Physica A 457 (2016) 8–33

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Interdependence between Greece and other European stock markets: A comparison of wavelet and VMD copula, and the portfolio implications

Syed Jawad Hussain Shahzad [a,b,*], Ronald Ravinesh Kumar [c,d,e], Sajid Ali [b], Saba Ameer [a]

[a] COMSATS Institute of Information Technology, VC, Islamabad, Pakistan
[b] University of Malaysia Terengganu, Malaysia
[c] The University of the South Pacific, Suva, Fiji
[d] Queensland University of Technology, Gardens Point, Brisbane, QLD 4001, Australia
[e] Bolton Business School, University of Bolton, Deane Rd, Bolton BL3 5AB, UK

HIGHLIGHTS

- The interdependence of Greece and other European stock markets is examined.
- Distinction between short and long term dynamics of stock market returns is made.
- Lower tail dependence shows sudden increase in comovement during crises.
- European stock markets have higher interdependence with Greece stock market.
- Two-asset portfolio VaR provides potential markets for Greece stock diversification.

ARTICLE INFO

Article history:
Received 10 August 2015
Received in revised form 3 February 2016
Available online 6 April 2016

Keywords:
Wavelets
VMD copula
Portfolio
Contagion and interdependence
European stock markets
Greece

ABSTRACT

The interdependence of Greece and other European stock markets and the subsequent portfolio implications are examined in wavelet and variational mode decomposition domain. In applying the decomposition techniques, we analyze the structural properties of data and distinguish between short and long term dynamics of stock market returns. First, the GARCH-type models are fitted to obtain the standardized residuals. Next, different copula functions are evaluated, and based on the conventional information criteria and time varying parameter, Joe–Clayton copula is chosen to model the tail dependence between the stock markets. The short-run lower tail dependence time paths show a sudden increase in comovement during the global financial crises. The results of the long-run dependence suggest that European stock markets have higher interdependence with Greece stock market. Individual country's Value at Risk (VaR) separates the countries into two distinct groups. Finally, the two-asset portfolio VaR measures provide potential markets for Greece stock market investment diversification.

© 2016 Elsevier B.V. All rights reserved.

* Corresponding author at: COMSATS Institute of Information Technology, VC, Islamabad, Pakistan.
E-mail addresses: jawadhussain@vcomsats.edu.pk, jawad.kazmi5@gmail.com (S.J.H. Shahzad), kumar_RN@usp.ac.fj, ronaldravinesh.kumar@hdr.qut.edu.au, rrk1mpo@bolton.ac.uk, ronaldkmr15@gmail.com (R.R. Kumar), sajid.mahr@gmail.com (S. Ali), sabaameer88@gmail.com (S. Ameer).

http://dx.doi.org/10.1016/j.physa.2016.03.048
0378-4371/© 2016 Elsevier B.V. All rights reserved.

1. Introduction

The impacts and consequences of inextricably linked and interdependent financial markets become evident and pronounced in turmoil market conditions [1–5]. The contagion effects are mainly recognized by a significant increase in the (short term) co-movements between the stock markets during and/or after a financial crisis. In this situation, international portfolio diversification becomes less effective compared to the periods of stable markets and conditions.

The stock market return distributions are characterized as non-normal, that is, fat tailed and leptokurtic in behavior, which implies that return affects market interdependence asymmetrically [6–8]. Therefore, an increase in asymmetric interdependence, especially following a financial crisis, makes the linear statistical measures such as correlation a less useful and informative device to capture asymmetric dynamics of stock markets returns. Further, because correlations provide linear relationship between the markets, it does not capture tail dependence and nonlinear transformations of the stock market return distribution. At least for these reasons, the copulas approach [9] is widely used to examine the tail dependence between financial time series [10,11]. Moreover, from a risk management point of view and especially during the periods of financial crisis, the approach becomes extremely useful to understand the impact of changes in stock markets dependence on the portfolio's Value-at-Risk (VaR) [12].

