring their cross-quantile dependencies. Instead of focusing on international diversification, we investigate the links between energy and nonenergy commodity indices.

The quantile cross-spectral analysis is a novel approach (Barunik and Kley, 2019) and still not widely used in economic and financial studies. It outperforms several econometric methods, such as the causality-in-quantile (Jeong et al., 2012) and quantile-on-quantile (Sim and Zhou, 2015). The quantile cross-spectral analysis investigates the dynamics of the connectedness between two markets at different quantiles of the joint distribution and also at various frequency business cycles. However, the main advantages of this framework is its ability to examine the connectedness between commodity markets at normal, bull and bear market events, as well as at several frequency time horizons (short-, medium-, and long-term).

The major contribution of this study to the growing strand of literature lies in the following: (i) the key novelty is to revisit the dynamics of the dependence between energy (global energy index) and nonenergy (nonfuel, agriculture, food, beverages, oil and meals, grains, raw materials, fertilizers, metals and minerals, precious metals) commodities using the quantile cross-spectral analysis. (ii) So, we attempted to examine the quantile dependence structure for the majority of the global nonenergy commodity indexes versus the global energy commodity index, which provides a general and clear overview about the connectedness between global commodity indexes to the investors, policymakers, and research scholars. (iii) In comparison to the earlier empirical researches, the novelty of this study is that we used a large monthly dataset dating back to 1960 to provide new and accurate dynamic dependence for the energy-nonenergy commodity market pairs.

The focus on energy-related commodities stems from the importance these commodities have in different phases of the economic cycle, with spikes and troughs directly related to current and expected levels of general economic activity. While the supply-side factors are to some degree exogenous, in the sense that much control lies in the hands of producers such as OPEC, the demand side is to no small degree affected by the economic outlook. In this respect, the last

decades have brought numerous global economic disruptions, such as the global financial crisis during 2007–2008, followed by the European sovereign debt crisis and Greek government debt crisis in 2010–2015, all of which started in the financial sector but then profoundly affected the real economy.

Apart from the indirect effects, energy commodities have also exhibited high intrinsic volatility. Oil, for example, experienced marked declines in the 2014–2016 period, recovering only in 2018. Oversupply in North America, disagreements among the largest oil producers and the economic slowdown in China have contributed to the unprecedented market downturn.

In this paper, we explore the interrelationships of energy and nonenergy commodity indices. Previous literature on correlations in commodity returns provides very diverse hedging implications (Albulescu et al., 2020; Lucotte, 2016; Mensi et al., 2020; Kristoufek, 2015; Tiwari et al., 2018). As the results on comovement of energy and nonenergy commodity prices are not entirely clear, we take a different approach and explore the cross-quantile dependencies between commodity market indices using the framework of Baruník and Kley (2019).

There are several advantages to performing the analysis on the quantiles instead of focusing on the mean. First, according to the literature on contagion, some relationships between commodities may manifest specifically in times of market downturns. Here, focusing on the left tail of the return distribution might allow us to identify relationships that would otherwise remain undetected. To test for this phenomenon, we perform our analysis on multiple different quantiles, including the median. Second, in the portfolio diversification context, a global market downturn may represent the gravest potential situation, in which portfolio managers must rely heavily on the diversification effect. Information on (possibly significant and positive) relationships in the lower quantiles of the joint return distributions might provide critical information for portfolio construction. Third, separating different quantiles, such as those in the lower and upper tails, offers separate information on the joint behavior in bad and good times, opening a path for directional strategies. By focusing on quantile behavior, we follow the studies of Baumöhl (2019) on comovements among cryptocurrencies and forex, Baumöhl and Shahzad (2019) on stock markets, Maghyereh and Abdoh (2020) on gold and Islamic securities and Wu (2020) on global crude oil and China's commodity sectors.

The rest of the paper is structured as follows. An overview of the related literature is presented in section 2. In section 3, we display the econometric specification used in the study. Section 4 describes the dataset and variables and introduces the summary statistics. The discussion of the empirical results is provided in section 5, and section 6 concludes the paper.

## **2. Review of the relevant literature**

The literature on the connectedness between energy and nonenergy commodities has attracted great empirical attention over the last decade. However, energy prices have experienced several shocks due to political turmoil, civil strife, international wars, and terrorism attacks. Examples of such episodes are, among others, the Arab Spring; the Syrian and Libyan war in 2011; the Syrian civil war escalation from 2012 to the present; the ISIS escalation in Iraq in 2013–2017; the Paris attacks in 2015; the war in Yemen from 2012 to the present; and the North Korea–US crisis in 2017–2018. Accordingly, these negative and violent events affected energy and nonenergy market prices, which in turn exerted an influence on the global economy. These dynamics are of great importance for understanding the connectedness between energy and nonenergy commodity prices.

Recently, some empirical studies have examined the connectedness between energy and nonenergy commodities. In this regard, Liu et al. (2020) studied the energy-water relationship and stated that nonenergy commodities determine worldwide water use. Wei Su et al. (2019) investigated the causal effects between energy and agricultural commodity prices. Their empirical findings (based on the rolling window approach) showed a time-varying bidirectional relationship between the two markets. In this vein, other academic researchers have studied the interconnectedness between energy market prices and agricultural commodity prices. The related empirical studies are Kang et al. (2019), Fowowe (2016), Fasanya and Akinbowale (2019), Dahl et al. (2019), Mokni and Ben-Salha (2020), Nazlioglu (2011), Gardebroek and Hernandez (2013), Reboredo (2012), and Pal and Mitra (2019). Using a time-frequency and network analysis, Kang et al. (2019) examined the frequency domain spillover effects between energy prices and the agricultural commodity market. The empirical findings demonstrated an asymmetric and bidirectional interplay between the two markets. Further, agricultural commodities are beneficial for short-term portfolio diversification. In the same context, Fowowe

(2016) found no causal relationship between agricultural commodity prices in South Africa and global energy prices. His findings exhibited a neutral connection between the energy–agricultural commodity price pair. Considering the same economy, Shiferaw (2019) examined the time-varying dependence structure between energy prices and agricultural commodity prices by implementing a Bayesian multivariate GARCH approach. His findings—namely, that in South Africa, agricultural commodity prices were strongly and significantly connected with energy prices—were the opposite of those uncovered by Fowowe (2016). Employing the methods of Diebold and Yilmaz (2012) and Diebold and Yilmaz (2009), Fasanya and Akinbowale (2019), and Dahl et al. (2019) documented significant spillovers in the transmission mechanism between the energy market and agricultural commodity markets. Their empirical findings were beneficial for different economic agents, such as policymakers, investors, regulators, and portfolio managers. Mokni and Ben-Salha (2020) implemented a causality-in-quantiles framework to study the nexus between the energy price and the world food price. The authors used monthly data for the long period of 1960–2019 and found a bidirectional Granger-causal link between the focal markets. The causal effects of energy prices on food prices appear under all food market conditions, whereas in the context of bearish and bullish market events, food prices Granger-cause energy prices. Nazlioglu (2011) examined the nonlinear causal dependence structure between the world oil price and agricultural commodity prices of corn, soybeans, and wheat and confirmed the hypothesis of a neutral relationship between oil and agricultural commodities. Reboredo (2012) and Gardebroek and Hernandez (2013) examined comovement between energy prices and some agricultural commodities. These studies used different econometric frameworks, such as multivariate GARCH and copulas. The empirical findings documented the neutral feedback of agricultural commodity prices to oil price spreads. A few other studies—for instance, those of Albulescu et al. (2020) and Ji et al. (2018)—used copula functions to explore comovement and the dependence structure between energy markets and nonenergy commodity markets. Albulescu et al. (2020) documented asymmetric connectedness between energy, agriculture and metal commodity markets under bull and bear market conditions. Ji et al. (2018) employed a novel dependence-switching copula technique to analyze time-varying risk spillovers between energy and nonenergy commodities. The authors stated that the energy price displays stronger tail dependence on bearish market events than on bullish market event. However, risk

spillovers between energy and nonenergy commodity prices are more significant in a bearish regime.

More recently, the studies of Barbaglia et al. (2020) and Liu et al. (2021) revealed the existence of significant causal effects between energy and nonenergy commodities. Barbaglia et al. (2020) employed a rolling window and network analysis based on the VAR model and concluded that there is evidence of bidirectional volatility spillover transmission between energy and agricultural commodity prices as well as between energy and biofuel commodities. Liu et al. (2021) examined the features of energy, metal and agriculture commodity price information based on a complex network and transfer entropy. The findings revealed that price information network transmission varies across time scales with several levels of intensity.

