Temporal and spectral dependence between the energy commodities using wavelet-based copula

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Overview

Energy commodities plays a significant role in economic research due to its significance in the economy. Understanding the statistical properties and time-varying dependence dynamics of energy commodities has important implications for asset allocation, investment and risk management, and policymaking (see e.g. Karyotis and Alijani, 2016; Andreasson et al., 2016). Furthermore, the energy-related costs are significantly important for the decision making and success of entrepreneurs and industrial organizations. Unlike the actors in financial markets, the participants in commodity markets have different term objectives, for instance, industrial entities, power stations, general population, and standard financial investors. Hence, the resulting time series from such process is a combination of information from several interacting agents operating at different frequencies and distinctive term objectives. Therefore, the standard time series econometric models that consider as segregate the frequency and the time components results in losing information from either one domain. Therefore, in distinction with previous contributions on dependence dynamics between energy commodities, we employ wavelet-based copula to evaluate the connectedness structure over time and in different frequencies. More specifically, we implement maximal overlap discrete wavelet transform (MODWT) as introduced by Percival and Walden (2000) to decompose the underlying return series into short-, medium-, and long-run signal. Furthermore, we evaluate the dependence dynamics between crude oil and other energy commodities by applying time-varying student t-copula on each series. This paper evaluates the dynamic dependence between the futures markets of five energy related commodities over the period from July 2001 to June 2016 using daily data. Our findings indicate that gasoline and heating oil exhibits significantly large and stable dependence structure with crude oil over the original and the decomposed returns series. Furthermore, the dependence structure between crude oil and coal is rather moderate over the short- and medium-run horizon. Whereas, crude oil and natural gas exhibits the price decoupling behavior over the short-run horizon as the linkage structure is close to zero. Finally, our findings indicate that crude oil significantly affects the volatility in other energy commodities.

Methods

Over the recent years, the applied research on dependence dynamics of energy commodities has grown significantly. However, these studies mainly rely on standard time series econometric models, which do not account for information from both time and frequency domain simultaneously. Wavelet transform is an effective tool for time series analysis as it enables us to simultaneously study the time and the frequency component of the underlying series. We employ the maximal overlap discrete wavelet transform (MODWT), which is a modified version of discrete wavelet transform (DWT), to decompose the underlying time series. The DWT decomposes the underlying time series signal X_t into a set of subsequent signals based on two types of filters called the scaling filter and the wavelet filter. Let us denote the wavelet filter and the scaling filter by h_l and g_l where $l = 0, \dots, L-1$, respectively. We can then obtain the jth level wavelet and scaling coefficients, $W_{j,t}$ and $V_{j,t}$, as follows:

$$W_{j,t} = \sum_{l=0}^{L-1} h_{j,l} X_{t-1 \ mod \ N}, \qquad and \qquad V_{j,t} = \sum_{l=0}^{L-1} g_{j,l} X_{t-1 \ mod \ N}.$$

The MODWT scaling and wavelet filter, $\widetilde{g_l}$ and $\widetilde{h_l}$, at jth level of transformation are defined as:

$$\tilde{h}_{j,l} = h_{j,l}/2^{j/2} \qquad \text{and} \qquad \tilde{g}_{j,l} = g_{j,l}/2^{j/2}$$

Similarly, the MODWT wavelet and scaling coefficients can be obtained as follows:

$$\widetilde{W}_{j,l} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{h}_{j,l} X_{t-1 \ mod \ N}, \qquad and \qquad \tilde{V}_{j,l} = \frac{1}{2^{j/2}} \sum_{l=0}^{L-1} \tilde{g}_{j,l} X_{t-1 \ mod \ N}.$$

We chose nearby futures prices of the five energy commodities as they reflect the expectation of investors about the expected spot price. Specifically, our sample consists of energy commodities trading at NYMEX/COMEX, namely, WTI crude oil (CL), natural gas (NG), coal (QL), gasoline (RB), and heating oil (HO). The data is extracted from the commodity research bureau (CRB) database for the period of July 2001 to June 2016. Based on the log-returns, we decompose the underlying series into a set of wavelets capturing short-, medium-, and long-run trend. Furthermore, we employ time-varying student t-copula on each series to evaluate the dependence dynamics between crude oil and other energy commodities over various investment horizon.