The contagion in stock markets can be evident, at minimum, through four channels. First, investors can face liquidity constraints due to huge losses in investment in a diversified portfolio and thus create adverse reactions in a market. A sharp fall in one market causes a reduction in investors wealth and thereby withdrawal from risky assets [13,14]. This phenomenon can arise even when the investors are rational and the markets are perfect, and the vulnerability in the market can be perpetuated by financial intermediaries [15,16]. Further, the illiquidity during a financial crisis compels money managers, convergence traders and arbitrageurs to sell their assets and this action spreads across the markets [17–20]. The efforts to reduce VaR and marked to market requirement can also trigger asset liquidation [21]. Second, the influence of judgments and preferences due to uncertainty in a market can make investors to revise (upward) their risk assessments and this can trigger an increase in risk premia due to fall in risky assets prices. The rise in uncertainty results in "flight to quality", that is, a shift from risky to safe assets [22–26]. Third, herding behavior due to the inherent emotional biases of investors can result in the market participants perceiving that trading behavior reflects the private information and this gets cascaded to market prices. A rational agent can also follow the herd to avoid high information costs. Kodres and Pritsker [27] argue that asymmetric information increase the markets' vulnerability to crises due to cross-market rebalancing. A portfolio manager's compensation is usually linked with performance which imitates their behavior towards herding. The mimetic behavior is an intrinsic feature of human nature shared by financial market participants [28–30]. The final channel through which contagion may arise is the counterparty credit risk. The business relations between the firms effect non-distressed firms when other firms are in financial distress. The interdependence among the firms (suppliers or consumers of the products) transmits financial distress signal to others. Market participants may anticipate these difficulties and therefore may bid down a whole range of assets after the bankruptcy announcement [31–33].

The study analyzes Greece debt crisis and the subsequent portfolio implication on the European stock markets. As a brief background, Greece joined the European Union (EU) in 1981 during which period it realized an unprecedented economic growth which was duly supported by huge loans and government deficits to finance infrastructure development. While experiencing periods of miraculous growth, the government of Greece accumulated huge debts and reportedly understated deficits which became a greater concern for the investors and the international community, especially after Greece decided to join the Eurozone in 1999 and gave up drachma (Greek currency) to adopt euro with other 18 European Union (EU) countries.[1] Amidst this development, the global financial crisis (GFC) of 2007–08 put additional stress on the Greek debt level and adversely affected the growth resulting in a 20% decline in GDP (gross domestic product) from 2008 to 2010. Since 2010, the pessimistic investment outlook of Greece has resulted in a number of investors and financial institutions withdrawing and selling Greek bonds and other portfolios to minimize the risk and losses. This further raised the unemployment level and extenuated Greek government's debt level resulting in the Euro area (Euro) sovereign debt crisis. The onset of the rising debt levels and the high government deficit was a Greek problem further signals the failure and danger of having a common currency coupled with high debt levels, at least for those countries that are part of the EU (example Portugal and Italy). In efforts to come out of its depressed economic situation, the Greek parliament over the years have finalized three bailout programs with International Monetary Fund (IMF), European Central Bank (ECB) and the EU which nevertheless required implementation of stringent reforms from Greece, and passed six austerity packages.[2] While these measures apparently position Greece on the path to economic recovery and hence as an active player in the EU community and beyond, the impact and possibility of further economic depression remains a huge concern. Moreover, since Greece is an important member of the Eurozone, any major economic, financial and/or political developments including the option to exit from the Eurozone, will have a flow-on and knock-on effects on other countries, and especially those in the Eurozone.

Against this background, we examine the interdependence between 12 European stock markets and its portfolio implications using daily data from January 1, 2000 to April 31, 2015. The market characteristics of Greece are shown in Fig. 1.

1 Although the decision to adopt euro was made in 1999, the formal operationalization with 340.75 drachma to a euro took place in 2002.

