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RESEARCH ARTICLE

# Short-run wavelet-based covariance regimes for applied portfolio management

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## Abstract

Decisions on asset allocations are often determined by covariance estimates from historical market data. In this paper, we introduce a wavelet-based portfolio algorithm, distinguishing between newly embedded news and long-run information that has already been fully absorbed by the market. Exploiting the wavelet decomposition into short- and long-run covariance regimes, we introduce an approach to focus on particular covariance components. Using generated data, we demonstrate that short-run covariance regimes comprise the relevant information for periodical portfolio management. In an empirical application to US stocks and other international markets for weekly, monthly, quarterly, and yearly holding periods (and rebalancing), we present evidence that the application of wavelet-based covariance estimates from short-run information outperforms portfolio allocations that are based on covariance estimates from historical data.

## KEYWORDS

portfolio management, short-run trends, wavelet decomposition

## 1 | INTRODUCTION

Capital allocation between volatile stocks is at the center of portfolio formation decisions, and adequate estimates of the unknown covariance matrix describe crucial information for strategic portfolio allocations. Historical data contain information about both short- and long-run information, and conclusions drawn from respective covariance estimates provide limited insight regarding periodical diversification opportunities.

In this paper, we introduce a wavelet-based approach to improve the future performance of portfolio allocations. Employing a multi-horizon nonparametric filter—the wavelet transformation—we develop a covariance estimator to distinguish between newly embedded information content of underlying historical market prices and news

that has been fully absorbed by the market.<sup>1</sup> To assess the relevance of competing information components, we apply a simple mean-variance efficient portfolio allocation algorithm and study the out-of-sample performance of wavelet-based covariance estimates.<sup>2</sup>

<sup>1</sup>Wavelet decomposition describes an adequate approach to filter financial time series. In comparison to alternative filtering methods—that is, Fourier analysis—wavelet decomposition does not require periodicity in financial time series, events can be localized, and it is applicable to multivariate time series. For a thorough study on the advantages of the application of wavelet transformation to financial time series, we refer to Gençay et al. (2005), Conlon et al. (2018), and the references therein.

<sup>2</sup>The concept of mean-variance portfolio optimization, as introduced by Markowitz (1952), represents a widely accepted approach that takes account of the quantitative tradeoff between risk and return of an investment. As described by Kolm et al. (2004), Markowitz's portfolio diversification has been instrumental in the development and understanding of financial markets, whereas adequate estimates of the unknown covariance matrix of the underlying assets represent crucial information that determines strategic portfolio allocations (see DeMiguel et al., 2009; Mailliet et al., 2015).

Ramazan Gençay passed away after this manuscript had been completed.

News arrives at markets at certain times expectedly as proxied by analysts, but also at times it arrives unexpectedly. Typically, news would cause the evolution of the historical price to deviate significantly from its long-term average; such deviations may or may not be permanent. Depending on the nature of such news, the historical volatility pattern of the data, and the nature of the seasonal patterns, the full extent of the news impact may not be obvious from observing the raw data. Namely, a certain threshold of newly embedded deviations may be blended with long-term average features of the data, radiating an illusion that changes are not as large, attributing short-run changes falsely to long-term growth. Therefore, it is not necessarily rewarding to work with raw data directly to identify shorter term newly embedded covariances, but to split the raw data into its short-run and long-run components.

To identify different covariance regimes, we draw on Berger and Gençay (2018) and Conlon et al. (2018) and apply wavelet decomposition, which is well suited to identify short-run and long-run regimes of the underlying return series. Initially, wavelet decomposition was introduced into financial return series by Percival and Walden (2000) and Gençay et al. (2001). Since then, the application of signal processing techniques to financial data triggered a growing field of research that mainly deals with the decomposition of financial return series into short-run and long-run trends. For instance, Gençay et al. (2010) provide evidence for the existence of different financial volatility regimes across different trends, and Gençay et al. (2005) apply the capital asset pricing model (CAPM) to deconstructed return series of international stock indices and illustrate that fundamental risk increases for long-run trends. Rua and Nunes (2012) confirm this finding for emerging markets, whereas Gallegati (2012) deconstructs return series of stock market indices of the G7 countries, Brazil, and Hong Kong to assess changing correlation regimes between deconstructed return series. Conlon et al. (2018) also study wavelet-based correlation estimates of G7 countries and provide evidence for different patterns between deconstructed return series; in particular, dependence between long-run seasonalities appears to be stronger than suggested by the original data.<sup>3</sup>

Moreover, as wavelet transformation does not only allow for a deconstruction but also for a reconstruction

of a deconstructed financial return series, Berger and Gençay (2018) present a novel approach which allows the investor to reconstruct deconstructed financial return series by excluding particular information components of the underlying data. Also, Conlon et al. (2018) reconstruct financial return series to assess correlation estimates. In this study, we add to this literature and empirically study the out-of-sample performance of portfolios that consider covariance estimates of deconstructed return series. In contrast to the growing field of literature that deals with dependence between denoised long-run trends of financial data, our results provide evidence that it is the covariance of short-run regimes that describes the relevant information for out-of-sample portfolio performances.<sup>4</sup>

Specifically, we expand the analysis of univariate return series by Berger and Gençay (2018) and apply a wavelet filter to deconstruct return series into different covariance regimes and reconstruct the return series by taking either short-run, middle-run, or long-run regimes into account. Furthermore, based on the reconstructed versions of the original return series, we discuss simple mean-variance efficient portfolio optimization and assess its out-of-sample performance. Analogous to DeMiguel et al. (2009) and Maillet et al. (2015) we evaluate the risk-adjusted performance of competing portfolio allocations and the setup of the assessment will be twofold.

First, we set up a simulation analysis, and simulate return series which are described by different patterns of long-memory effects to assess the relevance of short- and long-run memory of a return series on portfolio allocations. By investigating reconstructed return series that take either short-run or long-run memory into account, we shed light on the relevant information for applied portfolio management in the presence of incomplete information on the underlying market conditions.

Second, we assess the out-of-sample performance of mean-variance efficient portfolios that are based on reconstructed return series and compare the performance with the mean-variance efficient portfolio allocations based on daily raw data. To take account of different market sizes and regimes, we assess stocks that are listed at leading indices of both developed and emerging stock markets. We also take account of different holding periods and assess daily, weekly, monthly, quarterly, and yearly portfolio rebalancing. The results indicate that middle-run and long-run covariance regimes should be excluded from the original time series, as it impacts the out-of-sample performance of daily portfolio management.

The findings add to the results of Berger and Gençay (2018) and Conlon et al. (2018), and to papers on covari-

<sup>3</sup>Reboredo and Rivera-Castro (2014) assess dependence between deconstructed European and US stocks and oil prices and find evidence of increased dependence between long-run seasonalities after 2008. Dewandaru et al. (2015) analyze dependence between Asian stocks, Andries et al. (2014) between interest rates, stock prices, and exchange rates, and Tan et al. (2014) analyze dependence between US and Asian equity markets.

<sup>4</sup>See Gallegati (2012), Berger and Uddin (2016), and the references therein.

ance estimates that help improve mean-variance optimization problems.<sup>5</sup> We demonstrate the identification of relevant covariance regimes for periodical mean-variance portfolio optimization and present an innovative application of wavelet-based portfolio optimization. The introduced approach allows the investor to extract short-run regimes of financial return series in order to improve out-of-sample performance metrics.

The paper is structured as follows. Section 2 describes the relevant methodology, and the empirical portfolio analysis is presented in Section 3. Results regarding the simulation study are given in Section 4, and Section 5 concludes.

## 2 | METHODOLOGY

In this section, we present a methodological approach of wavelet filtering that enables us to deconstruct and reconstruct the short-run component of the underlying return series. In addition, we introduce the portfolio allocation algorithm, which will be applied to the reconstructed return series and quality criteria of our analysis.

### 2.1 | Maximal overlap discrete wavelet transform

We introduce the maximal overlap discrete wavelet transform (MODWT) as described by Gençay et al. (2001) and Percival and Walden (2000).<sup>6</sup> The MODWT approach describes an expansion of the classical approach of discrete wavelet transformation (DWT; see ; Zhu et al., 2014). As the number of observations remains constant at each level of decomposition and is characterized by shift invariance, the MODWT approach is predestined for a rolling window out-of-sample analysis.<sup>7</sup>

As presented by Gençay et al. (2001), the choice of wavelet filter is directly linked to a scaling filter and describes the core of wavelet decomposition. Let  $h_{j,l}$  be the

DWT wavelet filter, with  $l = 1, \dots, L$  describing the length of the filter and  $j = 1, \dots, J$  the level of decomposition, then the corresponding scaling filter is determined by  $g_{j,l}$ .<sup>8</sup>

Further, as the MODWT filter describes an expansion of the DWT concept, the MODWT wavelet and scaling filter are directly obtained from DWT filters by

$$\tilde{h}_{j,l} = h_{j,l}/2^{j/2} \quad (1)$$

and

$$\tilde{g}_{j,l} = g_{j,l}/2^{j/2}. \quad (2)$$

In this vein, as the underlying data of this study are described by daily return series,  $r = \{r_t, \quad t = 1, 2, \dots, N\}$ , to deconstruct the series into  $J$  frequencies, wavelet coefficients of level  $j$  are achieved by the convolution of  $r$  and the MODWT filters (see Percival & Walden, 2000):

$$\tilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} r_{t-l} \mod N \quad (3)$$

and

$$\tilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} r_{t-l} \mod N, \quad (4)$$

with  $L_j = (2^j - 1)(L - 1) + 1$ . In contrast to DWT, the application of MODWT results in wavelet coefficients that comprise the same number of observations at all scales and which can be expressed in matrix notation:

$$\tilde{W}_j = \tilde{\omega}_j r \quad (5)$$

and

$$\tilde{V}_j = \tilde{v}_j r. \quad (6)$$

As we aim to utilize MODWT for an out-of-sample portfolio application, we are interested in the maximum number of boundary-free coefficients. Therefore, we use the Haar filter that has the smallest number of coefficients leading to  $\tilde{h}_{1,0} = \frac{1}{2}$ ,  $\tilde{h}_{1,1} = -\frac{1}{2}$  and  $\tilde{g}_{1,0} = \frac{1}{2}$ ,  $\tilde{g}_{1,1} = \frac{1}{2}$  for  $j = 1$ .