Results

Table 1 presents the unconditional correlation analysis between crude oil and energy commodities by employing three alternative measures of dependence, i.e., Pearson, Kendall, and Spearman. Based on the correlation analysis, we can see that the heating oil and gasoline exhibits the strongest correlation with crude oil. The correlation with coal is relatively moderate. Whereas, the dependence dynamics between natural gas and crude oil is weakest in the case of undecomposed returns. It is noteworthy that the undecomposed return series do not provide insight on how the dependence structure varies across different frequencies. Therefore, we decompose the underlying returns series into eight subsequent signals using MODWT and by employing Daubechies (1992) least asymmetric LA(8) wavelet and scaling filter. Furthermore, we employ the correlation measures on the decomposed series to evaluate how the dependence structure varies across short-, medium-, and long-run trends. Specifically, the short-run trend reflects the changes between 2 and 4 succeeding days, medium-run captures the dynamics between 32 and 64 days, and long-run trend provides estimates of 128 and 256 days. In general, the short-run dependencies presented in panel b of Table 1 closely follows the dependence structure of the original returns series for gasoline, coal, and heating oil. However, the dependence structure of natural gas poses negative dependence with crude oil. This indicates that addition of natural gas with crude oil can help in attaining diversification benefits over the short-run horizon. The dependence structure of decomposed return series characterizing the medium-run trend indicates that the linkage became stronger between crude oil and the energy commodities. This provides evidence that with the increase in investment horizon, the potential for portfolio diversification significantly reduces. Similarly, the long-run estimates in panel d indicates a significant upsurge in dependence dynamics with crude oil. It is noteworthy that the correlation between crude oil and coal nearly doubled in the long-run as oppose to short-, and medium-run trend. These findings indicate that the market participants should pay close attention to the crude oil price fluctuations as it can significantly influence the price dynamics of other energy commodities.

Table 1. Undecomposed and multi-scale correlation analysis between crude oil and energy commodities.

The table presents correlation coefficients from Pearson, Kendall, and Spearmann for the undecomposed returns and decomposed series between crude oil and agricultural commodities. Panel B, C, and D presents the coefficients from the decomposed series representing short-, medium-, and long-run trend, respectively.

a) Original returns series

	Pearson	Kendall	Spearman
Gasoline	83.44%	65.19%	82.76%
Coal	23.60%	13.51%	19.40%
Natural gas	6.67%	4.65%	6.92%
Heating oil	89.20%	71.17%	88.15%

b) Short-run trend

	Pearson	Kendall	Spearman
Gasoline	84.91%	66.10%	83.42%
Coal	25.31%	13.56%	19.93%
Natural gas	-0.88%	-0.99%	-1.41%
Heating oil	90.29%	73.01%	89.67%

c) Medium-run trend

	Pearson	Kendall	Spearman
Gasoline	86.47%	66.48%	85.00%
Coal	27.09%	18.96%	27.80%
Natural gas	32.56%	26.06%	37.75%
Heating oil	91.12%	73.37%	90.31%

d) Long-run trend

	Pearson	Kendall	Spearman
Gasoline	87.57%	60.14%	79.04%
Coal	63.09%	28.33%	40.14%
Natural gas	26.32%	9.57%	14.35%
Heating oil	95.24%	72.01%	88.79%

Conclusion

In this paper, we contribute to the co-movement literature of energy commodities by evaluating the interconnection between crude oil and the energy commodities using MODWT and time-varying copula. The main finding of this paper is that some of the energy commodities exhibits strong co-movement over various investment horizons. This suggests the importance of time and spectral components when assessing the dependence between the energy markets. Our analysis indicates that crude oil, gasoline, and heating oil are strongly correlated and thus imply great exposure to risk when added together in a portfolio. The interrelation between crude oil and coal is rather moderate over the short- and medium-run trend, however, it increases significantly over the long-run horizon. On the other hand, natural gas is unrelated with other energy commodities over short-run horizon and thus provides potential for diversification.

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