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Dependence and risk management in oil and stock markets. A wavelet-copula analysis

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ABSTRACT

Using wavelets and copulas, we examined the implications for risk management of the oil-stock dependence structure at different time scales. First, using the Haar à trous wavelet we decomposed the signals into frequency components in order to identify the main lead/lag co-movements before and after the onset of the current global financial crisis, with the watershed occurring on 15 September 2008. Second, we characterized average and tail dependence between oil and stock prices across time scales using a wide range of static and time-varying copula functions. Third, we examined potential diversification and downside risk reduction benefits for different mixed oil-stock portfolios at different time scales. Our empirical evidence reveals that oil-stock return dependence, before 15 September 2008, was weak for finer time scales but increased considerably as the time scale lengthened. After this date, dependence increased significantly for all time scales, providing evidence of contagion and interdependence. We also found evidence of asymmetric tail dependence over the long run before 15 September 2008 and of upper and lower tail dependence thereafter. Finally, we found evidence of diversification benefits and downside risk reductions for some mixed oil-stock portfolios over the short run before 15 September 2008, although the corresponding gains were reduced for coarser time scales. After this date, gains considerably decreased, especially over the long run.

1. Introduction

In recent years, the puzzling swing in crude oil prices, even after the beginning of the financial crisis, has revitalized interest in the impact of oil price shocks on the economy and, in particular, on financial markets. Investors are especially interested to know how oil price shocks affect stock prices and whether this impact has the same intensity in shorter compared to longer time scales. The impact of an oil price shock on stock markets is complex, as any increase in oil prices affects a firm's future cash flows and discount factors. Furthermore, the transmission of these effects to stock prices may vary for different time horizons, with reverberating and repeated effects on cash flows and discount factors. Oil shock transmission to market transactions may also be affected by the time scale, given that oil and stock investors operate according to different investment horizons. Therefore, oil and stock investors need to be aware that the relationship between oil and stock prices may differ at different time scales and under different market circumstances, a fact that has practical implications in terms of portfolio design and risk management.

In this paper, we studied oil and stock market dependence for different time scales using wavelets and copulas. The relationship between oil and stock returns has been investigated extensively, yielding mixed results regarding the impact of oil price movements on stock prices and of oil price volatility on stock market returns. Thus, the existing empirical literature on the oil-stock market relationship provides evidence of a negative link (see, e.g., Refs. [16,33,34,42,53], among others), a positive link (see, e.g., Refs. [6,20,21,41]) and no link (see, e.g., Refs. [5,28,29,37,58]). Other studies have reported that the oil-stock relationship was nonlinear and could change as a result of specific events like the recent global financial crisis (see, e.g., Refs. [8,12,14,17,22,38,47,50,55,62]). However, most of these studies have examined the oil-stock nexus for just 1 or, at most, 2 time scales (the short- and the long-run), paying little attention to the specific dependence structure for oil and stock markets by considering different times scales. In this paper, using

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wavelets and copulas we fill this gap and contribute to the current literature in 3 ways.

First, our research is novel in that, as far as we are aware, this is the first time that the oil-stock market dependence structure is examined at different time scales. We thus extend previous analyses of wavelet oil-stock interactions (see, e.g., Refs. [31,50], Madaleno and Pinho, 2014) by modelling dependence at different time scales using copulas, a methodology that provides information on both average and tail dependence (joint extreme movements). The resulting information enhances understanding of the relationship between oil and stock markets in boom and bust markets at different time scales. Such information is crucial for portfolio decision making and risk assessment for different investment horizons. Likewise, by considering multiscale copula types, we extend previous copula analyses of oil-stock market dependence for a single time scale as applied by several authors (see, e.g., Refs. [2,10,58,60,63]).

Second, we contribute to the literature by examining how the dependence structure between oil and stock markets changed for different time scales before and after the onset of the financial crisis. Thus, our analysis extends the evidence regarding changes in oil or stock market dependence on other markets for a single time scale, as reported by Aloui et al. [1], Reboredo [46], Wen et al. [60] and Reboredo et al. [51].

A third way in which we contribute to the existing oil-stock market empirical literature is that we investigate the implications of multiscale oil-stock average and tail dependence for portfolio management at different time scales. In assessing the risk associated with mixed oil-stock portfolios (compared to a single-stock portfolio) in terms of risk diversification and downside risk gains, we extend copula analyses for a single time scale as performed by Aloui et al. [1] for oil and exchange rates, Boubaker and Sghaier [11] for exchange rates and Reboredo [49]for oil and carbon markets.