2 The recent bailout was in August 2015 when Greece defaulted on the IMF.

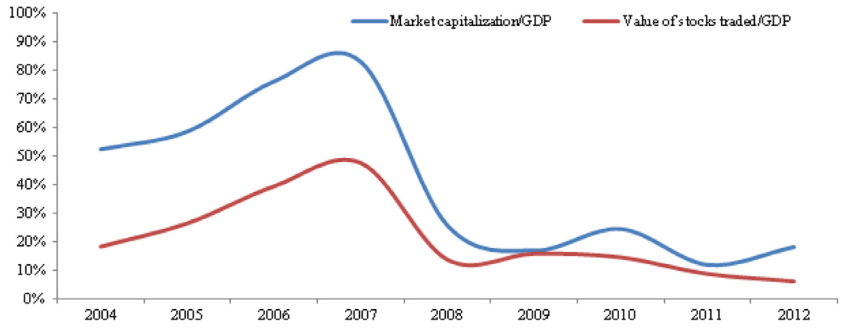


Fig. 1. Market capitalization/GDP and value of stock traded/GDP of Greece.
Source: World Bank (2015).

Following, Gallegati [3] and Dewandaru et al. [34], we consider a sudden increase in short-term (long-term) dependence after a shock as contagion (interdependency) effect. To distinguish between short- and long-term variations of European stock markets, we use an advance multi-resolution technique known as the Variational Mode Decomposition (VMD) for the decomposition of stock market returns. The non-recursive VMD of Dragomiretskiy and Zosso [35] decomposes a time series into different modes that collectively reproduce the input signal. These decomposed time series are compact around a center pulsation with a limited bandwidth and is updated by Wiener filtering in Fourier domain, and a Lagrangian multiplier is used to enforce exact signal reconstruction. Hence, the low (high) frequency modes obtained through VMD presents the long (short) term dynamics of the original signal. This mode-by-mode decomposition is used to examine the change in stock market dependence for short- and long-run.

Further, to get a deeper understanding, we strengthen the VMD approach with wavelet decomposition analysis (WDA), where the latter is used to de-noise the data and address the irregularities that can arise in time and scale measurements—a feature which is an important consideration in modeling high frequency financial time series data. The discrete wavelet transform (DWT) has a number of variants such as summlet, coilet, Haar, debauchies, a trous, among others. The most widely used type of DWT is the Maximal overlap wavelet transform (MODWT) (see for example Refs. [36–41], among others for detailed exposition). However, for our purpose, we use a more recently developed Harr a trous wavelet (HTW) of Murtagh et al. [42]. Unlike MODWT which has efficiency depending on the boundary condition and thus requires the removal of some biased wavelet coefficients at each scale, HTW is immune against the boundary effect and thus preserves the information derived from the data analytics.

In what follows, we examine the tail dependence [43], with a special focus on the change in dependence regime for short- and long-term decomposed stock returns. Finally, we demonstrate the implications of a change in dependence regime for portfolio risk management using scale-by-scale ratio of Value-at-Risk (VaR). The remainder of the paper is set out as follows. In Section 2, we discuss the methods used. Section 3 presents the empirical results, and finally, Section 4 concludes.

2. Methodology

The analysis is performed in four steps: (i) the marginal distribution for each random variable is obtained through ARMA–GARCH models with skewed t-distribution; (ii) the standardized residuals are decomposed into short- and long-term coefficients using HTW and VMD approaches; (iii) a wide range of copula functions and best copula is chosen based on different information criteria; and, (iv) portfolio implications of short- and long-run lower tail dependence are examined to highlight implications of Greece debt crisis.

2.1. Marginal distributions model

The estimation of tail dependence based on copula models is done in a two-step procedure [44]. First, the marginal distribution of each time series is estimated by applying the ARMA–GARCH models and keeping the standardized residuals. Next, the copula parameters are estimated using the coefficients of the marginal models. A correct specification of marginal distributions is obtained when the probability transformations of the residuals is *i.i.d.* and uniformly distributed [45]. We characterize the marginal densities of the stock markets returns (r_t) using an ARMA(p, q) model:

$$r_t = \emptyset_0 + \sum_{j=1}^{p} \emptyset_j r_{t-j} + \varepsilon_t - \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}, \tag{1}$$

where p and q are non-negative integers; $\emptyset_j$ and θ_i are the autoregressive (AR) and moving average (MA) parameters; $\varepsilon_t = \sigma_t z_t$, where σ_t^2 is the conditional variance that has dynamics as given by a threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model introduced by Zakoian [46] with the objective to account for the most important stylized features of marginal distributions such as fat tails and the leverage effect.

