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A wavelet based approach to measure and manage contagion at different time scales

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HIGHLIGHTS

- We apply wavelet analysis to study tail dependence between US stocks.
- Based on decomposed time series we build portfolios that minimize short-run volatility.
- Stronger dependence between US stocks is not only present after the outbreak of financial crisis (2008) but also in the long run.
- Portfolios that minimize the short-run volatility outperform portfolio compositions that are based on raw return series.

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ABSTRACT

We decompose financial return series of US stocks into different time scales with respect to different market regimes.

First, we examine dependence structure of decomposed financial return series and analyze the impact of the current financial crisis on contagion and changing interdependencies as well as upper and lower tail dependence for different time scales.

Second, we demonstrate to which extent the information of different time scales can be used in the context of portfolio management. As a result, minimizing the variance of short-run noise outperforms a portfolio that minimizes the variance of the return series.

1. Introduction

As dependence between financial asset returns tends to increase in turmoil market times [1–3], portfolio diversification becomes less effective when needed the most. Moreover, as extreme observations of stock market returns affect dependence of financial assets asymmetrically (see Refs. [4–6] or [7]), so to say, dependence increases in collective market downturns, linear correlation measure lacks in capturing this asymmetric dependence. Additionally, triggered by the fact that linear correlation does not capture tail dependence and nonlinear transformations of the marginal return distribution, the application of copulas (introduced to financial time series by Embrechts et al. [8]) has become a widely accepted tool to capture nonlinear dependences such as tail dependence between financial time series (see Refs. [1,9–11,7]).

Another growing field of research in the context of dependence analysis, initially applied to signal processing (i.e. Mallat [12] and Starck et al. [13]) is represented by decomposing time series via wavelet decomposition into different components accounting for characteristics of particular time frequencies, so called time scales. In contradiction to Fourier Analysis, which is mainly applied to spectral analysis, the localization of a certain event in time is still possible (see Refs. [14–16]) and wavelet decomposition enables us to filter any given signal into a time-scale presentation. However, the non-decimated

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wavelet decomposition by Percival and Walden [17] ensures the localization of an event in any time scale and short-run dependence and long-run persistence can be analyzed by explicitly focusing on the respective time scales of decomposed series. Although the wavelet approach goes back to Mallat [12], its application to financial time series is relatively new (see Refs. [18,19]).

Gallegati [3] applies this frequency domain analysis by decomposing return series of financial markets and defines a short rise of dependence as contagion and a persistent raise in dependence structure between two assets as interdependence. Based on the wavelet decomposition of return series into different time scales, the correlation coefficients of different frequencies indicate that contagion between international stock markets affects not only short-term movements but also long-term correlation. As well, Boubaker and Sghaier [20] decompose return series of financial markets into different time scales to assess the presence of long memory behavior of dependence between stock markets and currencies. Aloui and Hkiri [21] investigate co-movements of fragmented return series of emerging stock markets and Lo Cascio [22] decomposes UK real GDP to investigate higher time scales (the long-run structure) of the data apart from external short-run shocks that are captured by lower time scales. Reboredo and Rivera-Castro [23] analyze dependence between oil prices and stock returns and Jammazi and Aloui [24] combine wavelets with neural networks to investigate crude oil prices. Fernandez-Macho [25] finds high correlations between European stock markets in the long run, Huang et al. [26] find high correlations between crude oil prices and futures in the middle run and Dewandaru et al. [27] assess contagion between Asian stock markets.

However, as most of the studies investigate the dependence between decomposed return series of stock indices, commodities or exchange rates, we add to the literature by exploring dependence structure between decomposed return series of stocks with regard to financial portfolio optimization. In particular, we analyze return series that are listed in the Dow Jones Industrial Index (DJI) in the time from 2000–2013.

Analogous to Gallegati [3] and Dewandaru et al. [27], we define a short raise of dependence after a shock as contagion and higher dependences in the long run as interdependency. Further, we apply the discrete wavelet decomposition to decompose financial return series into different time scales. Additionally, as proposed by Boubaker and Sghaier [20], we apply elliptical and Archimedean copulas accounting for symmetric and asymmetric tail dependence and explicitly investigate the impact of changing dependence regimes for each time scale in calm and turmoil market times. Along the lines of Gallegati [3], we discriminate between contagion and interdependence and add to the correlation analysis of the author by allowing for tail dependences within each time scale.

Further, we underline the importance of our analysis for applied portfolio management by illustrating to which extent the information of each time scale can be used to model portfolio composition. More concretely, to the best of our knowledge we are the first to assess the performance of minimum variance portfolio strategies as defined by Markowitz [28], by minimizing the variance of different time scales and show that minimizing the covariance matrix of short-run noise outperforms the "classical" minimum variance approach based on return series in terms of risk adjusted performance measure.

The remainder of the paper is structured as follows: Section 2 states the relevant methodology and in Section 3 we present the data and the decomposed return series. In Section 4 we evaluate the dependences between the decomposed return series and show up the relevance for portfolio management and Section 5 concludes.

2. Methodology

2.1. Wavelet analysis

Wavelet methods allow for the decomposition of a time series into several components, each of which accounts for the time series properties of a particular frequency band. In particular, wavelet decomposition allows to tell apart short-term characteristics from the long-run properties of a time series.

The balance point of wavelet decomposition is given by the choice of wavelet filter. In this vein, the applied wavelet filter (h_l) to decompose the signal X need to fulfill the following criteria:

$$\sum_{l=0}^{L-1} h_l = 0, \tag{1}$$

$$\sum_{l=0}^{L-1} h_l^2 = \frac{1}{2}, \tag{2}$$

and

$$\sum_{l=0}^{L-1} h_l h_{l+2n} = 0, \tag{3}$$

for all integers n with L as the length of the filter.

Eq. (1) ensures that within the applied filter length, deviations above 0 get neutralized by deviations below 0 whereas Eq. (2) ensures that deviations do exist and according to Eq. (3), are described by orthogonality to even shifts. This is where the name wavelet originally comes from, since Eqs. (1) and (2) lead to "small waves".