The aforementioned review demonstrates that the majority of the econometric frameworks used are vector autoregressive models, multivariate GARCH models, copula functions, Granger causality tests, time-frequency analyses, and network analyses, among others. The applications of these methods mostly focused on the time-varying dependence structure between energy and nonenergy commodity markets without considering connectedness in the transmission mechanism across quantiles of the whole distribution (except the few recent studies which used copulas). Therefore, the novel econometric cross-quantile-based approach developed by Baruník and Kley (2019) seems appropriate for addressing this gap. Few recent research studies have focused on the cross-quantile dependencies of market pairs and, more specifically, on the cross-quantile dependence between commodity markets. In this context, the study of Su et al. (2017) is the only study to have addressed the cross-quantile connectedness of commodity markets, documenting significant interdependence of energy market prices across several quantiles of the conditional distribution.

To the best of our knowledge, the current empirical research is the first in the literature to investigate cross-quantile dependencies between the energy market index and nonenergy commodity market indices. Overall, vast empirical research has focused on the mean-to-mean connectedness of energy and nonenergy commodity markets without considering information transmission in the dependence structure across various quantiles of the overall distribution functions. In other words, this branch of literature has paid less attention to the dependence structure between commodity markets over different quantiles of the conditional distributions.



On the other hand, a very thin empirical literature has shed some light on the interplay of causal effects between energy and nonenergy commodities using the cross-quantile dependence framework. While previous studies ignored quantile dependencies across commodity markets, in this empirical research, we are interested in the dynamics of the interplay between energy and nonenergy commodity markets and how they spill over across different quantiles of the overall distribution functions.

**Table 1.** Relevant literature on the connectedness between energy and nonenergy commodities.

Author	Energy/Nonenergy commodities	Sample period	Methodology
Adhikari and Putnam (2020)	Energy (Crude Oil, West Texas Intermediate [WTI], Gasoline, Heating Oil, Natural Gas), Grains (Corn, Oats, Soybeans, Wheat), Livestock (Live Cattle, Feeder Cattle, Lean Hogs)	September 30, 1992–December 31, 2017; Daily Frequency	Linear Factor Model, Copulas
Ur Rehman et al. (2019)	Energy (Crude Oil, Gas, Coal), Nonenergy (Gold, Silver, Copper, Platinum, Palladium, Wheat)	January 2010–June 2018; Weekly Frequency	Non-linear ARDL (NARDL), Non-linear Causality-in-Quantile
Wu (2020)	Non-ferrous metals, Energy, Petrochemicals, Cereal, Oil & Fats, Softs, WTI	September 2004–June 2020; Weekly Frequency	GO-GARCH, Quantile-on-Quantile, Quantile Coherency
Yahya et al. (2020)	S&P Global Clean Energy Index, Non-ferrous metals, WilderHill Clean Energy Index, NYSE ARCA Technology Index	November 2003–May 2019; Daily Frequency	Cross-Quantilogram, Granger-Causality in Quantiles, Time-varying Copulas (DCC-Student-t-Copula)
Pal and Mitra (2019)	WTI, Corn, Soybeans, Oats, Wheat	January 3, 2000–January 4, 2018; Daily Frequency	DCC, ADCC, GO-GARCH
Awasthi et al. (2020)	Total Return Index of S&P, Goldman Sachs	March 22, 2011–February 25, 2020; Weekly	Quantile Cointegration, Granger Causality in

	Commodity Index (GSCI), Crude Oil, Gold, Silver, WTI	Frequency	Quantiles
Liu (2014)	WTI, Cushing Oklahoma, Corn, Soybeans, Oats, Wheat	January 3, 1994–December 31, 2012; Daily Frequency	Detrended Cross-Correlation Analysis (DCCA)
Lucotte (2016)	Cereals, Dairy, Meat, Sugar, Vegetable Oils, Composite Food Index, Crude Oil Index (WTI, Brent, Dubai)	January 1990–May 2015; Monthly Frequency	VAR Analysis
de Nicola et al. (2016)	Energy (Coal, Crude Oil, Natural Gas), Agricultural Crops (Barley, Maize, Rice, Sorghum, Soybean Oil, Wheat), Food (Coffee, Sugar)	January 1970–May 2013; Monthly Frequency	VAR Analysis
Ji and Fan (2012)	Energy: Commodity Research Bureau (CRB) Index (Crude Oil, Heating Oil, Gasoline, Natural Gas), Agriculture Crops (Soybean, Wheat, Corn, Cotton, Orange Juice, Sugar, Cocoa, Coffee, Live Cattle, Lean Hogs), Metals (Gold, Silver, Copper, Aluminum, and Nickel)	July 7, 2006–June 30, 2010; Daily Frequency	Asymmetric Bivariate EGARCH
Barbaglia et al. (2016)	Energy (Crude Oil, Natural Gas), Agriculture (Corn, Soy Oil, Sugar, Wheat, Cotton), Metals (Aluminum, Copper, Lead, Nickel, Zinc, Gold, Silver)	November 1, 2013–November 2, 2015; Daily Frequency	Sparse Multiclass VAR, Network Analysis
Tiwari et al. (2018)	Energy (Crude Oil), Agricultural Crops	January 1980–May 2017; Monthly Frequency	Wavelet Coherence Analysis, Wavelet

	(Bananas, Barley, Coal, Cocoa Beans, Coffee, Cotton, Fishmeal, Groundnuts, Maize, Oranges, Swine, Poultry, Rice, Rubber, Fish, Tea, Wheat, Wool)		Multiple Cross-correlation, Linear Causality, Nonlinear Causality
Yoon et al. (2019)	Energy (WTI); Metal (Gold)	December 2, 1999–June 11, 2018	VAR-GVD, Network Topology
Zhang and Broadstock (2020)	Energy (WTI), Nonenergy (Beverage, Fertilizers, Food, Metals, Precious Metals, Raw Materials)	January 1982–June 2017; Monthly Frequency	VAR, Forecast Error Variance Decomposition (FEVD)
Shahzad et al. (2019)	Energy (WTI), Nonenergy (Gold, Silver, Titanium, Palladium, Platinum)	July 1, 1996–June 29, 2016; Daily Frequency	VAR for VaR Approach, Cross-quantilogram Method

### 3. The quantile cross-spectral framework

To examine the connectedness across different distribution quantiles and frequencies for energy and nonenergy commodity indices, we use the econometric approach recently developed by Baruník and Kley (2019): quantile coherency. The method quantifies the dynamic dependence between two stationary time series. The main advantage of Baruník and Kley's (2019) approach is that the measure was designed to detect any general type of dependence structure across different frequencies and quantiles – as opposed to methodologies focusing on the average states (e.g., Diebold and Yilmaz, 2009, 2012). In this respect, copulas present useful tool to address dependencies across different quantiles, even though they applications usually do not primarily focus on the frequency domain. On the other hand, while Baruník and Křehlík's (2018) frequency-domain spillover index is an extension of Diebold-Yilmaz methodology focusing on frequencies, it is still fitted to mean-to-mean analysis of spillovers.

Following Baruník and Kley (2019), let  $X_{t,E}$  and  $X_{t,N}$ ,  $t \in \mathbb{Z}$  be the two stationary processes of the energy and nonenergy commodity price indices, and  $q_{X_E}(\tau_1)$  and  $q_{X_N}(\tau_1)$  be their

$\tau_1$ -quantiles, respectively. Let  $I\{A\}$  be the indicator function for event  $A$ , taking values of 1 when event  $A$  occurs and zero otherwise.