Due to the fact that our study aims at the exclusion of particular regimes from the original return series, we make use of the properties of wavelet analysis that allow for a reconstruction of the deconstructed series. Thus, based on the MODWT-specific concept of multiresolution analysis (MRA), the underlying original return series can be reconstructed by simply summing up all coefficients and the smoothed version of decomposition step  $J$ :

$$r = \sum_{j=1}^J \tilde{\omega}_j^T \tilde{W}_j + \tilde{v}_J^T \tilde{V}_J = \sum_{j=1}^J \tilde{D}_j + \tilde{S}_J. \quad (7)$$

In this setup  $\tilde{D}_j = \tilde{\omega}_j^T \tilde{W}_j$  describes the detail coefficients and  $\tilde{S}_J = \tilde{v}_J^T \tilde{V}_J$  the corresponding smoothed version of the return series. Further,  $\tilde{D}_j$  functions as the local details of

<sup>5</sup>For example, Maillet et al. (2015) assess financial data and present a two-step algorithm based on least squares regressions to achieve robust portfolio allocations with respect to parameter uncertainty. Palczewski and Palczewski (2014) study the impact of sampling frequency and covariance error on mean-variance portfolio allocation and find that the estimation error of covariance matrices is market specific. Also, Harvey et al. (2010) incorporate higher moments of the return distributions to improve robustness of portfolio optimization and conclude that information on skewness and kurtosis helps improve the out-of-sample performance of mean-variance efficient portfolios. Levy and Kaplanski (2015) assume that financial returns can be described by different volatility regimes and demonstrate the costs of ignoring this fact within the mean-variance framework.

<sup>6</sup>In contrast to Fourier analysis, the decomposition of a return series via wavelet approach events can be localized throughout the decompositions.

<sup>7</sup>Due to boundary conditions, only the observations at the beginning of each series are reduced.

<sup>8</sup>The respective scaling (low-pass) filter  $g_{j,l}$ , depends on  $h_{j,l}$  by quadratic mirror filtering and is given by  $g_l = -1^l h_l$

the trend at level  $j$  and captures the short-term dynamics (low levels) of the original return series, whereas long-term fluctuations are described by high levels. Consequently,  $\tilde{S}_j$  is defined as the smoothed version (longer term moving weighted averages) of the time series.

Based on the introduced setup, which allows for a decomposition and reconstruction of the underlying return series, we follow Berger and Gençay (2018) and reconstruct deconstructed return series by excluding particular levels of decomposition.

Hence, after a return series is deconstructed into  $J$  scales, we reconstruct the series by excluding the highest scales that comprise the long-run information of the underlying return series. More concretely, in our analysis we deconstruct every series eight times and discuss three different reconstructed versions of the original return series:

$$r_{\text{SR}} = \sum_{j=1}^3 \tilde{D}_j, \quad (8)$$

$$r_{\text{MR}} = \sum_{j=4}^5 \tilde{D}_j, \quad (9)$$

$$r_{\text{LR}} = \sum_{j=6}^8 \tilde{D}_j. \quad (10)$$

Consequently, based on eight decomposition levels of the original return series, we achieve three reconstructed versions of the original return series that exclusively comprises the information of interest by summing up the relevant detail coefficients.

Table 1 provides the underlying economic interpretation of the detail coefficients for daily return series. For instance, the short-run regime ( $r_{\text{SR}}$ ) comprises changes within a month ( $\tilde{D}_1, \tilde{D}_2, \tilde{D}_3$ ), middle-run ( $r_{\text{MR}}$ ) changes within 3 months ( $\tilde{D}_4, \tilde{D}_5$ ), and long-run regime ( $r_{\text{LR}}$ ) comprises changes between half a year and 2 years ( $\tilde{D}_6, \tilde{D}_7, \tilde{D}_8$ ). For a thorough introduction to MODWT in the context of financial data we refer to Gençay et al. (2001), and for an intuitive economic introduction to wavelet analysis we refer to Crowley (2007) and Gençay et al. (2010).

**TABLE 1** Economic interpretation of deconstructed daily return series

Definition	Horizon	Detail
Short run	2–4 days	D1
Short run	4–8 days	D2
Short run	8–16 days	D3
Middle run	16–32 days	D4
Middle run	32–64 days	D5
Long run	64–128 days	D6
Long run	128–256 days	D7
Long run	256–512 days	D8

## 2.2 | Portfolio allocation

Based on a historical financial return series, including its filtered versions (see Equations 8 and 9), we introduce the competing versions of the original return series (comprising short run, middle run and long run, respectively) to the portfolio optimization problem.

Owing to the focus on the return series, we apply the covariance matrices of the reconstructed return series to the widely accepted Markowitz portfolio optimization setup (see Markowitz, 1952) and assess the global minimum variance allocation, whereby we restrict our analysis to the absence of short sellings:

$$\min_{w_t} w_t^T H_t w_t \quad \text{s.t.} \quad 1_N^T w_t = 1. \quad (11)$$

In this setup, only the estimate of the covariance matrix ( $H_t$ ) of the underlying series (either original or reconstructed) impacts portfolio allocations. As this strategy ignores expected returns, differences between portfolio allocations are directly linked to differences in the underlying covariance matrices.<sup>9</sup>

In order to discuss the relevance of the underlying covariance matrices that contain information on different seasonalities, we assess the out-of-sample performance of the mean-variance efficient portfolio allocation by competing performance metrics. In this vein, we apply competing evaluation criteria as presented in DeMiguel et al. (2009) and evaluate the out-of-sample returns by different performance metrics.

In order to compare portfolio allocations that aim at minimizing covariance of particular seasonalities, we define allocations based on raw data as the benchmark and assess the information ratio of strategy  $k$  against a benchmark  $b$  strategy. As presented by Grinold and Kahn (2000), an adequate information ratio is given as follows:

$$\text{IR}_k = \frac{\frac{1}{n} \sum (r_k - r_b)}{\hat{\sigma}_{\text{TE}}} = \frac{\hat{\mu}_{\text{TE}}}{\hat{\sigma}_{\text{TE}}}. \quad (12)$$

Here,  $r_k$  and  $r_b$  describe the vector of portfolio returns for strategy  $k$  and  $b$  respectively,  $\frac{1}{n} \sum (r_k - r_b)$  is the average tracking error ( $\hat{\mu}_{\text{TE}}$ ), and  $\hat{\sigma}_{\text{TE}}$  describes the standard deviation of the tracking error—that is, portfolio return relative to benchmark returns.<sup>10</sup> We define covariance estimates that take the unfiltered return series into account as the benchmark, and therefore this information ratio allows us to quantify the difference between the out-of-sample performance of wavelet-based covariance estimates. Specifically, we compare the impact of excluded information against covariance estimates based on nonfiltered series to

<sup>9</sup>We refer to Jagannathan and Ma (2003) for a thorough discussion on the impact of competing restrictions for applied portfolio management.

<sup>10</sup>The standard deviation is defined as  $\hat{\sigma}_{\text{TE}} = \sqrt{\frac{1}{n} \sum (r_k - r_b)^2}$ .



evaluate the information content of short-run, middle-run, and long-run information components.

Additionally, we also assess the risk-adjusted out-of-sample returns by assessing the out-of-sample Sharpe ratio of strategy  $k$  to gain deeper insights into the structure of the competing out-of-sample returns:

$$SR_k = \frac{\hat{\mu}_k}{\hat{\sigma}_k}. \quad (13)$$

Here,  $\hat{\mu}_k$  describes the out-of-sample returns generated by strategy  $k$  divided by their sample standard deviation  $\hat{\sigma}_k$ . This ratio allows us to compare average out-of-sample return and volatility of each strategy with each other. Doing so enables us to gain deeper insights into the nature of out-of-sample returns and allows us to compare the impact of short-run, mid-run, and long-run information on both out-of-sample volatility and return from an investor's perspective.

To add to the Sharpe ratio performance, especially in the case of negative average returns, we assess two alternative measures that add to the information provided by the Sharpe ratio.