$$\sigma_t^2 = \omega + \sum_{k=1}^{r} \beta_k \sigma_{t-k}^2 + \sum_{h=1}^{m} \alpha_h \varepsilon_{t-h}^2 + \sum_{h=1}^{m} \lambda_h 1_{t-h} \varepsilon_{t-h}^2, \tag{2}$$

where ω is a constant; is σ_{t-k}^2 the previous period's forecast error variance (GARCH component). ε_{t-h}^2 is news about volatility from previous periods (ARCH component); $1_{t-h} = 1$ if $\varepsilon_{t-h} < 0$, otherwise 0 and where λ captures leverage effects. For $\lambda > 0$, the future conditional variance will increase proportionally more following a negative shock than a positive one with the same magnitude. Note that when $\lambda = 0$, the volatility model in Eq. (2) is termed as GARCH model; z_t is an *i.i.d.* random variable with zero mean and unit variance that follows a Hansen's [47] skewed-t density distribution and is specified as:

$$f(z_t, \nu, \eta) = \begin{Bmatrix} bc\left(1 + \dfrac{1}{\nu - 2}\left(\dfrac{bz_t + a}{1 - \eta}\right)^2\right)^{-(\nu+1)/2} & z_t < -a/b \\ bc\left(1 + \dfrac{1}{\nu - 2}\left(\dfrac{bz_t + a}{1 + \eta}\right)^2\right)^{-(\nu+1)/2} & z_t \geq -a/b \end{Bmatrix} \tag{3}$$

where ν and η are the degree of freedom parameters $(2 < \nu < \infty)$ and the symmetric parameter $(-1 < \eta < 1)$. The constants a, b and c are given by: $a = 4\eta c\left(\frac{\nu-2}{\nu-1}\right)$, $b^2 = 1 + 3\eta^2 - a^2$, and $c = \Gamma\left(\frac{\nu+1}{2}\right)/\sqrt{\pi(\nu-2)}\,\Gamma\left(\frac{\nu}{2}\right)$, respectively. If $\eta = 0$ and $\nu \to \infty$, then the skew-t converges to the standard Gaussian distribution, and if $\eta = 0$ and ν is finite the skew-t converges to the symmetric Student-t distribution.

2.2. Time series decomposition

We utilize two different decomposition approaches, the wavelet and variation mode decompositions, and compare their suitability to model the dynamic dependence between stock markets of interest. Wavelet analysis provides useful information regarding the behavior of time series by utilizing both frequency and time domains. The wavelet approach can be used to decompose the time series into different time-scaled components and represents the variability and structure of the stochastic processes on scale-by-scale basis. The discrete wavelet (DWT) and the continuous wavelet (CWT) are two distinguished wavelet transform classes often used (see for example Refs. [36–39], among others).

Further, the DWT is particularly helpful for noise reduction and data compression. However, the DWT lacks translation-invariance and this problem can be overcome by using redundant or non-decimated wavelet transform [48]. Maximum overlap discrete wavelet transform (MODWT) is a well known non-decimated wavelet transform used to overcome translation-invariance problem and is widely used in economics, finance and statistics.[3]

Notably, the estimated MODWT variance cannot be efficient unless all the boundary-dependent coefficients are excluded and the squares of the remaining coefficients are averaged. The unbiased estimator of wavelet variance depends on the removal of all wavelet coefficients affected by boundary conditions which may lead to the loss of information. However, the removal of some of the wavelet coefficients will not result in an exact reconstruction of the time series [49]. A straightforward solution to the tricky problem of time series boundary effects can be overcome by the non-decimated or redundant version of Haar wavelet transform (HTW) developed by Murtagh et al. [42]. The HTW makes it computationally possible to consider the resulting HTW variance estimator as an alternative variance that enables signal analysis using all the wavelet coefficients.