The quantities

$$\gamma_k^{j_1, j_2}(\tau_1, \tau_2) := \text{Cov} \left( I \{ X_{t+k, j_1} \leq q_{X_{j_1}}(\tau_1) \}, I \{ X_{t, j_2} \leq q_{X_{j_2}}(\tau_2) \} \right) \quad (1)$$

for  $k \in \mathbb{Z}$ ,  $\tau_1, \tau_2 \in [0, 1]$  and  $j_1, j_2 \in \{E, N\}$  are used to construct the matrix of quantile cross-covariance kernels

$$\Gamma_k(\tau_1, \tau_2) := \left( \gamma_k^{j_1, j_2}(\tau_1, \tau_2) \right)_{j_1, j_2 \in \{E, N\}} \quad (2)$$

Further, define the rank-based copula cross-periodograms using

$$d_{n,R}^j(\omega, \tau) := \sum_{t=0}^{n-1} I \{ \hat{F}_{n,j}(X_{t,j}) \leq \tau \} e^{-i\omega t} \quad (3)$$

where  $\omega \in \mathbb{R}$ ,  $j \in \{E, N\}$  and  $\hat{F}_{n,j}(x)$  is the empirical distribution function of  $X_{t,j}$  within a sample of length  $n \in \mathbb{N}$ . Consequently, the estimator of quantile cross-spectral density becomes

$$I_{n,R}^{j_1, j_2}(\omega, \tau_1, \tau_2) := \frac{1}{2\pi n} d_{n,R}^{j_1}(\omega, \tau_1) d_{n,R}^{j_2}(\omega, \tau_2) \quad (4)$$

To estimate rank-based copula cross-periodograms consistently, the values are smoothed across frequencies:

$$\hat{G}_{n,R}^{j_1, j_2}(\omega, \tau_1, \tau_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} W_n \left( \omega - \frac{2\pi s}{n} \right) I_{n,R}^{j_1, j_2} \left( \frac{2\pi s}{n}, \tau_1, \tau_2 \right) \quad (5)$$

where the weights  $W_n$  are taken from Baruník and Kley (2019). Finally, the estimator of quantile coherency is calculated as

$$\hat{C}_{n,R}^{j_1, j_2}(\omega, \tau_1, \tau_2) := \frac{\hat{G}_{n,R}^{j_1, j_2}(\omega, \tau_1, \tau_2)}{\sqrt{\hat{G}_{n,R}^{j_1, j_1}(\omega, \tau_1, \tau_1) \hat{G}_{n,R}^{j_2, j_2}(\omega, \tau_2, \tau_2)}} \quad (6)$$

for  $\tau_1, \tau_2 \in [0, 1]$ ,  $\omega \in \mathbb{R}$  and  $j_1, j_2 \in \{E, N\}$ .

#### 4. Dataset and preliminary analysis

Our study is based on monthly data covering the period 1960:M1 to 2019:M10. We collect our dataset from the World Bank. Each energy and nonenergy commodity index is measured as the average of the relevant components with base year 2010. We display the full

descriptions and details of the commodity index prices in Table 2. All the details and definitions are extracted from the World Bank definitions of commodity indices. Certain descriptive statistics for the commodity index returns are reported in Table 3. It is shown that the data encompass 718 observations. Compared to the return of the nonenergy commodity indices (except the index for fertilizers), the energy commodity index return is more volatile in terms of standard deviation. This may indicate that the energy commodity index is riskier than the nonenergy indices. Further, except for the commodity indices for grains and raw materials, the nonenergy commodity indices and the energy commodity index display negative skewness, suggesting a long left tail in their distributions. We also emphasize the high kurtosis coefficients on all the commodity indices, suggesting that the return commodity series exhibit peaks (extreme returns) in comparison to the normal distribution. Regarding the Jarque-Bera statistic, we highlight that the energy and nonenergy commodity return series are not normally distributed. On the other hand, when referring to the autoregressive conditional heteroskedasticity (ARCH)-Lagrange multiplier (LM) test statistic, we reject the null hypothesis of no ARCH effect for all the return series. In the Appendix (Figures A.1–A.2), we plot the evolution of the commodity indices prices in terms of levels and returns, respectively.

**Table 2.** Commodity indices and description.

Commodity index	Label	Commodity description
Energy	ENERGY	<p>Coal (Australia), from January 2015, port thermal, free on board (FOB) Newcastle, 6,000 kcal/kg spot price. 2002–2014, thermal GAR, FOB piers, Newcastle/Port Kembla, 6,300 kcal/kg (11,340 btu/lb), less than 0.8%, sulfur 13% ash; previously 6,667 kcal/kg (12,000 btu/lb), less than 1.0% sulfur, 14% ash</p> <p>Coal (Colombia), thermal GAR, FOB Bolivar, 6,450 kcal/kg, (11,200 btu/lb), less than 1.0%, sulfur 16% ash from August 2005 onwards; during years 2002–July 2005, 11,600 btu/lb, less than .8% sulfur, 9% ash, 180 days forward delivery</p> <p>Coal (South Africa), from January 2015, FOB Richards Bay, net as received (NAR), 6,000 kcal/kg, sulfur less than 1%, forward month 1; from February 13, 2017 to December 2017, thermal NAR netback assessment</p> <p>FOB Richards Bay 6,000 kcal/kg; during 2006–February 10, 2017, thermal NAR; during 2002–2005, 6,200 kcal/kg (11,200 btu/lb), less than 1.0%, sulfur 16% ash; years 1990–2001 6390 kcal/kg (11,500 btu/lb)</p> <p>Crude oil, average spot price of Brent, Dubai and WTI, equally weighted</p> <p>Crude oil, UK Brent 38° API</p> <p>Crude oil, Dubai Fateh 32° API for years 1985–present; 1960–84 refer to Saudi Arabian Light, 34° API.</p> <p>Crude oil, US, WTI 40° API</p> <p>Natural gas index (Laspeyres), average of Europe, US and Japan (liquefied natural gas [LNG]), weights based on 5-year average consumption volumes, updated every 5 years, except for the 11-year period of 1960–70</p> <p>Natural gas (Europe), from April 2015, Netherlands Title Transfer Facility (TTF), April 2010–March 2015, average import border price and a spot price component, including UK; for June 2000–March 2010, prices exclude UK</p> <p>Natural gas (US), spot price at Henry Hub, Louisiana</p> <p>LNG (Japan), import price, cost, insurance, and freight (CIF) ; most recent two months' averages are estimates</p>
Nonfuel	NONFUEL	A composite of the agriculture, fertilizers, and metals and minerals indices
Agriculture	AGRICLTR	A composite of the beverages, food and raw materials indices
Beverages	BEVERGS	<p>- Cocoa (ICCO), International Cocoa Organization daily price, average of the first three positions on the terminal markets of New York and London, nearest three future trading months</p> <p>- Coffee (ICO), International Coffee Organization indicator price, other mild Arabicas, average New York and Bremen/Hamburg markets, ex-dock</p> <p>- Coffee (ICO), International Coffee Organization indicator price, Robustas, average New York and Le Havre/Marseilles markets, ex-dock</p>