As introduced by Sortino and van der Meer (1991), we assess the Sortino ratio as a natural extension of the Sharpe ratio to take account of the asymmetric pattern of financial volatility:

$$SoR_k = \frac{\hat{\mu}_k}{\sqrt{\frac{1}{n} \sum_{t=1}^T [\min(r_k, 0)]^2}}. \quad (14)$$

This ratio allows us to study the impact of wavelet decomposition on the left tail of the return distribution. That is, we will analyze the impact of covariance estimates, which exclusively take particular information components into account, on the distribution of negative out-of-sample returns.

Additionally, as described by Shadwick and Keating. C. (2002), we take into account the  $\Omega$ -ratio, to capture the information in the higher moments of wavelet-out-of-sample return distributions to provide deeper insights into the impact of wavelet-based covariance estimates:

$$OR_k = \frac{\int_0^\infty [1 - F(r_k)] dr_k}{\int_0^\infty F(r_k) dr_k}. \quad (15)$$

As we deal with daily prices, we set the threshold to 0, which leads us to distinguish between upside and downside potential.<sup>11</sup>

### 3 | SIMULATION ANALYSIS

In order to assess the relevance of different information components, we set up a simulation analysis that allows us to control for the existence of long-memory effects of the underlying return series. As the introduced deconstruction of financial return series via wavelet transformation implies a decomposition of variance and covariance of the underlying return series (see Percival & Walden, 2000), the decomposition of financial return series leads to a decomposition of both the risk of an asset (conditional variance) and diversification effects between assets (covariance), whereas information on different seasonalities (i.e., short run, middle run and long run) directly impacts portfolio optimization. Thus the aim of this simulation study is to mimic both realistic volatility and dependence schemes of financial assets. Therefore, we draw on the presented simulation analysis in Berger and Gençay (2018) and simulate daily return series that are characterized by different memory regimes (short run, middle run, and long run). Additionally, we introduce time-varying dependence structure as described by Engle (2009) to assess the performance of portfolio allocations that take particular covariance regimes into account.

#### 3.1 | Setup of the analysis

To mimic the conditional volatility patterns of daily return series, we assume a process that is described by time-varying conditional volatility. For that reason, we apply an extension of the widely accepted GARCH approach (Bollerslev, 1986) to simulate daily return series of realistic length. Specifically, we control for memory effects by applying the FIGARCH(1,  $d$ , 1) approach as presented by Baillie and Morana (2009) to generate conditional volatility processes, which are given as follows:

$$\sigma_t^2 = \Omega + (1 - \beta(L) - \phi(L)(1 - L)^d)r_{t-1}^2 + \beta\sigma_{t-1}^2. \quad (16)$$

Here,  $\Omega$  describes a constant and  $r_{t-1}$  the return from the previous period. The parameter  $d$  controls for the memory of the process and allows the autocorrelation of the process to decay at a hyperbolic rate, whereas  $\phi(L)$  and  $\beta(L)$  describe the lag polynomials. According to Baillie and Morana (2009), the parameters will be estimated via maximum-likelihood method under the assumption of normality.

As presented by Gençay et al. (2001), FIGARCH(1,  $d$ , 1) processes with  $d \in [0, 0.5]$  are predestined to mimic conditional financial return variance with different memory schemes, whereas the memory of the conditional volatility increases with  $d$ . Because of that, we apply different parametrizations of  $d = 0.05, 0.15, 0.35$  and  $0.45$  to discuss four different memory schemes, namely the transition

<sup>11</sup>For a thorough introduction to out-of-sample assessment of financial portfolio allocations, we refer to DeMiguel et al. (2009) and the references therein.

from short-term memory ( $d = 0.05$ ) to long-term memory ( $d = 0.45$ ); additionally, to control for the memory of the simulated return series, and assume a constant mean return.<sup>12</sup>

As we focus on portfolio allocations based on simulated return series, we assess multiple simulated return series simultaneously and introduce realistic dependence schemes between the simulated univariate return series. In line with stylized facts concerning the dependence of financial return series—that is, dependence varies over time—we introduce time-varying dependence via a dynamic conditional correlation (DCC) approach, as introduced by Engle (2002).

For this reason, as presented by Engle (2009), based on multiple simulated FIGARCH(1,  $d$ , 1) series, we implement the assigned DCC structure between series  $i$  and series  $j$  following an iterative multiperiod process. Let  $\bar{R}$  be the sample correlation and  $\alpha_{DCC}$  and  $\beta_{DCC}$  the DCC parameters. Based on this step, we proceed iteratively, so to speak, conditionally on period  $t$ , and model the dependence structure between asset  $i$  and  $j$  for  $t + 1$ :

$$Q_{t+1} = (1 - \alpha_{DCC} - \beta_{DCC}) * \bar{R} + \alpha_{DCC} * (e_{i,t}^{sim} e_{j,t}^{sim}) + \beta_{DCC}(Q_t), \quad (17)$$

$$R_{t+1} = \text{diag} \left\{ Q_{t+1}^{-1/2} \right\} Q_{t+1} \text{diag} \left\{ Q_{t+1}^{-1/2} \right\}, \quad (18)$$

$$(e_{i,t+1}^{sim} \ e_{j,t+1}^{sim}) = (e_{i,t+1} \ e_{j,t+1}) * \sqrt{R_{t+1}}. \quad (19)$$

Here, parameters  $\alpha_{DCC}$  and  $\beta_{DCC}$  control for the news impact and persistence of the process. As described in Engle (2009), financial return series are typically described by a parametrization of  $\alpha = 0.05$  and  $\beta = 0.90$ .<sup>13</sup> As a target correlation, we mimic stocks that are listed under the same index and assume slightly positive correlated assets to assess a portfolio that consists of five simulated stocks that are characterized by a correlation matrix as follows:<sup>14</sup>

$$\bar{R} = \begin{bmatrix} 1 & 0.8 & 0.4 & 0.3 & 0.5 \\ & 1 & 0.2 & 0.1 & 0.3 \\ & & 1 & 0.4 & 0.1 \\ & & & 1 & 0.7 \\ & & & & 1 \end{bmatrix}. \quad (20)$$

Based on the simulated return series, we deconstruct each series into three different trends, as described by Equations 7–10 in Section 2.1. Then, we estimate the

mean-variance efficient portfolio allocations (Equation 11) based on the deconstructed and the original return series and analyze the out-of-sample performance of each allocation strategy via rolling window analysis.

The setup of the simulation study can be summarized as follows:

1. We generate five return series comprising 1,500 observations via the FIGARCH(1,  $d$ , 1) approach ( $r^{sim}$ ).
2. We introduce time-varying conditional correlation via the DCC approach.
3. We deconstruct each return series via the MODWT approach.
4. We reconstruct the deconstructed return series and achieve  $r_{SR}^{sim}$ ,  $r_{MR}^{sim}$  and  $r_{LR}^{sim}$ , and the simulated return series  $r^{sim}$ .
5. We build mean-variance efficient portfolios via the rolling-window approach. The size of the window is 500 days and we analyze 1,000 out-of-sample portfolio returns.
6. We assess the out-of-sample performance via the introduced quality criteria (see Section 2.2).

For each parametrization of  $d$  we repeat the simulation 1,000 times to assess the robustness of the results.<sup>15</sup>

### 3.2 | Results of the analysis

As the results of the conducted simulation analysis do not differ markedly for different parametrizations of DCC parameters by each simulation run, in the remainder of this section we present the analysis of the average statistics of each memory scenario.<sup>16</sup>

Table 2 presents the results of the conducted simulation analysis. That is, for four different scenarios of time series memory ( $d = 0.05$ ,  $d = 0.15$ ,  $d = 0.35$ , and  $d = 0.45$ ), we assess the performance of portfolio allocations that minimize the covariance matrix of reconstructed return series that exclusively take into account short-run (SR), middle-run (MR), or long-run information (LR) of the original series. As a benchmark, we assess portfolio allocations based on the original (raw) simulated return series (Original).<sup>17</sup> The presented results describe the out-of-sample performance for 1,000 days.

The absolute average returns increase when the simulated return series are characterized by longer memory ( $-0.036\%$  for  $d = 0.05$  and  $-0.231\%$  for  $d = 0.45$ ).

<sup>12</sup>It should be noted that the application of an AR process impacts the memory of the underlying return series and makes it difficult to control for the memory of the underlying return series. Moreover, we discuss both positive and negative average returns.

<sup>13</sup>A detailed description on the simulation of time-varying conditional correlation is given by Berger (2016).

<sup>14</sup>The values of the applied correlation matrix are similar to average correlations of US stocks that are listed in the Dow Jones Index (DJI).

<sup>15</sup>Note that this setup describes a multivariate extension of the simulation of univariate return series as presented in Berger and Gençay (2018).

<sup>16</sup>Individual statistics for all 1,000 simulations for each scenario are available upon request. Furthermore, as the presented results are robust against simulated upward and downward trends, we present the results for simulated return series characterized by negative average returns.

<sup>17</sup>The memory scenarios are similar to Berger and Gençay (2018).