2.2.1. The Haar a trous wavelet

The wavelet function is a small wave and can be manipulated (stretched or squeezed over time) to extract the frequency components from a complex signal. The so-called autocorrelation shell representation (redundant algorithm) uses the dilations and translations of the autocorrelation functions of compactly supported wavelets. The scaling and the wavelet functions are chosen to satisfy the following equations:

$$\frac{1}{2} x \emptyset\left(\frac{x}{2}\right) = \sum_k h(k)\, \emptyset(x - k) \quad \text{and} \tag{4}$$

$$\frac{1}{2} x \psi\left(\frac{x}{2}\right) = \sum_k g(k)\, \psi(x - k) \tag{5}$$

[3] The authors thank an anonymous reviewer for highlighting this point and providing subsequent references.

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

$$S_j(t) = \sum_{l=-\infty}^{+\infty} h(l)\, S_{j-1}(t + 2^{j-1} \times l) \quad \text{and} \tag{6}$$

$$d_j(t) = \sum_{l=-\infty}^{+\infty} g(l)\, S_{j-1}(t + 2^{j-1} \times l). \tag{7}$$

Notably, the signals can be directly derived from the autocorrelation shell coefficients. 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 get a series of smoothed versions s_j with s_0 being the finest scale and referring to the normalized raw series. Given a smoothed signal at two consecutive resolution levels, the detailed signal $d_j(t)$ at the level j, can be derived as:

$$d_j(t) = S_{j-1}(t) - S_j(t). \tag{8}$$

The set $d = \{d_1(t), d_2(t), \ldots, d_j(t), s_j(t)\}$ represents the wavelet transform of the signal up to scale J, and the signal can be expressed as a sum of the wavelet coefficients and scaling coefficient:

$$x(t) = S_j(t) + \sum_{j=1}^{J} d_j(t). \tag{9}$$

The above Eqs. (4)–(9) presented HTW is a decimated wavelet and a non-decimated or redundant version is developed by Murtagh et al. [42]. The non-decimated Haar algorithm provides a convincing and computationally very straightforward solution to the time series boundary effects problem [42]. In non-decimated Haar algorithm the low-pass filter h (e.g. 1/16) is replaced by the simple non-symmetric filter $h = (1/2, 1/2)$. The original signal is then convolved by using the filter h as follows:

$$S_{j+1} = \frac{1}{2}(S_{j,t-2^j} + S_{j,t}). \tag{10}$$

Then, the scaling coefficients at higher scales can be easily obtained from the scaling coefficients at lower scales as follows:

$$D_{j+1}(t) = c_j(t) - c_{j+1}(t). \tag{11}$$

The HTW utilizes a threshold procedure i.e. a threshold value λ is selected to filter the wavelet coefficients (cf. [50]). We follow Donoho [48] and calculate the "optimum" value of the threshold level as $\lambda = \sqrt{2\log(T)\sigma^2}$, where, T is the length of the decomposed time series, and σ^2 the variance of the noise, i.e. variance of the detailed coefficients at the first decomposition level.

2.2.2. Variational mode decomposition

The fundamental concept of VMD is to decompose a time series f into discrete k number of sub-series (known as modes) u_k, and the bandwidth of each mode is limited in spectral domain. Each decomposed variational mode k is assumed to be compressed around a center pulsation, ω_k, which is determined along with the decomposition. The algorithm to determine the bandwidth of a time series requires: (i) obtaining a unilateral frequency spectrum for each mode u_k by computing the associated analytic signal by means of the Hilbert transform; (ii) for each mode, shifting the mode's frequency spectrum to baseband by mixing with an exponential tuned to the respective estimated center frequency; and (iii) estimating the bandwidth through Gaussian smoothness of the demodulated signal [35]. Thus, the resulting constrained variational problem can be given as:

$$\min_{\{u_k\},\{\omega_k\}} = \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k^t} \right\|_2^2 \right\} \quad \text{s.t.} \sum_k u_k = f \tag{12}$$