		<ul style="list-style-type: none"> <li>- Tea, average three auctions, arithmetic average of quotations at Calcutta, Colombo and Mombasa/Nairobi</li> <li>- Tea (Colombo auctions), Sri Lankan origin, all tea, arithmetic average of weekly quotes</li> <li>- Tea (Calcutta auctions), leaf, include excise duty, arithmetic average of weekly quotes</li> <li>- Tea (Mombasa/Nairobi auctions), African origin, all tea, arithmetic average of weekly quotes</li> </ul>
Food	FOOD	<p>Oil and meals, grains and other food</p> <p>Bananas (Central and South America), major brands, free on truck (FOT) Southern Europe, including duties; prior to October 2006, FOT Hamburg</p> <p>Bananas (Central and South America), major brands, US import price, FOT US Gulf ports</p> <p>Meat, beef (Australia/New Zealand), mixed trimmings 85%, East Coast, 7–45 day deferred delivery, FOB port of entry, beginning January 1995; previously cow forequarters</p> <p>Meat, chicken (US), Umer Barry North East weighted average for broiler/fryer, whole birds, 2.5 to 3.5 pounds, USDA grade A from 2013 onwards; 1980–2012, Georgia Dock weighted average, 2.5 to 3 pounds, wholesale; previously World Bank estimates</p> <p>Meat, sheep (New Zealand), frozen whole carcasses Prime Medium (PM) wholesale, Smithfield, London beginning January 2006; previously Prime Light (PL)</p> <p>Oranges (Mediterranean exporters) navel, European Union indicative import price, CIF Paris</p> <p>Shrimp, (US), brown, shell on, headless, in frozen blocks, source Gulf of Mexico, 26 to 30 count per pound, wholesale US beginning 2004; previously New York</p> <p>Sugar (EU), European Union negotiated import price for raw unpackaged sugar from African, Caribbean and Pacific (ACP) under Lomé Conventions, CIF European ports</p> <p>Sugar (US), nearby futures contract, CIF</p> <p>Sugar (World), International Sugar Agreement (ISA) daily price, raw, FOB and stowed at greater Caribbean ports</p>
Oil and Meals	OILS_MLS	<p>Coconut oil (Philippines/Indonesia), from January 1999, crude, CIF NW Europe; previously, bulk, CIF Rotterdam</p> <p>Copra (Philippines/Indonesia), bulk, CIF NW Europe</p> <p>Fishmeal, German, 64% protein, EXW Hamburg beginning January 1999</p> <p>Groundnuts (US), Runners 40/50, cost and freight (CFR) NW Europe. Europe beginning January 1999; previously (US), Runners 40/50 shelled basis, CIF Rotterdam</p> <p>Groundnut oil, US crude, FOB South-East beginning January 1999; previously any origin, CIF Rotterdam</p> <p>Palm oil (Malaysia), RBD, CIF Rotterdam beginning December 2001; previously Malaysia 5%, CIF NW Europe, bulk, nearest forward</p> <p>Palm kernel oil (Indonesia/Malaysia), crude, CIF NW Europe beginning August 2001; previously Malaysian, nearest forward</p> <p>Soybean meal, Brazilian pellets 48% protein, CIF Rotterdam beginning January 1999; for 1990–1998, 45/46% CIF Rotterdam, nearest forward; previously US origin 44%</p> <p>Soybean oil, Dutch crude degummed, FOB NW Europe beginning January 1999; previously crude, FOB ex-mill Netherlands, nearest forward</p> <p>Soybeans, US No. 2 yellow meal, CIF Rotterdam beginning December 2007; previously US origin, nearest forward</p>
Grains	GRAINS	<p>Barley (US) feed, No. 2, spot, 20 days to arrive, delivered Minneapolis from May 2012 onwards; for 1980–April 2012 Canadian, feed, Western No. 1, Winnipeg Commodity Exchange, spot, wholesale farmers' price</p> <p>Maize (US), No. 2, yellow, FOB US Gulf ports</p> <p>Rice (Thailand), 5% broken, white rice (WR), milled, indicative price based on weekly surveys of export transactions, government standard, FOB Bangkok</p> <p>Rice (Thailand), 25% broken, WR, milled indicative survey price, government standard, FOB Bangkok</p> <p>Rice (Thailand), 100% broken, A-1 Super from 2006 onwards, government standard, FOB Bangkok; prior to 2006, A-1 Special, a slightly lower grade than A-1 Super</p> <p>Rice (Vietnam), 5% broken, WR, milled, weekly indicative survey price, minimum export price, FOB Hanoi</p> <p>Sorghum (US), No. 2 milo yellow, Texas export bids for grain delivered to export elevators, rail-truck, FOB Gulf ports</p> <p>Wheat (Canada), No. 1, Western Red Spring (CWRS), in store, St. Lawrence, export price</p> <p>Wheat (US), No. 1, hard red winter, ordinary protein, export price delivered at the US Gulf port for prompt or 30-day shipment</p> <p>Wheat (US), No. 2, soft red winter, export price delivered at the US Gulf port for prompt or 30-day shipment</p>
Raw Materials	RAW_MTR	<p>Timber:</p> <p>Logs (Africa), sapele, high quality (loyal and marchand), 80 centimeters or more, FOB Douala, Cameroon beginning January 1996; previously of unspecified dimension</p> <p>Logs (Southeast Asia), meranti, Sarawak, sale price charged by importers, Tokyo beginning February 1993; previously average of Sabah and Sarawak weighted by Japanese import volumes</p> <p>Plywood (Africa and Southeast Asia), Lauan, 3-ply, extra, 91 centimeters x 182 centimeters x 4 millimeters, wholesale price, spot Tokyo</p> <p>Sawnwood (Africa), sapele, width 6 inches or more, length 6 feet or more, firsts and seconds (FAS) Cameroonian ports</p> <p>Sawnwood (Southeast Asia), dark red seraya/meranti, select and better quality, average 7 to 8 inches; length average 12 to 14 inches; thickness 1 to 2 inch(es); kiln dry, CFR UK ports, with 5% agent's commission, including premium for products of certified sustainable forest beginning January 2005; previously excluding premium</p> <p>Woodpulp (Sweden), softwood, sulfate, bleached, air-dry weight, CIF North Sea ports</p> <p>Other Raw Materials:</p>

		<p>Cotton (Cotton Outlook "Cotlook A index"), middling 1-3/32 inch, traded in Far East, CFR beginning 2006; previously Northern Europe, CIF</p> <p>Cotton (US), Memphis/Eastern, middling 1-3/32 inch, Far East, C/F beginning October 2008; previously CIF Northern Europe</p> <p>Rubber (Asia), ribbed smoked sheet (RSS) No. 3 grade, Singapore Commodity Exchange Ltd. (SICOM) nearby contract beginning 2004; for 2000–2003, Singapore RSS No. 1; previously Malaysia RSS No. 1</p> <p>Rubber (any origin), RSS No. 1, in bales, Rubber Traders Association (RTA), spot, New York</p> <p>Rubber (Asia), technically specified rubber (TSR) 20, SGX/SICOM nearby futures contract</p> <p>Tobacco (any origin), unmanufactured, general import, CIF, US</p>
Fertilizers	FERTIL	<p>Diammonium phosphate (DAP), spot, FOB US Gulf</p> <p>Phosphate rock, FOB North Africa</p> <p>Potassium chloride (muriate of potash), FOB Vancouver</p> <p>Triple superphosphate (TSP), spot, import US Gulf</p> <p>Urea, (Ukraine), FOB Black Sea</p>
Metals and Minerals	MET_MIN	<p>Aluminum (LME) London Metal Exchange, unalloyed primary ingots, high grade, minimum 99.7% purity, settlement price beginning 2005; previously cash price</p> <p>Copper (LME), grade A, minimum 99.9935% purity, cathodes and wire bar shapes, settlement price</p> <p>Iron ore, spot in US dollars/dry ton and contract in US cents/dry metric ton units (dmtu). For December 2008–present, spot, (any origin) fines, 62% Fe, CFR China; for 2006–2008 (November) spot, 63.5% Fe. Earlier data refer to annual contract prices (Brazil for Europe), VALE Carajas mines sinter feed, FOB Ponta da Madeira for years 1987–2009; Itabira mines FOB Tubarão for years 1960–86. Dmtu, i.e., 1% Fe-unit.</p> <p>Iron ore (any origin) fines, spot price, CFR China, 62% Fe beginning December 2008; previously 63.5%</p> <p>Lead (LME), refined, 99.97% purity, settlement price</p> <p>Nickel (LME), cathodes, minimum 99.8% purity, settlement price beginning 2005; previously cash price</p> <p>Steel products index</p> <p>Steel, Cold-rolled coil/sheet (Japan) producers' export contracts (3- to 12-month terms) FOB mainly to Asia</p> <p>Steel, Hot-rolled coil/sheet (Japan) producers' export contracts (3- to 12-month terms) FOB mainly to Asia</p> <p>Steel, Rebar (concrete reinforcing bars) (Japan) producers' export contracts (3- to 12-month terms) FOB mainly to Asia</p> <p>Steel, Wire rod (Japan) producers' export contracts (3- to 12-month terms) FOB mainly to Asia</p> <p>Tin (LME), refined, 99.85% purity, settlement price</p> <p>Zinc (LME), high grade, minimum 99.95% purity, settlement price beginning April 1990; previously special high grade, minimum 99.995%, cash price</p>
Precious Metals	PRECS_MET	<p>Gold (UK), 99.5% fine, London afternoon fixing, average of daily rates</p> <p>Platinum (UK), 99.9% refined, London afternoon fixing</p> <p>Silver (UK), 99.9% refined, London afternoon fixing; prior to July 1976 Handy &amp; Harman. Grade prior to 1962 unrefined silver</p>

Source: World Bank.