Our empirical analysis was conducted for Brent oil and for the MSCI world stock market index for the period January 2000 to June 2015. From a multiscale perspective, we identified breaks in dependence between oil and stock returns by decomposing Brent and MSCI volatilities using the discrete HTW (Haar à trous wavelet) transform introduced by Murtagh et al. [39]. Multiple breaks were detected from the finest to coarsest scales, so the sample was split into 2 subperiods (hereafter referred to as the pre-onset and post-onset periods), with the breakpoint marked by 15 September 2008, the date the Lehman Brothers filed for bankruptcy. Then, to each subsample we applied a two-step procedure that consisted of decomposing the standardized residuals obtained through the appropriate ARMA (autoregressive–moving-average)–GARCH (generalized autoregressive conditional heteroskedasticity) models and then obtaining, from the multiscale uniform variables, the 3D wavelet-based copula densities for both short and long horizons that featured the salient properties of data. We then used a broad set of time-varying copula models to encircle the dependence behaviours across scales. Regarding dependence over different time scales, we found that pre-onset oil-stock return dependence was weak for lower time scales but increased considerably with higher time scales. In contrast, the fact that dependence increased significantly for all time scales in the post-onset period provided evidence of contagion and interdependence. Tail dependence displayed a similar pattern: tail independence for the mid-run, asymmetric dependence for the long-run in the pre-onset period, and increased tail dependence across time scales in the post-onset period. As for the implications of dependence for risk management at different time scales, our results on the potential diversification and downside risk reduction benefits of different kinds of mixed oil-stock portfolios indicate diversification benefits and downside risk reductions in oil-stock portfolios for finer time scales in the pre-onset period; however, these gains varied depending on portfolio composition, with considerably reduced risk gains in the post-onset period, especially for coarser time scales. This evidence is consistent with the change in the dependence structure of the oil and stock markets.

The remainder of the article is organized as follows. In Section 2, we describe the HTW and the copula methodology, along with the different types of copula functions characterizing dependence structures. In Section 3 we describe the main features of our data and discuss preliminary results. In Sections 4 and Section 5, we report our results regarding oil-stock dependence for different time scales and discuss the implications for risk analysis. Finally, Section 6 concludes the paper.

2. Methodology

Below we briefly describe, in turn, the HTW methodology for decomposing oil and stock price returns for different time scales and the copula methodology for characterizing dependence structures. We also discuss the relevance and limitations of the proposed wavelet-copula approach.

2.1. Wavelets

2.1.1. Discrete wavelet transform

The application of discrete wavelet transforms to time series analysis potentially suffers from a lack of translation invariance. To overcome this problem, several authors recommend using redundant or non-decimated wavelet transforms (see, e.g., Ref. [19]). A redundant algorithm is based on what is referred to as an autocorrelation shell representation that uses dilations and translations of the autocorrelation functions of compactly supported wavelets. Scaling and wavelet functions are chosen to satisfy the following equations (respectively):

$$\frac{1}{2} \times \varphi\left(\frac{x}{2}\right) = \sum_k h(k)\varphi(x-k), \tag{1}$$

$$\frac{1}{2} \times \psi\left(\frac{x}{2}\right) = \sum_k g(k)\psi(x-k), \tag{2}$$

where h is a discrete scaling low-pass filter and where g refers to a discrete high-pass filter associated with the wavelet function. The smoothed and detailed signals for a given resolution j and for a position t are obtained by the following convolutions (respectively):

$$s_j(t) = \sum_{l=-\infty}^{+\infty} h(l)s_{j-1}\left(t + 2^{j-1} \times l\right), \tag{3}$$

$$d_j(t) = \sum_{l=-\infty}^{+\infty} g(l)s_{j-1}\left(t + 2^{j-1} \times l\right). \tag{4}$$

An important property of the autocorrelation shell coefficients is that signals can be directly derived from them. In each step, the series is convolved with a cubic B-spline filter h with $(2j-1) \times 1$ zeros inserted between the B-spline filter coefficients at level j. We thus obtain a series of smoothed versions s_j, where s_0, the finest scale, refers to the normalized raw series. Given a smoothed signal at 2 consecutive resolution levels, the detailed signal $d_j(t)$ at level j can be derived as:

$$d_j(t) = s_{j-1}(t) - s_j(t). \tag{5}$$