**TABLE 2** Out-of-sample results of the applied simulation study

	Original	SR	MR	LR
<i>d</i> = 0.05				
$\bar{r}_{sim}$	-0.036%	-0.036%	-0.037%	-0.035%
min	-0.535%	-0.535%	-0.535%	-0.550%
max	0.334%	0.334%	0.327%	0.338%
$\bar{\sigma}_{sim}$	0.0009	0.0009	0.0009	0.0009
IR <sub>mv</sub>		0.044	-0.035	0.026
TE <sub>mv</sub>		0.0000	0.0001	0.0004
<i>d</i> = 0.15				
$\bar{r}_{sim}$	-0.066%	-0.066%	-0.066%	-0.070%
min	-0.92%	-0.92%	-0.91%	-1.04%
max	0.79%	0.79%	0.79%	0.93%
$\bar{\sigma}_{sim}$	0.0022	0.0022	0.0022	0.0025
IR <sub>mv</sub>		0.002	0.004	-0.035
TE <sub>mv</sub>		0.0001	0.0002	0.0011
<i>d</i> = 0.35				
$\bar{r}_{sim}$	-0.150%	-0.150%	-0.150%	-0.145%
min	-1.42%	-1.40%	-1.49%	-1.64%
max	1.05%	1.06%	1.09%	1.45%
$\bar{\sigma}_{sim}$	0.0028	0.0028	0.0029	0.0034
IR <sub>mv</sub>		-0.053	0.032	0.033
TE <sub>mv</sub>		0.0001	0.0003	0.0015
<i>d</i> = 0.45				
$\bar{r}_{sim}$	-0.231%	-0.232%	-0.238%	-0.237%
min	-10.03%	-10.03%	-10.03%	-10.71%
max	10.38%	10.38%	10.41%	11.68%
$\bar{\sigma}_{sim}$	0.0202	0.0203	0.0203	0.0213
IR <sub>mv</sub>		-0.007	-0.085	-0.022
TE <sub>mv</sub>		0.0004	0.0008	0.0025

Note.  $\bar{r}_{sim}$  describes the average out-of-sample return of the mean-variance efficient portfolio, min and max describe the respective minimum and maximum out-of-sample returns, and  $\bar{\sigma}_{sim}$  gives the average standard deviation. IR<sub>mv</sub> describes the sum of deviations from the applied benchmark strategy and TE<sub>mv</sub> describes the ratio of average deviation from the benchmark divided by  $\bar{\sigma}_{sim}$ . Here, the benchmark is defined as the portfolio based on raw data (Original).

Although different memory scenarios lead to different average returns, our results provide evidence for the importance of short-run information. Comparing the out-of-sample performance of portfolios that minimize the covariance matrix of the original simulated return series against the portfolios that minimize the reconstructed return series indicates that the SR out-of-sample returns are closer to the original return than MR and LR.

For instance, if the simulated return series is characterized by less memory (*d* = 0.05), the average out-of-sample portfolio returns based on extracted long-run regimes (LR) is 3% lower in comparison to out-of-sample returns based on raw data. The information that is captured by extracted middle-run regimes (MR) results in portfolio returns that are 1% lower and the returns-based short-run regimes (SR) differ by 0.1%. This tendency remains stable for differ-

ent memory scenarios (*d* = 0.15, 0.35, and 0.45). In this vein, the applied information ratio (IR<sub>mv</sub>) allows for a comparison of the portfolio strategies vis-à-vis the applied benchmark (original). In this particular simulation setup, lower information ratios are preferred against higher values, indicating that the assessed strategy does not deviate from the out-of-sample returns based on raw return series. However, portfolio allocations based on extracted long-run regimes suggest different diversification effects and therefore lead to different portfolio allocations. Hence the results underpin the fact that the information captured by extracted short-run regimes describes the relevant information for periodical portfolio management.

## 4 | EMPIRICAL STUDY

### 4.1 | Data

The empirical study comprises different stocks, which are listed under leading indices of nine different countries. In order to indicate robustness of the empirical results, we analyze different currency denominations and focus on both developed and emerging markets. We discuss assets that are listed on the leading North American, German, and British stock markets as representatives of developed markets. Additionally, we assess Canadian and Australian stocks as representatives for smaller indexes. To analyze emerging markets, we stick to the definition of O'Neil (2001) and assess stocks that are listed under the leading indices of the so-called BRIC states. That is, we assess shares that are listed on the Brazilian, Russian, Indian, and Chinese stock exchanges. For all countries we assess daily market quotes and analyze more than 11 years of data ranging from January 2, 2006, to May 20, 2016.<sup>18</sup> By splitting our sample into subsamples, we are able to take into account the market turmoil beginning in 2007.

Table 3 presents an overview of the applied data. For all countries, we analyze all stocks that are listed under the leading stock index of the respective country. Moreover, we exclude all stocks that were listed or delisted after 2006 from our analysis to ensure a consistent sample size for the assessment of different sub-samples.

Table 4 presents the averaged descriptive statistics of the analyzed assets for each stock index. Obviously, the assessed stocks that are listed under indices of developed markets are characterized by lower risk ( $\sigma$  ranges between 0.007 and 0.008) and extreme negative losses in compar-

<sup>18</sup>This period refers to the limits of the assessed out-of-sample period and comprises up to 2,675 daily market quotes. Owing to data-intensive rolling window and wavelet analysis, the assessed market prices range from August 6, 2003, up to May 20, 2016 (up to 3,305 observations). Owing to country-specific bank holidays, the number of observations differs marginally by each country.



**TABLE 3** Overview of the underlying assets assessed in the empirical analysis

	Index	Period	Frequency	# Assets
<i>Developed markets</i>				
USA	DJI 30	2006–2016	Daily	28
UK	FTSE	2006–2016	Daily	27
Germany	DAX 30	2006–2016	Daily	29
<i>Small markets</i>				
Canada	TSX 60	2006–2016	Daily	54
Australia	ASX	2006–2016	Daily	19
<i>Emerging markets (BRIC)</i>				
Brazil	Bovespa	2006–2016	Daily	32
Russia	RTS Index	2006–2016	Daily	15
India	BSE Sensex	2006–2016	Daily	25
China	SSE Index	2006–2016	Daily	36

*Note.* Due to the fact that we exclude assets that were listed or delisted in the investigated period from 2006 to 2016, not all assets from each index are analyzed. DJI 30 is Dow Jones Industrial Average, FTSE is Financial Times Stock Exchange, DAX is German stock index, TSX 60 is a stock market index of 60 large companies listed on the Toronto Stock Exchange, ASX is Australian Securities Exchange, Bovespa is a stock exchange located in Sao Paulo, RTS Index is Russia Trading System Index, BSE Sensex is Bombay Stock Exchange Sensitive Index, and SSE Index is Shanghai Stock Exchange Index.

**TABLE 4** Average descriptive statistics of the assessed assets

	$\mu$	$\sigma$	min	max	skew	kurt
<i>Developed markets</i>						
DJI 30	0.000	0.007	-0.059	0.062	-0.039	11.369
FTSE	0.000	0.008	-0.099	0.067	-0.796	22.917
DAX 30	0.000	0.008	-0.072	0.066	-0.119	8.702
<i>Small markets</i>						
TSX 60	0.000	0.009	-0.083	0.088	0.212	21.176
ASX	0.000	0.007	-0.057	0.072	0.365	11.250
<i>Emerging markets</i>						
Bovespa	0.000	0.011	-0.072	0.109	1.687	49.187
RTS Index	0.000	0.011	-0.119	0.123	0.029	21.494
BSE Sensex	0.000	0.010	-0.076	0.077	0.018	6.684
SSE Index	0.000	0.016	-0.079	0.071	0.776	55.936

*Note.*  $\mu$  and  $\sigma$  describe the sample average log returns and the average standard deviation for assets listed in the respective market; min and max describe the average minimum and maximum for each asset, and skew and kurt the average skewness and kurtosis of each asset. Detailed information for each index is provided in Table 3.

ison to positive gains (skewness ranges between  $-0.039$  and  $-0.796$ ) in comparison to stocks that are listed under indices of emerging markets, which are characterized by higher risk and a longer right tail ( $\sigma$  ranges between 0.010 and 0.016; skewness ranges between 0.029 and 1.687). According to the presented averaged descriptive statistics, the investigated stocks of small markets are characterized by similar risk as developed markets ( $\sigma$  ranges between 0.007 and 0.009) but by positive skewness like emerging markets (skewness ranges between 0.212 and 0.365)