**Table 3. Descriptive statistics for the return time series (monthly data).**

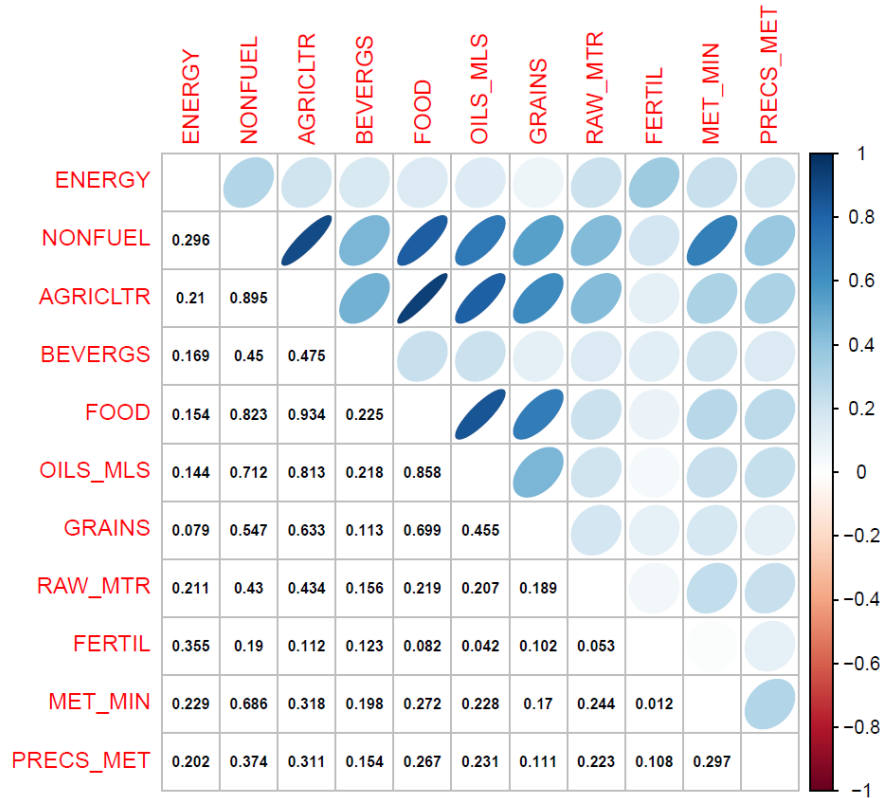
Variable	Obs	Min	Quartile_1	Quartile_3	Max	Mean	Std Dev	Skew	Kurtosis	J-B statistic	p-value	ARCH-LM	p-value
ENERGY	718	-31.4858	-0.4305	0.9486	16.8742	0.0959	3.7103	-1.8160	14.5909	6798.9772	0.000	155.3894***	0.000
NONFUEL	718	-17.5127	-0.5126	0.7011	7.9309	0.0860	1.7300	-1.5314	18.4855	10556.6727	0.000	11.5520*	0.072
AGRICLTR	718	-14.2983	-0.6093	0.7378	8.0357	0.0844	1.7455	-0.4397	9.0783	2503.7376	0.000	21.4270**	0.018
BEVERGS	718	-13.0555	-1.1596	1.2127	22.5453	0.0706	3.2593	1.1896	8.5376	2363.9463	0.000	18.9698**	0.040
FOOD	718	-17.5398	-0.8558	0.8997	12.1938	0.0908	2.2788	-0.3397	8.5198	2198.8152	0.000	35.6666***	0.000
OILS_MLS	718	-21.6289	-1.1413	1.2143	17.7196	0.0759	3.3131	-0.3594	8.7679	2329.4573	0.000	142.8902***	0.000
GRAINS	718	-23.4114	-1.1816	1.1011	21.0628	0.0900	3.1352	0.3288	9.9671	3002.5117	0.000	17.2710*	0.068
RAW_MTR	718	-9.3674	-0.4215	0.6278	9.7542	0.0760	1.5525	0.1630	8.4811	2168.4058	0.000	214.6949***	0.000
FERTIL	718	-61.5161	-0.4680	0.6618	45.2952	0.0904	5.3915	-0.0967	45.2919	61651.4620	0.000	59.9221***	0.000
MET_MIN	718	-25.7286	-0.6773	0.8929	13.4686	0.0886	2.7624	-1.2884	15.4567	7384.3793	0.000	11.4933*	0.074
PRECS_MET	718	-17.2504	-0.4416	0.6370	29.8386	0.1535	2.7057	1.6131	25.9801	20602.8414	0.000	9.1956*	0.056

Note: \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.



## 5. Results

We begin our analysis by looking at the standard Pearson correlations, as visualized in Figure 1. Energy commodities exhibit rather low correlations with their nonenergy counterparts, ranging from 0.07 (Grains) to 0.36 (Fertilizers). These preliminary findings are in sharp contrast with the results of Shiferaw (2019), who found that agricultural commodities were strongly and significantly connected with energy prices. Of course, one can find a relationship in a Granger-causal sense (e.g., Nazlioglu, 2011), although the overall effect of this dependence is rather low. Averages, however, are not sufficient to reveal the full picture of dependence among the time series.

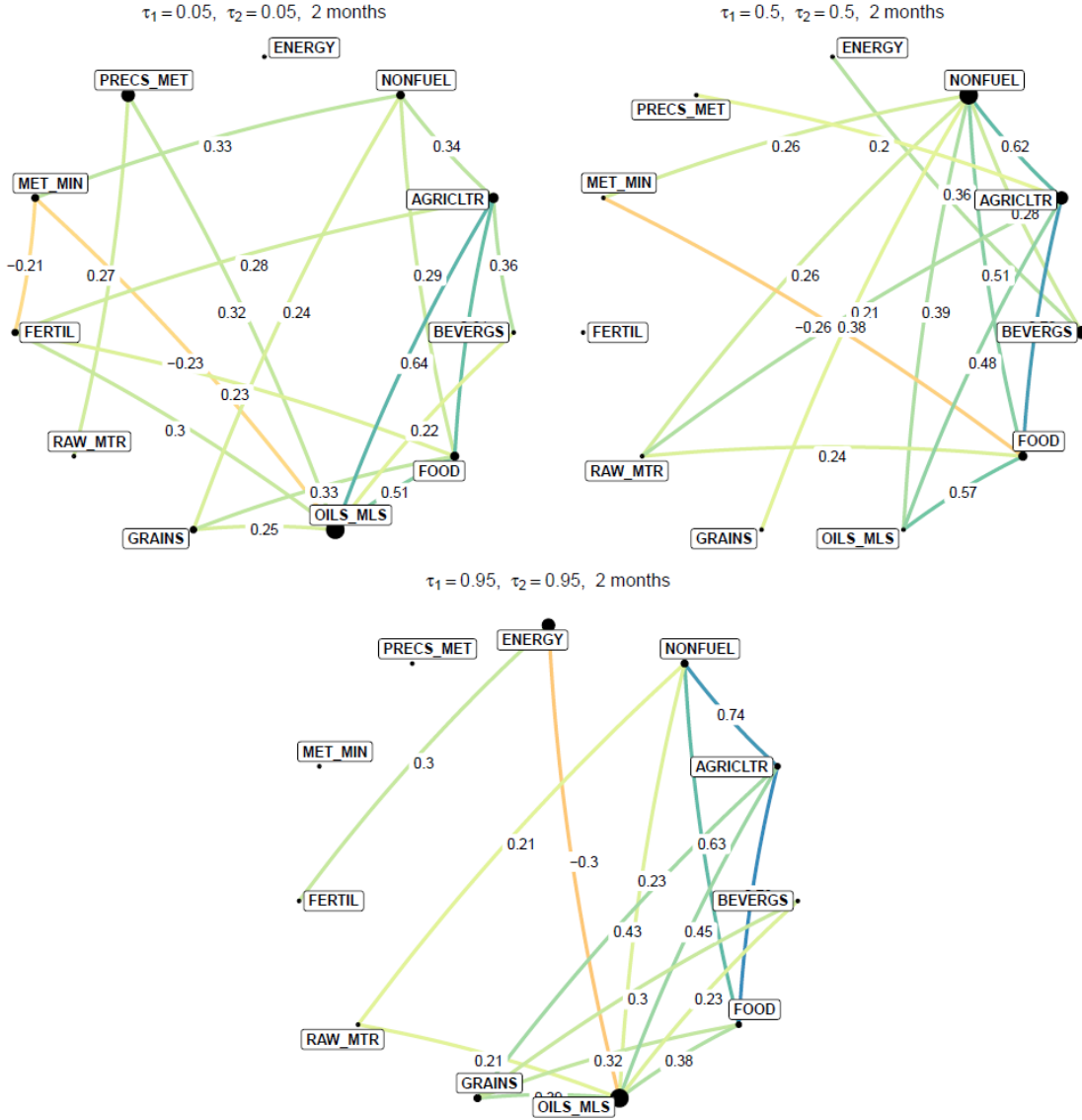


**Figure 1.** Correlations among energy and nonenergy commodities.

### 5.1. Commodity dependence during booms and busts

We present our results of the quantile dependence analysis in the form of networks, where the node size represents betweenness centrality and the edge labels (and color scale) depict the estimated quantile coherencies. Our focus is on three frequencies, 2 months, 6 months,

and 12 months, capturing mutual dependencies among energy and nonenergy commodities from the short-, mid-, and long-term perspectives. More detailed results are available upon request.



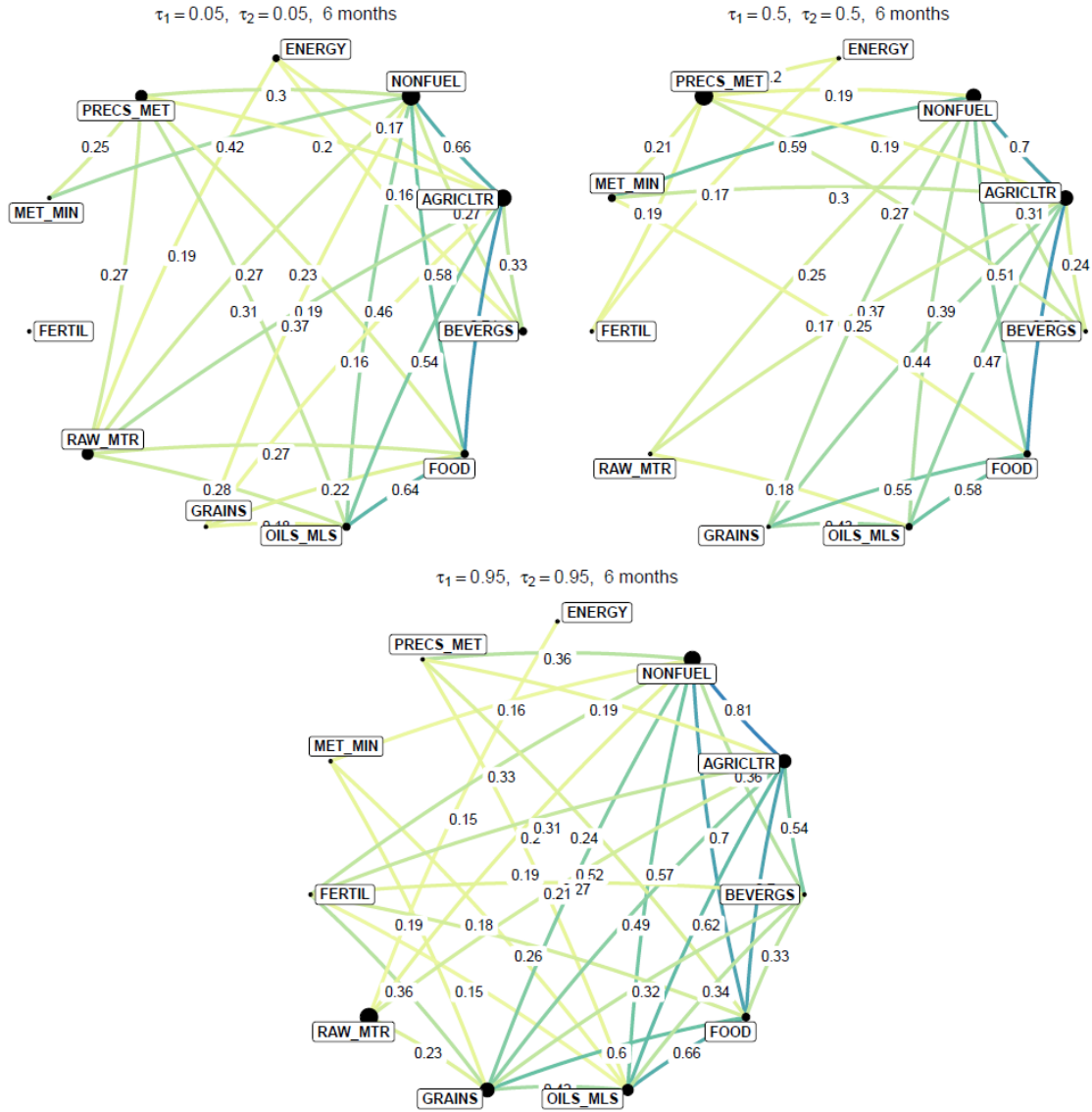
**Figure 2.** Quantile dependence from a short-term perspective.

*Note: The upper left panel depicts the 5<sup>th</sup>-to-5<sup>th</sup> quantile dependence (extreme negative returns); the upper right panel depicts the 50<sup>th</sup>-to-50<sup>th</sup> quantile dependence; and the bottom panel depicts the 95<sup>th</sup>-to-95<sup>th</sup> quantile dependence (extreme positive returns).*

From the short-term perspective, when we look at the extreme negative tail of commodity returns (i.e., the 5<sup>th</sup>-to-5<sup>th</sup> quantile dependence), energy commodities are isolated in our network representation (see the left panel of Figure 2). This simply means that none of the estimated quantile coherency was statistically significant at the 5% level. The result is slightly different at

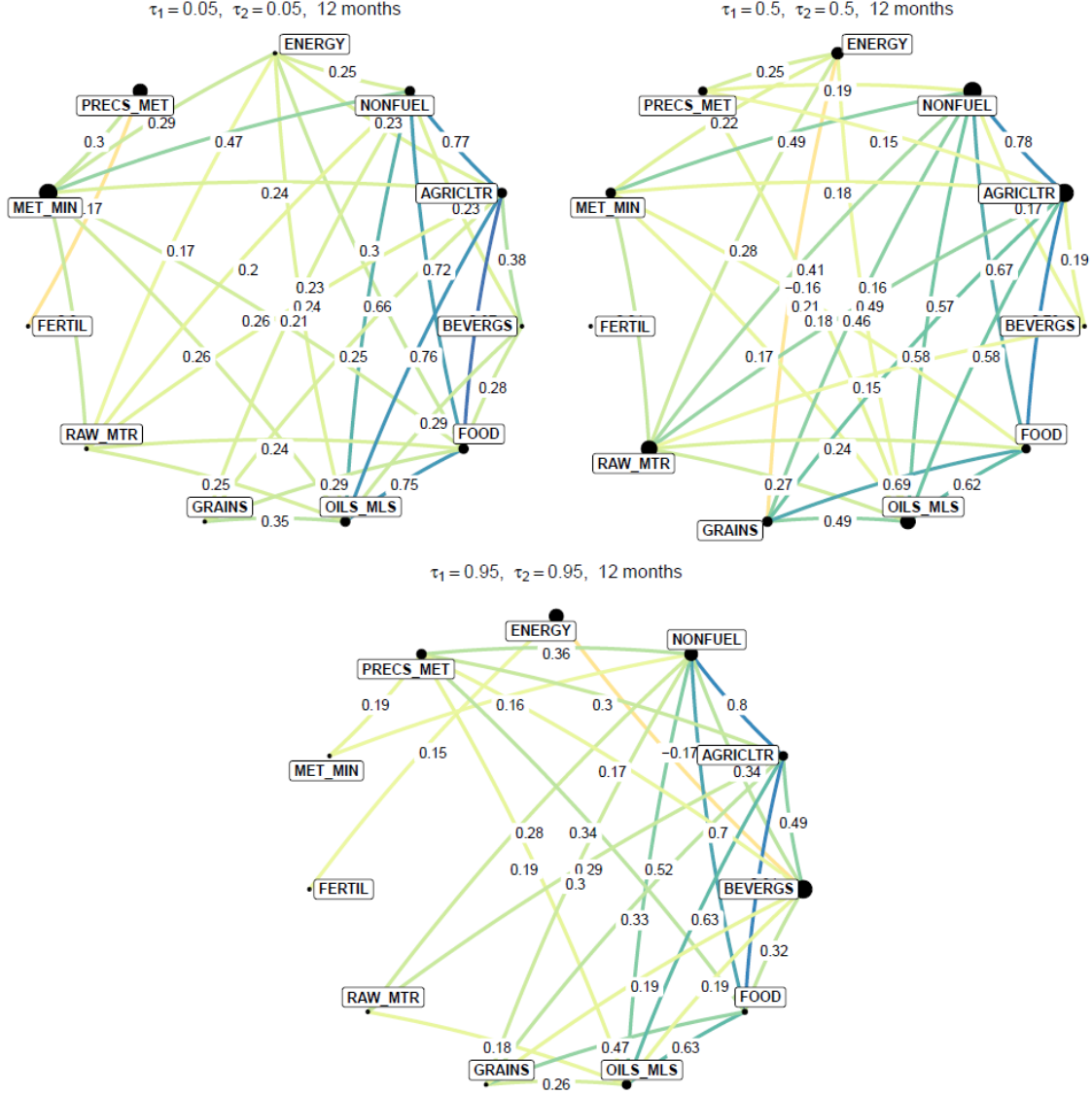
the (0.5|0.5) quantiles, where energy commodities are significantly linked to beverages (0.359), and at the (0.95|0.95) quantiles, where energy is positively associated with fertilizers (0.305) but negatively associated with oils and meals (−0.297). It is clear that the relationships among energy and nonenergy commodities are distinct across different quantiles of their joint return distribution (in line with the findings of Albulescu et al., 2020). For example, metals and minerals are negatively associated with fertilizers and oils and meals at lower quantiles (0.05|0.05) and with food as a whole category at the median (0.5|0.5) and are totally independent when we look at the extreme positive tail of returns (0.95|0.95). Precious metals exhibit very similar behavior, and extreme positive returns are not associated with comovements of any other commodity. Extreme negative returns of precious metals are, however, linked to raw materials (0.271) and oils and meals (0.318).