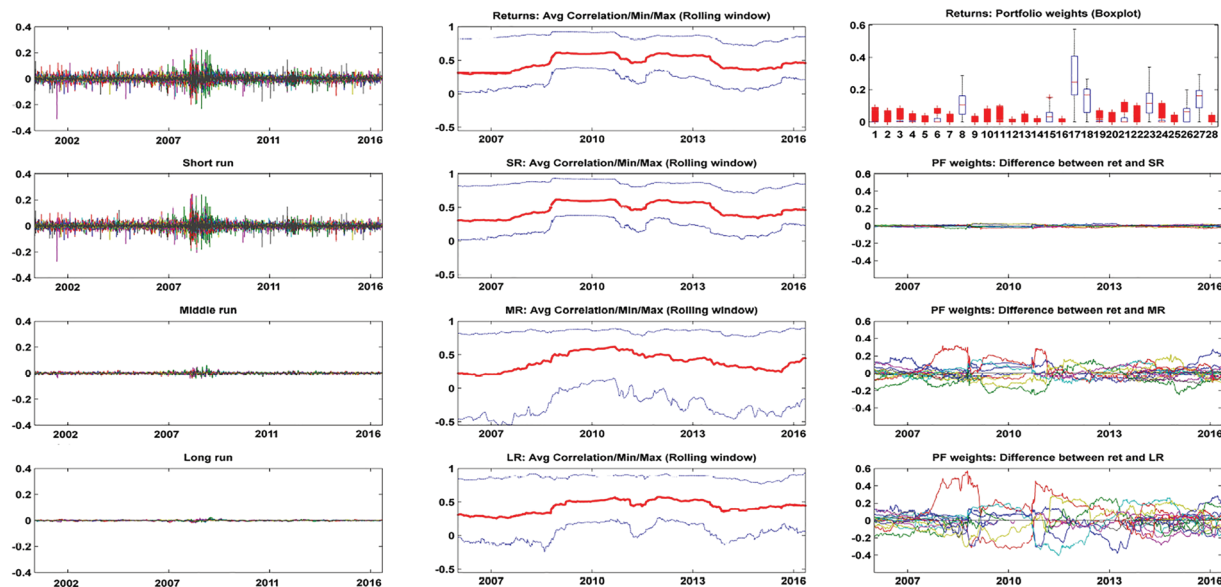
and describe an interesting compromise between stocks of developed and emerging markets.<sup>19</sup>

## 4.2 | Empirical results

To study the impact of different variance and dependence regimes on portfolio allocations, we deconstruct daily return series via MODWT to obtain reconstructed series that comprise either short-run, middle-run, or long-run covariance regimes of the underlying return series. The impact of competing information components on applied portfolio management, namely on variance and dependence and hence on portfolio allocations, is illustrated in Figure 1.

Figure 1 illustrates the impact of different regimes on volatility (left-hand panels), dependence structure (middle panels) and mean-variance efficient portfolio allocations (right-hand panels) for a portfolio that comprises all stocks that are listed under the Dow Jones Industrial Average. The left-hand panels illustrate the underlying data, which are treated as an input to determine covariance regimes. The upper left panel illustrates daily returns of 28 stocks and the panels below describe the reconstructed version of the original return series, which exclusively comprise short-run, mid-run, and long-run volatility regimes. Volatility of long-run regimes is smaller than short-run regimes and one-off shocks; that is, large negative returns impact short-run regimes but are not present in the reconstructed middle-run and long-run series. The panels in the middle of Figure 1 illustrate the maximum and minimum (blue lines) and the average (red line) of the rolling-window correlation coefficients based on 500 observations. Although the average of the correlation coefficients appears to be similar at each point in time, the minimum and maximum values show that dependence structure (i.e., diversification effects) between all 28 assets differs markedly. Middle-run and long-run dependence regimes are characterized by negative dependencies that are not present in the original return series and short-run regimes. The right-hand panels illustrate the impact of the competing covariance regimes on mean-variance efficient portfolio allocations. Based on the return series presented in the upper left panel, the upper right panel presents the quartiles of daily rebalanced portfolio weights for each asset via box plots. That is, for each asset the first and third quartiles of portfolio weights are the top and the bottom of boxes, the median is the band inside the box, and the lines outside the boxes depict variability outside the upper and lower quartiles. Also, the upper panel builds the basis for the lower three panels, which provide information about

<sup>19</sup>As our analysis comprises 265 stocks, a detailed list of descriptive statistics for each individual asset is available upon request to the authors.



**FIGURE 1** Daily return series of 28 assets 2000–2016 listed in the Dow Jones Industrial Average are presented in the upper left-hand panel (Returns). The lower left panels plot the level of the extracted short-run, mid-run, and long-run components (Short run, Middle run and Long run, respectively). The lower left-hand panels sum up to the upper left-hand panel (Returns) and illustrate the competing features of individual regimes. The middle panels plot the out-of-sample rolling average correlations based on 500 past observations (starting from January 2, 2006) and the minimum and maximum correlations for each scenario. The figures indicate that each extracted regime is characterized by different dependence scenarios that are crucial for applied portfolio management. The upper right-hand panel provides a box plot of the daily rebalanced portfolio weights for daily data. That is, for each asset the first and third quartiles of portfolio weights are the top and the bottom of the boxes, the median is the band inside the box, and the lines outside the boxes depict variability outside the upper and lower quartiles. Based on the upper right-hand panel, the lower right-hand panels illustrate the deviations of individual portfolio weights over time, when short-run, middle-run, and long-run information components are applied instead of daily return series [Colour figure can be viewed at [wileyonlinelibrary.com](http://wileyonlinelibrary.com)]

the differences between the portfolio allocations based on daily data (upper left panel) and the deconstructed regimes (lower left panels) for each asset at each point in time.

In comparison to middle-run and long-run covariance regimes, portfolio allocations based on short-run covariance regime lead to marginal differences in portfolio weights. This indicates that covariance regimes of daily data and covariance regimes of short-run components capture dominant dependence patterns and therefore lead to similar portfolio allocations at each point in time. In contrast to short-run covariance regimes, portfolio allocations that exclusively take middle-run or long-run covariance regimes into account differ markedly. Because of changes in the dependence structure between financial assets in middle- and long-run regimes (which are also reported in Gallegati, 2012), diversification effects change and hence portfolio weights differ markedly in comparison to allocations that take covariance regimes of daily data into account.

For all stocks, the results of the out-of-sample performance of the global minimum variance portfolios in the period from 2006 until 2010 are presented in Table 5. This table provides the descriptive statistics and perfor-

mance metrics of the daily out-of-sample portfolio returns from 2006 until 2010. The results for the period 2010–2016 and the crisis period 2007–2009 are presented in Table 6 and 7, respectively. The out-of-sample performance of the global minimum variance portfolios based on particular regimes indicates that the decomposition of return series into different covariance regimes impacts the portfolio performance. An exclusive focus on middle-run and long-run regimes does not lead to an improved portfolio performance in comparison to portfolios that take into account the complete information, which is provided by the original return series. Both the extracted middle-run and long-run information components describe information that is already fully absorbed by the market and therefore lead to different diversification effects. Thus the extracted middle- and long-run regimes, which are present in daily return series, comprise information on changing dependence regimes that appear to be of limited relevance for applied periodical portfolio management.

For instance, mean-variance efficient portfolio allocations that comprise stocks listed under DJI 30 lead to an average return of 0.015% and a Sharpe ratio of 0.014, whereas middle-run and long-run regimes lead to lower

TABLE 5 Empirical results: 2006–2010

	DJI 30			FTSE 30			DAX 30					
	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run
$\bar{r}$	0.015%	0.017%	0.002%	0.001%	0.010%	0.012%	0.009%	-0.018%	-0.023%	-0.022%	-0.034%	-0.009%
min	-7.79%	-7.63%	-7.69%	-7.82%	-8.15%	-8.04%	-8.79%	-10.37%	-7.25%	-7.59%	-8.48%	-7.69%
max	9.72%	9.85%	10.06%	10.31%	9.64%	9.79%	8.96%	8.69%	7.99%	8.26%	7.99%	9.30%
$\hat{\sigma}^2 \cdot 10^5$	11.828	11.906	13.970	15.268	13.575	13.626	14.775	16.356	14.268	14.702	14.841	14.311
SR <sub>mv</sub>	0.014	0.015	0.002	0.001	0.008	0.010	0.007	-0.019	-0.018	-0.028	-0.008	0.977
OR <sub>mv</sub>	1.045	1.051	1.006	1.003	1.026	1.032	1.022	0.958	0.945	0.948	0.920	0.977
SoR <sub>mv</sub>	0.019	0.022	0.002	0.001	0.012	0.015	0.010	-0.019	-0.025	-0.024	-0.037	-0.011
max <sub>id</sub>	0.384	0.375	0.452	0.428	0.408	0.401	0.407	0.536	0.614	0.616	0.625	0.526
IR <sub>1/N</sub>	0.005	0.007	-0.011	-0.012	0.038	0.041	0.039	0.010	-0.022	-0.021	-0.033	-0.007
TE <sub>1/N</sub>	0.008	0.008	0.008	0.008	0.010	0.010	0.009	0.009	0.009	0.009	0.010	0.009
IR <sub>mv</sub>	0.055	-0.047	-0.032	0.052	-0.003	-0.047	0.015	-0.035	0.027			
TE <sub>mv</sub>	0.000	0.003	0.004	0.000	0.004	0.006	0.001	0.003	0.005			
TSX 60			LSX 30			Bovespa						
$\bar{r}$	0.000%	0.002%	0.009%	0.004%	-0.017%	-0.015%	-0.025%	-0.029%	0.046%	0.049%	0.046%	0.047%
min	-5.14%	-5.12%	-6.62%	-6.38%	-7.58%	-7.66%	-7.53%	-6.41%	-7.00%	-6.89%	-8.16%	-9.27%
max	4.94%	5.05%	5.70%	5.98%	4.45%	4.32%	5.88%	5.48%	73.44%	73.44%	73.44%	70.14%
$\hat{\sigma}^2$	7.119	7.226	8.879	10.489	13.227	13.294	15.041	16.080	63.143	63.233	66.429	69.472
SR <sub>mv</sub>	0.000	0.002	0.009	0.003	-0.015	-0.013	-0.020	-0.023	0.018	0.019	0.018	0.018
OR <sub>mv</sub>	1.001	1.007	1.028	1.011	0.959	0.964	0.944	0.938	1.159	1.168	1.141	1.114
SoR <sub>mv</sub>	0.001	0.003	0.012	0.005	-0.020	-0.017	-0.028	-0.030	0.058	0.061	0.052	0.044
max <sub>id</sub>	0.392	0.390	0.327	0.406	0.493	0.483	0.527	0.609	0.496	0.493	0.537	0.635
IR <sub>1/N</sub>	-0.017	-0.015	-0.009	-0.016	-0.022	-0.019	-0.035	-0.036	-0.007	-0.006	-0.007	-0.007
TE <sub>1/N</sub>	0.010	0.010	0.009	0.009	0.009	0.009	0.008	0.008	0.025	0.025	0.025	0.024
IR <sub>mv</sub>	0.034	0.022	0.006	0.060	-0.024	-0.025	0.044	0.001	0.001			
TE <sub>mv</sub>	0.000	0.004	0.005	0.000	0.003	0.005	0.001	0.003	0.007			

Continues

TABLE 5 Continues

	RTS			BSE			SSE			Long run	Middle run	Short run	Long run
	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run	Daily data				
$\bar{r}$	0.001%	0.005%	0.022%	0.008%	0.094%	0.096%	0.091%	0.063%	0.091%	0.092%	0.094%	0.136%	
min	-16.40%	-15.68%	-13.28%	-12.98%	-7.01%	-7.06%	-7.15%	-6.47%	-7.12%	-7.19%	-7.87%	-9.84%	
max	9.60%	10.06%	9.38%	12.41%	10.27%	10.39%	11.71%	7.57%	4.05%	4.12%	4.43%	5.45%	
$\hat{\sigma}^2$	30.283	30.716	29.258	39.168	18.134	18.304	19.971	19.903	9.709	9.976	12.801	17.744	
$SR_{mv}$	0.000	0.003	0.013	0.004	0.070	0.071	0.065	0.045	0.092	0.093	0.083	0.102	
$OR_{mv}$	1.002	1.010	1.040	1.013	1.221	1.224	1.204	1.135	1.439	1.439	1.385	1.483	
$SoR_{mv}$	0.001	0.004	0.017	0.006	0.100	0.102	0.094	0.064	0.134	0.135	0.115	0.154	
$max_{dd}$	0.734	0.734	0.693	0.729	0.317	0.319	0.344	0.314	0.183	0.189	0.176	0.169	
$IR_{1/N}$	-0.013	-0.011	-0.002	-0.009	0.018	0.019	0.015	-0.011	-0.017	-0.016	-0.015	0.006	
$TE_{1/N}$	0.019	0.018	0.016	0.017	0.010	0.010	0.010	0.011	0.020	0.020	0.020	0.020	
$IR_{mv}$	0.045	0.041	0.006	0.026	-0.007	-0.049	0.030	0.008	0.066				
$TE_{mv}$	0.001	0.005	0.012	0.001	0.004	0.006	0.001	0.004	0.007				

Note:  $\bar{r}$  and  $\hat{\sigma}^2$  describe the mean and variance and min/max the respective minimum/maximum of the out-of-sample returns.  $SR_{mv}$  describes the Sharpe ratio of the minimum variance strategy.  $SoR_{mv}$  is the Sortino ratio, and  $OR_{mv}$  is the Omega ratio. The maximum drawdown is given by  $max_{dd}$ , and  $IR_k$  and  $TE_k$  describe the information on the deviation from the assessed strategy vis-à-vis benchmark strategy  $k$  and the respective information ratio. Here,  $k$  is given by equally weighted strategy (1/N) and mean-variance efficient portfolios based on raw return series (mv).

TABLE 6 Empirical results: 2010–2016

	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run
DJI 30					FTSE 30				DAX30			
$\bar{r}$	0.027%	0.027%	0.029%	0.030%	0.016%	0.015%	0.012%	0.007%	0.045%	0.045%	0.043%	0.048%
min	-3.80%	-3.82%	-3.60%	-4.06%	-3.66%	-3.65%	-4.49%	-4.29%	-5.65%	-5.61%	-5.45%	-7.63%
max	3.69%	3.72%	3.98%	4.45%	3.97%	3.95%	3.96%	3.52%	3.40%	3.37%	3.63%	3.62%
$\hat{\sigma}^2 \cdot 10^5$	5.019	5.035	5.222	6.133	6.813	6.833	7.424	7.618	8.037	8.086	8.193	9.115
$SR_{mv}$	0.038	0.038	0.041	0.038	0.019	0.018	0.014	0.008	0.050	0.050	0.047	0.051
$OR_{mv}$	1.111	1.112	1.119	1.111	1.053	1.051	1.038	1.022	1.145	1.145	1.137	1.149
$SoR_{mv}$	0.054	0.054	0.058	0.053	0.026	0.026	0.019	0.011	0.070	0.070	0.067	0.071
$max_{id}$	0.167	0.164	0.172	0.158	0.203	0.202	0.207	0.264	0.197	0.197	0.220	0.219
$IR_{1/N}$	-0.013	-0.013	-0.008	-0.008	-0.019	-0.020	-0.026	-0.034	0.016	0.016	0.013	0.020
$TE_{1/N}$	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.006	0.007	0.007	0.007	0.007
$IR_{mv}$	0.005	0.014	0.008		-0.017	-0.016	-0.027		0.004	-0.007	0.012	
$TE_{mv}$	0.000	0.002	0.003		0.000	0.002	0.003		0.000	0.002	0.003	
TSX 60				LSX 30				Bovespa				
$\bar{r}$	0.042%	0.042%	0.035%	0.027%	0.021%	0.020%	0.021%	0.022%	0.041%	0.041%	0.042%	0.028%
min	-3.38%	-3.45%	-3.51%	-3.48%	-3.71%	-3.76%	-3.98%	-3.91%	-10.57%	-10.57%	-10.39%	-10.00%
max	3.08%	3.20%	2.81%	2.91%	2.41%	2.41%	2.67%	2.66%	33.54%	33.61%	31.62%	28.81%
$\hat{\sigma}^2 \cdot 10^5$	3.630	3.636	4.214	4.955	5.672	5.710	6.230	6.638	14.741	14.863	14.615	14.332
$SR_{mv}$	0.070	0.070	0.054	0.038	0.028	0.027	0.026	0.027	0.034	0.034	0.035	0.024
$OR_{mv}$	1.215	1.216	1.160	1.110	1.078	1.074	1.072	1.074	1.150	1.151	1.149	1.090
$SoR_{mv}$	0.100	0.100	0.077	0.054	0.040	0.038	0.037	0.038	0.063	0.064	0.063	0.041
$max_{id}$	0.132	0.126	0.148	0.165	0.203	0.208	0.199	0.191	0.247	0.250	0.289	0.219
$IR_{1/N}$	0.055	0.055	0.044	0.031	0.032	0.030	0.030	0.031	0.041	0.042	0.044	0.033
$TE_{1/N}$	0.006	0.006	0.005	0.005	0.005	0.005	0.005	0.005	0.012	0.012	0.012	0.011
$IR_{mv}$	0.009	-0.027	-0.042		-0.033	-0.003	0.002		0.011	0.004	-0.027	
$TE_{mv}$	0.000	0.003	0.004		0.000	0.002	0.003		0.000	0.003	0.005	

Continues



TABLE 6 Continued

	RTS			BSE			SSE			Long run	Middle run	Long run
	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run	Daily data			
$\bar{r}$	0.056%	0.058%	0.051%	0.028%	0.058%	0.058%	0.048%	0.035%	0.198%	0.197%	0.188%	0.228%
min	-11.27%	-11.17%	-10.85%	-10.42%	-5.37%	-5.34%	-5.22%	-6.00%	-10.08%	-10.05%	-9.99%	-8.73%
max	5.20%	5.03%	5.19%	4.91%	3.61%	3.67%	4.11%	4.61%	24.55%	24.55%	24.55%	24.55%
$\hat{\sigma}^2 \cdot 10^5$	14.533	14.301	16.915	17.733	6.392	6.403	6.871	8.648	381.265	381.571	382.603	383.639
$SR_{mv}$	0.046	0.049	0.039	0.021	0.072	0.073	0.058	0.037	0.032	0.032	0.030	0.037
$OR_{mv}$	1.144	1.152	1.121	1.060	1.214	1.217	1.167	1.106	1.704	1.692	1.624	1.775
$SoR_{mv}$	0.063	0.066	0.054	0.028	0.107	0.108	0.084	0.053	0.220	0.215	0.198	0.251
$max_{dd}$	0.285	0.281	0.325	0.340	0.180	0.178	0.196	0.284	0.426	0.436	0.494	0.466
$IR_{1/N}$	0.028	0.033	0.019	-0.017	0.046	0.048	0.027	0.004	0.029	0.029	0.028	0.034
$TE_{1/N}$	0.006	0.006	0.007	0.007	0.006	0.006	0.006	0.006	0.060	0.060	0.060	0.060
$IR_{mv}$	0.039	-0.011	-0.050	0.007	0.021	-0.036	-0.049	0.006	-0.013	-0.029	0.053	0.060
$TE_{mv}$	0.001	0.004	0.006	0.006	0.000	0.003	0.005	0.001	0.001	0.003	0.006	0.006

Note.  $\bar{r}$  and  $\hat{\sigma}^2$  describe the mean and variance and min/max the respective minimum/maximum of the out-of-sample returns.  $SR_{mv}$  describes the Sharpe ratio of the minimum variance strategy,  $SoR_{mv}$  is the Sortino ratio and  $OR_{mv}$  is the Omega ratio. The maximum drawdown is given by  $max_{dd}$ , and  $IR_k$  and  $TE_k$  describe the information on the deviation from the assessed strategy against benchmark strategy  $k$  and the respective information ratio. Here,  $k$  is given by equally weighted strategy (1/N) and mean-variance efficient portfolios based on raw return series (mv).