From the medium- and long-term perspectives, energy commodities are linked to nonenergy commodities to a greater extent, especially when we consider extreme negative comovements. This is a well-documented stylized fact about returns (Baruník and Kley, 2019). It shows that returns are more dependent during business cycle downturns or market turmoil than during upturns or bull markets. The same applies with energy commodities. In the long term, energy is connected to nonenergy commodities (0.247), agriculture (0.226), food (0.297), oils and meals (0.226), raw materials (0.166), and metals and minerals (0.291). Extreme positive returns of energy commodities are associated in the long term only with beverages (−0.174) and fertilizers (0.152). Note that in Figure 3 and Figure 4, every node has at least one connection, meaning that at least one statistically significant coherency is found for each commodity considered in our study.



**Figure 3.** Quantile dependence from a medium-term perspective.

*Note: The upper left panel depicts the 5<sup>th</sup>-to-5<sup>th</sup> quantile dependence (extreme negative returns); the upper right panel depicts the 50<sup>th</sup>-to-50<sup>th</sup> quantile dependence; and the bottom panel depicts the 95<sup>th</sup>-to-95<sup>th</sup> quantile dependence (extreme positive returns).*



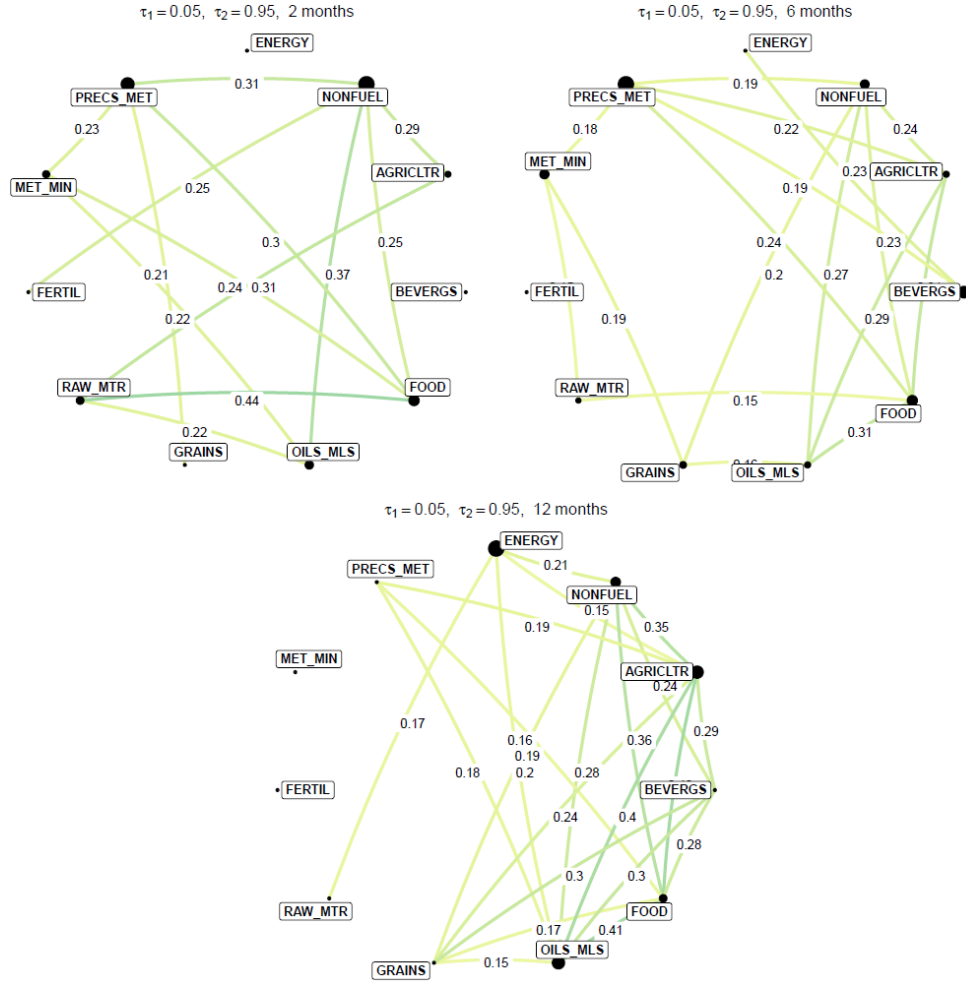
**Figure 4.** Quantile dependence from a long-term perspective.

*Note: The upper left panel depicts the 5<sup>th</sup>-to-5<sup>th</sup> quantile dependence (extreme negative returns); the upper right panel depicts the 50<sup>th</sup>-to-50<sup>th</sup> quantile dependence; and the bottom panel depicts the 95<sup>th</sup>-to-95<sup>th</sup> quantile dependence (extreme positive returns).*

## 5.2. Asymmetric commodity dependence

Using a quantile coherency measure, we can track down dependence at any quantile of the joint return distribution across different frequencies. In addition to our previous results, we show in this section how connected commodity returns are when we consider the relationship between extreme negative returns on one commodity and extreme positive returns on another (of course, this relationship might be from the opposite perspective – not (0.05|0.95) but rather (0.95|0.05); however, these results are basically identical).

Figure 5 shows the existence of asymmetric commodity dependence, similar to the finding of Albulescu et al. (2020). From a short-term perspective, energy commodities are still isolated, as shown in Figure 2. From the medium-term perspective, energy is linked to beverages (0.226) and, in the long term, to nonenergy (0.214), agriculture (0.149), oils and meals (0.186), and raw materials (0.17).



**Figure 5.** Dependence at 5<sup>th</sup>-to-95<sup>th</sup> quantiles.

*Note: The upper left panel depicts the short-term dependence; the upper right panel depicts the medium-term dependence; and the bottom panel depicts the long-term dependence.*

The results can be comprehended in bearish, normal and bullish markets; for bearish market, we report the higher dependence of energy commodity with nonenergy, compared with bullish trend which confirm the findings of (Albulescu et al., 2020; Yahya et al., 2019), which

report that energy market is more connected with the other markets in financial crises. Similar trend of higher dependence is validated in normal market scenario, as reported in 0.5|0.5 quantiles, where energy commodity has dependence with beverage, precious metal, fertilizer, metal & minerals, raw material, grains and oil mills. During the bullish trend, the dependence of energy with nonenergy commodities are confirmed with oil mills, fertilizer, raw material and beverage, which urge to not use these assets to form the portfolio.

In view of portfolio construction, we report the findings in light of bearish, normal and bullish trend, the results are mentioned in Table A.1. While focusing on bearish trend, the portfolio managers and investors have to use grains, fertilizer and precious metals to minimize the portfolio risk. For normal market scenario, nonfuel, agriculture and food assets are best options for portfolio construction. In view of bullish market, nonfuel, agriculture, food, grains, metal & minerals and precious metals are best choices. However, one can see that the investors and portfolio managers have more option in bullish market than bearish market. The results compel that investors should be more careful in portfolio construction during the bearish market (Awasthi et al., 2020; Shahzad et al., 2019).

## 6. Conclusions

This research assessed the empirical evidence on the connectedness between energy and nonenergy commodity index prices using monthly time series data for the period spanning 1960:M1 to 2019:M10. The energy commodity index price includes coal, crude oil, and natural gas, whereas nonenergy commodity indices encompass metals, agriculture, and fertilizer commodities. In this empirical investigation, we conducted a quantile cross-spectral analysis for the energy-nonenergy pairs by employing the method of Baruník and Kley (2019), which enabled us to quantify the strength of the connectedness between commodity markets at several quantiles and frequency bands at the same time.

We summarize our main findings as follows. First, at the short-term horizon, it is noteworthy that the connectedness between energy and nonenergy commodity market index prices is distinct across quantiles of the conditional distribution. This result is in line with the results of Albuлесcu et al. (2020). This may suggest that at short-term horizon policymakers should adopt novel strategies at the extreme bearish market states in order to face with the low

(absence) connectedness between global energy commodity index and the global nonenergy commodity indexes. Furthermore, at the shortest horizon it is important for authorities to not pay further attention to the bad extreme negative and positive event effects on the global energy and nonenergy commodity indexes. For instance, it is found that the global energy index is not associated with all the global nonenergy commodity indexes at 0.05|0.05 quantiles, positively connected only with beverages at the intermediate quantiles (0.50|0.50), positively associated with fertilizers and negatively linked to oils and meals at 0.95|0.95 quantiles. Second, from the medium- and long-term perspectives, the energy commodity index is significantly connected to nonenergy commodity indices to a great extent, especially when we consider extreme negative comovements. At the medium-term horizon, policymakers should pay further attention in particular at bearish market states than at normal and bullish market conditions. In fact, the connectedness between commodity markets is more pronounced at 0.05|0.05 quantiles for the joint distribution of energy and nonenergy commodities. This may be due to the already mentioned stylized fact that returns are more dependent during business cycle downturns or market turmoil than during upturns or bull markets. Furthermore, investors and portfolio managers should learn from the quantile dependence structure between the global energy commodity market and nonenergy commodity markets when constructing their optimal portfolios of commodities. For instance. The global energy commodity index significantly and positively affects raw materials, beverages and agriculture indexes (at bearish market state), fertilizers and precious metals indexes (at normal market state), and raw materials index (at bullish market state). This may indicate that extreme lower, normal and extreme upper energy price shocks lead to and increase in beverages, agriculture, raw materials, fertilizers and precious metals prices. Therefore, the global energy commodity index may offer less diversification profits when combined with beverages, agriculture, raw materials, fertilizers or precious metals global indexes. However, international investors and portfolio managers can base their investment strategies in other commodities in order to make further benefits. In the long-term horizon, the global energy commodity market significantly and positively affects the majority of the global nonenergy commodities at the different kind of market states. However, investors, portfolio managers and policymakers should pay more attention to the connectedness between commodity markets in the longer horizon in particular at bearish market states. Third, our results reveal the presence of an asymmetric dependence structure between energy and nonenergy



commodity markets. The asymmetry in the connectedness between the global commodity markets is more pronounced at the extreme upper quantiles (bullish market state). Fourth, our results have important crucial policy implications for investors and policymakers.