TABLE 7 Empirical results: 2007–2009

	DJI 30			FTSE 30			DAX30					
	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Long run
$\bar{r}$	-0.007%	-0.004%	-0.021%	-0.021%	-0.019%	-0.016%	-0.017%	-0.064%	-0.084%	-0.085%	-0.086%	-0.058%
min	-7.79%	-7.63%	-7.69%	-7.82%	-8.15%	-8.04%	-8.79%	-10.37%	-7.25%	-7.59%	-8.48%	-7.69%
max	9.72%	9.85%	10.06%	10.31%	9.64%	9.79%	8.96%	8.69%	7.99%	8.26%	7.99%	9.30%
$\hat{\sigma}^2 \cdot 10^5$	17.864	18.001	21.378	23.389	20.031	20.107	21.855	24.384	18.960	19.639	19.792	18.497
$SR_{mv}$	-0.005	-0.003	-0.015	-0.014	-0.014	-0.011	-0.011	-0.041	-0.061	-0.060	-0.061	-0.043
$OR_{mv}$	0.985	0.991	0.956	0.958	0.961	0.967	0.968	0.886	0.834	0.835	0.835	0.885
$SoR_{mv}$	-0.007	-0.004	-0.021	-0.019	-0.019	-0.016	-0.016	-0.055	-0.080	-0.079	-0.079	-0.058
$max_{dd}$	0.384	0.375	0.452	0.428	0.402	0.396	0.403	0.530	0.614	0.616	0.625	0.523
$IR_{1/N}$	0.014	0.016	0.000	0.000	0.046	0.049	0.051	0.010	-0.014	-0.015	-0.015	0.009
$TE_{1/N}$	0.011	0.011	0.009	0.009	0.012	0.012	0.012	0.012	0.011	0.011	0.012	0.012
$IR_{mv}$	0.066	-0.046	-0.028	0.057	0.057	0.005	-0.061	-0.004	-0.004	-0.003	0.045	0.012
$TE_{mv}$	0.000	0.003	0.005	0.001	0.001	0.005	0.007	0.001	0.001	0.004	0.006	0.006
TSX 60												
$\bar{r}$	-0.021%	-0.020%	-0.010%	-0.015%	-0.090%	-0.086%	-0.084%	-0.098%	-0.066%	-0.063%	-0.073%	-0.080%
min	-5.14%	-5.12%	-6.62%	-6.38%	-7.58%	-7.66%	-7.53%	-6.41%	-7.00%	-6.89%	-8.16%	-9.27%
max	4.94%	5.05%	5.70%	5.98%	4.45%	4.32%	5.88%	5.48%	7.29%	7.50%	8.05%	12.98%
$\hat{\sigma}^2 \cdot 10^5$	10.335	10.500	12.829	15.487	22.751	22.897	25.406	27.747	17.930	18.012	22.855	33.679
$SR_{mv}$	-0.020	-0.019	-0.009	-0.012	-0.060	-0.057	-0.053	-0.059	-0.049	-0.047	-0.048	-0.044
$OR_{mv}$	0.943	0.947	0.973	0.964	0.844	0.851	0.861	0.851	0.850	0.857	0.854	0.872
$SoR_{mv}$	-0.027	-0.025	-0.012	-0.017	-0.077	-0.073	-0.069	-0.077	-0.065	-0.062	-0.065	-0.059
$max_{dd}$	0.392	0.390	0.327	0.406	0.310	0.303	0.338	0.394	0.496	0.493	0.537	0.635
$IR_{1/N}$	-0.008	-0.007	0.001	-0.004	-0.038	-0.035	-0.038	-0.045	-0.053	-0.051	-0.063	-0.078
$TE_{1/N}$	0.012	0.012	0.011	0.010	0.014	0.014	0.013	0.014	0.013	0.013	0.012	0.011
$IR_{mv}$	0.019	0.023	0.008	0.086	0.086	0.015	-0.011	0.041	-0.017	-0.017	-0.017	0.011
$TE_{mv}$	0.001	0.004	0.007	0.000	0.000	0.004	0.007	0.001	0.001	0.004	0.008	0.008

Continues

TABLE 7 Continued

	RTS			BSE			SSE			Long run	Middle run	Short run	Long run
	Daily data	Short run	Middle run	Long run	Daily data	Short run	Middle run	Daily data	Short run				
$\bar{r}$	-0.057%	-0.050%	-0.036%	-0.112%	-0.009%	-0.008%	-0.023%	-0.011%	0.012%	0.012%	0.014%	0.009%	
min	-16.40%	-15.68%	-13.28%	-12.98%	-6.64%	-6.59%	-7.11%	-6.47%	-2.27%	-2.32%	-2.36%	-2.95%	
max	9.60%	10.06%	9.38%	12.41%	5.44%	5.40%	5.13%	5.30%	2.37%	2.42%	2.35%	3.32%	
$\sigma^2 \cdot 10^5$	37.370	37.925	34.430	42.048	19.515	19.720	22.484	22.361	1.194	1.278	1.847	2.971	
$SR_{mv}$	-0.030	-0.026	-0.019	-0.055	-0.006	-0.005	-0.016	-0.008	0.033	0.032	0.032	0.017	
$OR_{mv}$	0.900	0.912	0.939	0.842	0.982	0.985	0.958	0.980	1.196	1.189	1.168	1.084	
$SoR_{mv}$	-0.038	-0.034	-0.026	-0.073	-0.009	-0.007	-0.021	-0.010	0.049	0.047	0.047	0.026	
$max_{dd}$	0.734	0.734	0.693	0.729	0.296	0.296	0.336	0.310	0.056	0.056	0.077	0.100	
$IR_{1/N}$	-0.014	-0.011	-0.006	-0.042	0.059	0.060	0.048	0.056	-0.002	-0.002	-0.001	-0.003	
$TE_{1/N}$	0.022	0.022	0.020	0.021	0.013	0.013	0.012	0.013	0.025	0.025	0.025	0.024	
$IR_{mv}$	0.061	0.036	-0.044	0.025	0.025	-0.035	-0.003	0.002	0.002	0.011	-0.009	0.024	
$TE_{mv}$	0.001	0.006	0.012	0.001	0.001	0.004	0.006	0.000	0.000	0.002	0.003	0.003	

Note:  $\bar{r}$  and  $\sigma^2$  describe the mean and variance and min/max the respective minimum/maximum of the out-of-sample returns.  $SR_{mv}$  describes the Sharpe ratio of the minimum variance strategy,  $SoR_{mv}$  is the Sortino ratio, and  $OR_{mv}$  is the Omega ratio. The maximum drawdown is given by  $max_{dd}$ , and  $IR_k$  and  $TE_k$  describe the information on the deviation from the assessed strategy against benchmark strategy  $k$  and the respective information ratio. Here,  $k$  is given by equally weighted strategy ( $1/N$ ) and mean-variance efficient portfolios based on raw return series ( $mv$ ).

average returns (middle run: 0.002%; long run: 0.001%) and lower Sharpe ratios (middle run: 0.002; long run: 0.001). In contrast to that, an exclusive focus on newly embedded information that is not absorbed by mid- and long-run regimes leads to improved performance metrics (average out-of-sample return increases by 13% and Sharpe ratio by 7%). Therefore, splitting raw data into competing information components allows the investor to identify shorter covariance regimes that are not processed by the market. Generally, the presented figures suggest that daily rebalanced portfolio allocations aimed at minimizing middle- and long-run covariance regimes of the assessed series do not improve the out-of-sample performance in terms of the applied portfolio metrics. Turning to the assessment of short-run regimes, the results indicate that the application of deconstructed short-run information leads to an improvement in terms of the applied quality criteria. In comparison to the out-of-sample performance of portfolios that minimize the conditional covariance matrix of daily data, the extraction of different covariance regimes allows us to focus explicitly on relevant short-run covariance regimes to improve portfolio metrics. For instance, as presented in Table 5, the average portfolio return of a portfolio that comprises assets listed under DJI 30 increases by 10% and Sharpe ratio by 7%.

Table 6 provides the results for the time from 2010 until 2016. Although both market times are characterized by different market regimes—that is, the period from 2006 to 2010 includes the outbreak and recovery of financial crisis, whereas the period between 2010 to 2016 is described by market upturns as a result of historically low interest rates—previous findings remain valid.

The extraction of middle- and long-run covariance regimes of daily data provides evidence that newly embedded information that is not absorbed by features of long-run regimes describes the relevant information for applied portfolio management. An exclusive focus on shorter covariance regimes leads to improved portfolio metrics for different portfolios comprising stocks that are listed under heterogeneous stock markets (developed and emerging markets) by taking account of different periods (2006–2010 and 2010–2016).

With particular focus on the market turmoil between June 2007 and June 2009 (see Table 7), portfolios that exclusively take the covariance matrix of short-run trends into account lead to smaller negative returns (e.g., DJI 30: average loss decreases by 41% if extracted short-run information is taken into account, TSX 60 by 5%, and RTS by 12.5%, respectively) in comparison to portfolios built on raw data.

Again, the results indicate that the extracted middle- and long-run covariance regimes, which are present in daily data series, provide different information from short-run

regimes. Our results clearly suggest that excluding mid-term and long-term deviations from the raw data improves the applied portfolio metrics. The extracted short-run covariance regimes describe news that impacts short-run changes in the data that are not absorbed by features of long-run covariance regimes and that comprise relevant information for daily portfolio management.

Consequently, the relevant information for daily portfolio management is adequately described by the extracted short-run covariance regimes of the respective daily return series. Splitting raw data into short-term and long-term components allows us to study the relevance of each information component via out-of-sample portfolio returns. Exclusively focusing on the short-run information apart from features of long-run information components of the assessed financial return series improves the assessed quality criteria. Although recent studies mainly point at stronger dependence regimes between the long-run seasonalities of stock returns (see, among others, Gallegati, 2012; Rua & Nunes, 2014; Tan et al., 2014), our results indicate that the information on different long-run regimes absorb relevant features of newly embedded covariance information and therefore should be excluded from daily data for the sake of improved out-of-sample performance metrics.<sup>20</sup>

### 4.3 | Different holding periods

To underline robustness of our results, we investigate the importance of particular covariance regimes for different holding periods.<sup>21</sup> Therefore, we perform the analysis of out-of-sample performance of the portfolio that comprises 28 stocks that are listed under the DJI for different holding periods.

Table 8 provides the out-of-sample performance of global mean-variance efficient portfolios with respect to different holding periods and hence different rebalancing periods: one day, one week, one month, one quarter and one year. The results describe the performance of the portfolio that comprises stocks that are listed under the DJI, and the out-of-sample period ranges from 2006 to 2016. Similar to the results in Tables 5–7, portfolio allocations

<sup>20</sup>To indicate the robustness of our findings, we have conducted two-sided *t*-tests. Our findings are statistically significant and results are available upon request to the authors.

<sup>21</sup>Note that our results are also robust to potential misspecifications in the covariance matrix, as described by Ledoit and Wolf (2004). To assess robustness we have also obtained all discussed covariance matrices via the shrinkage approach. As a result, the presented results do not change. In the interest of page constraints, Appendix Table A1 presents the results for US stocks.

**TABLE 8** Out-of-sample performance of mean-variance efficient portfolios based on daily data and short-run, middle-run and long-run information components with respect to different rebalancing periods (daily, weekly, monthly, quarterly and yearly) from 2006 to 2016

		Daily data	Short run	Middle run	Long run
Daily	$\bar{r}$	0.023%	0.023%	0.019%	0.019%
	min	-7.79%	-7.63%	-7.69%	-7.82%
	max	9.72%	9.85%	10.06%	10.31%
	$\hat{\sigma}^2 \cdot 10^5$	7.646	7.686	8.598	9.659
	SR <sub>mv</sub>	0.026	0.027	0.021	0.020
Weekly	$\bar{r}$	0.024%	0.024%	0.019%	0.019%
	min	-7.66%	-7.66%	-7.44%	-7.59%
	max	9.72%	9.85%	10.06%	10.31%
	$\hat{\sigma}^2 \cdot 10^5$	7.631	7.667	8.569	9.611
	SR <sub>mv</sub>	0.027	0.028	0.021	0.020
Monthly	$\bar{r}$	0.024%	0.025%	0.021%	0.020%
	min	-7.83%	-7.86%	-7.36%	-7.67%
	max	10.60%	10.47%	10.09%	10.14%
	$\hat{\sigma}^2 \cdot 10^5$	7.816	7.828	8.627	9.532
	SR <sub>mv</sub>	0.027	0.028	0.022	0.020
Quarterly	$\bar{r}$	0.024%	0.024%	0.019%	0.019%
	min	-7.83%	-7.86%	-7.36%	-7.10%
	max	10.60%	10.47%	10.09%	9.89%
	$\hat{\sigma}^2 \cdot 10^5$	7.883	7.894	8.617	9.127
	SR <sub>mv</sub>	0.026	0.027	0.021	0.020
Yearly	$\bar{r}$	0.023%	0.024%	0.019%	0.014%
	min	-7.64%	-7.67%	-7.28%	-8.12%
	max	10.15%	10.21%	9.92%	10.28%
	$\hat{\sigma}^2 \cdot 10^5$	7.937	7.952	8.635	9.593
	SR <sub>mv</sub>	0.026	0.027	0.021	0.014

*Note.* The portfolios comprise 28 stocks that are listed in the Dow Jones Industrial Average.  $\bar{r}$  and  $\hat{\sigma}^2$  describe the mean and variance and min/max the respective minimum/maximum of the out-of-sample returns. SR<sub>mv</sub> describes the Sharpe ratio of the minimum variance strategy.

that are based on extracted short-run covariance regimes are described by improved out-of-sample performance—for example, larger Sharpe ratios. Extracted properties of middle-run and long-run covariance regimes lead to different portfolio allocations. If the investor assesses raw data to determine covariance regimes, both middle- and long-run regimes absorb relevant features of short-run regimes.

To emphasize the impact of the identified covariance regimes for a portfolio manager, we assume that an investor invests in mean-variance efficient portfolios as presented in Table 8 in January 2006 and track the portfolio performance until May 2016. The revenues in May 2016 are presented in Table 9.

Table 9 provides the accumulated returns for the portfolio discussed in Table 8. The table presents the rate of return that an investment beginning from January 2006 has gained in May 2016 for different holding periods and competing covariance regimes. For each holding period, portfolio allocations that exclusively take into account short-run covariance regimes lead to larger gains. In comparison to raw data, the focus on short-run regimes leads to increased gains that are approximately 3–4% higher for the investigated holding periods. Furthermore, in line with the results in Tables 5–6, information about middle-run and long-run covariance regimes leads to portfolio returns

**TABLE 9** Performance of a mean-variance efficient portfolio (DJI 30) based on daily data and short-run, middle-run and long-run information components for different rebalancing periods. The strategies start from January 2, 2006 and end on May 20, 2016

	Holding period				
	1 day	1 week	1 month	1 quarter	1 year
Daily data	66.1%	71.0%	72.8%	70.0%	68.3%
Short run	69.7%	74.3%	75.2%	72.6%	72.3%
Middle run	49.7%	50.0%	54.1%	49.3%	49.8%
Long run	47.1%	48.5%	50.0%	49.5%	26.8%

that are approximately 16–23% lower than portfolios based on raw data.

Consequently, the focus on short-run covariance regimes that are not absorbed by middle- and long-run regimes, which are both present in daily data, leads to improved portfolio metrics no matter which holding period is applied. The empirical findings provide evidence for the relevance of the extracted short-run information in the context of applied portfolio management with respect to different holding periods. Splitting raw data into short- and long-run information allows an investor to extract relevant deviations that are not absorbed by features of long-run regimes in order to achieve larger risk adjusted



returns and smaller losses. According to different stock indices and sample periods, the results are robust vis-à-vis different volatility and market regimes.

## 5 | CONCLUSION

This paper adds to the growing field of wavelet-based risk measurements (see Berger & Gençay, 2018; Conlon et al., 2018) and demonstrates a novel perspective on what is the relevant information for applied portfolio optimization. Splitting raw data into short-run and long-run information components via wavelet decomposition allows the investor to identify latent covariance regimes in order to improve predictive portfolio performance. Specifically, investors are able to discard long-run information components that are of limited relevance for periodical portfolio exercises in order to improve portfolio performance.

The empirical assessment of nine different portfolios comprising stocks that are listed under both developed and emerging markets provides evidence that short-run covariance regimes of daily return series describe the crucial information for periodical portfolio optimization. Extracting newly embedded information content via shorter term covariance regimes allows the investor to achieve higher Sharpe ratios and smaller losses in market downturns. Moreover, the presented simulation study underlines that features of long-run covariance regimes are of minor relevance for global minimum variance portfolio optimization.

Therefore, this study presents an initial step towards a wavelet-based portfolio management algorithm, and the introduced wavelet-based approach allows for crucial insights into the relevant covariance regimes for modern portfolio theory. In this vein, identification of structural breaks and jumps in short-term frequencies describes a promising next step for wavelet-based portfolio optimization.

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## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## APPENDIX A

**TABLE A1** Out-of-sample performance of mean-variance efficient portfolios (DJI 30, 2006–2016) based on daily data and short-run, middle-run and long-run information components for US stocks. The covariance matrices are obtained via shrinkage approach

	Ret	SR	MR	LR
$\bar{r}$	0.022%	0.023%	0.020%	0.021%
min	-8.11%	-8.01%	-7.89%	-7.78%
max	9.96%	10.05%	9.77%	9.97%
$\hat{\sigma}^2$	0.0001	0.0001	0.0001	0.0001
SR <sub>mv</sub>	0.025	0.026	0.022	0.022

## AUTHOR BIOGRAPHIES

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