In a nutshell, from the investor's point of view, it is beneficial to adapt one's strategies when constructing portfolios of energy and nonenergy commodity assets based on the dynamics of the connectedness across quantile and frequency domains to mitigate risks and maximize benefits. From policymakers' standpoint, it is important to be more cautious to develop optimal strategies at short-, medium-, and long-term horizons.

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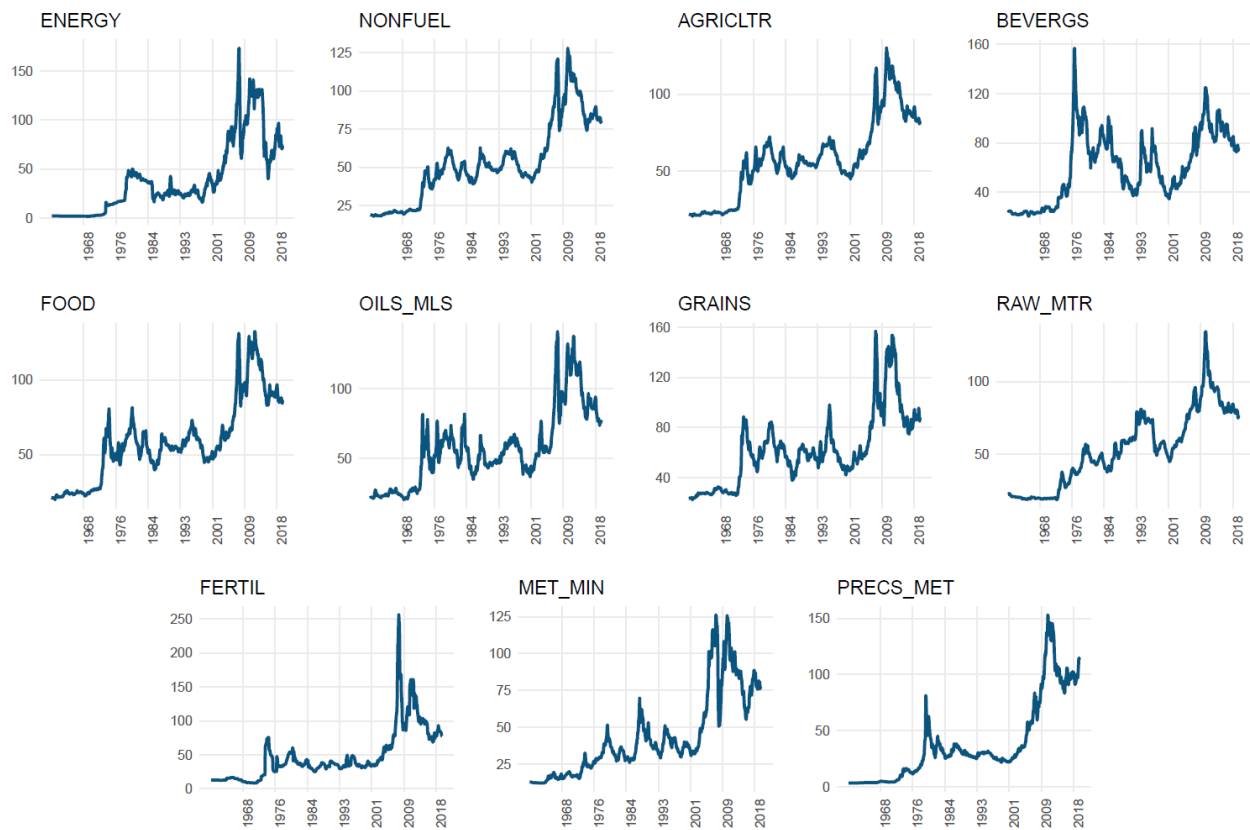
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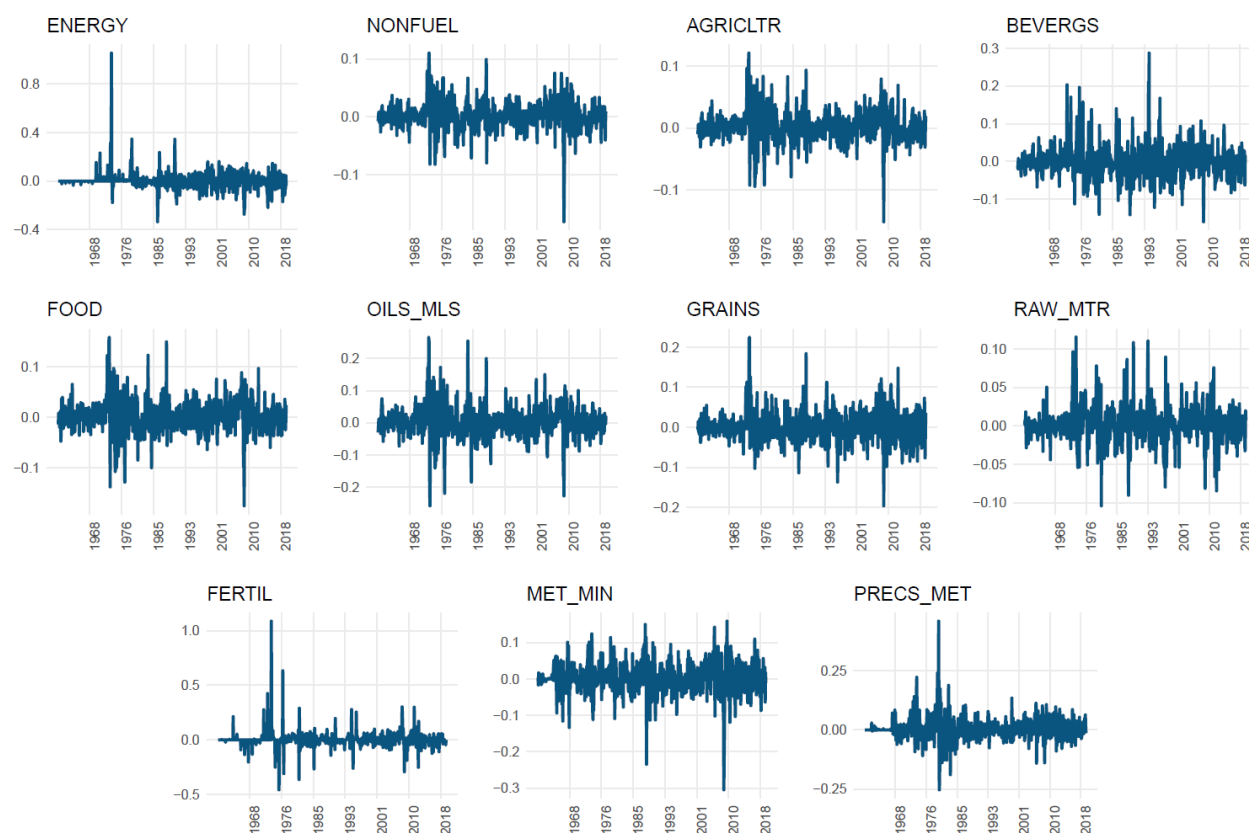
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## Appendix



**Figure A.1.** Level series of commodity price indices.



**Figure A.2.** Return series of commodity price indices.

**Table A.1.** Asset selection with energy in bearish, normal and bullish markets

Bearish	Normal	Bullish
Grains Fertilizer Precious metal	Non fuel Agriculture Food	Non fuel Agriculture Food Grains Metal & Minerals Precious metal