where, k indicates the set (number) of modes u of the original signal f; ω, δ and $*$ represent frequency, the Dirac distribution, and convolution, respectively. Thus, $\{u_k\} := \{u_1, \ldots, u_k\}$ and $\{\omega_k\} := \{\omega_1, \ldots, \omega_k\}$ are the sets of all variational modes and their central frequency, respectively. Eq. (1) decomposes the original signal into a set of modes with a limited bandwidth in Fourier domain. The solution to the original minimization problem is the saddle point of the following augmented Lagrange ($\mathcal{L}$) expression:

$$\mathcal{L}(u_k, \omega_k, \lambda) = \alpha \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] \right\|_2^2 + \left\| f - \sum u_k \right\|_2^2 + \left\langle \lambda, f - \sum u_k \right\rangle \tag{13}$$

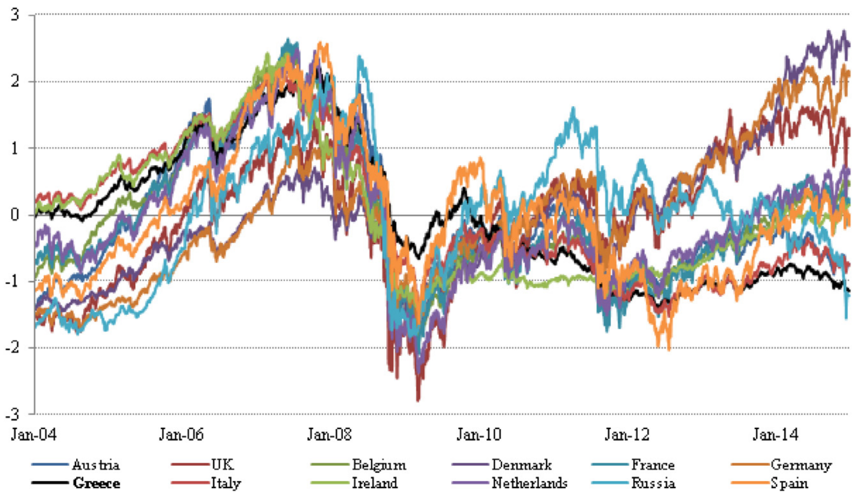


Fig. 2. Stock market trends—standardized prices.

where, λ is the Lagrange multiplier and $\|\bullet\|_p$ denotes the usual vector ℓp norm where $p = 2$. The solution to Eq. (13) is found in a sequence of k iterative sub-optimizations. Finally, the solutions for u and ω are found in Fourier domain and are given by:

$$u_n^{n+1} = \left(f - \sum_{i \neq k} u_i + \frac{\lambda}{2}\right) \frac{1}{1 + 2\alpha\left(\omega - \omega_k\right)^2} \tag{14}$$

$$\omega_n^{n+1} = \frac{\int_0^\infty \omega \left|u_k(\omega)\right|^2 \mathrm{d}_\omega}{\int_0^\infty \left|u_k(\omega)\right|^2 \mathrm{d}_\omega} \tag{15}$$

where, n is the number of iterations. Following Lahmiri [51], we set the number of modes k to ten.

2.3. Copula specifications

The short- and long-run periodicity series are obtained through HTW and VMD and the copula approach is utilized to examine the tail dependence between financial time series [43,52]. The approach is based on the Sklar [61] theorem as follows: Let $x_1, \ldots, x_n$ be the random variables, $F_1, \ldots, F_n$ are the corresponding marginal distributions and H is the joint distribution, then copula $C : [0, 1]^n \to [0, 1]$ exists such that $H(x_1, \ldots, x_n) = C(F_1(x_1), \ldots, F_n(x_n))$. On the other hand, if C is a copula and $F_1, \ldots, F_n$ are distribution functions, then H is a joint distribution with margins $F_1, \ldots, F_n$. The applicability of copulas as a multivariate dependence measure is widely used while analyzing the financial time series (cf. [53,54]).

Copulas are used to characterize the tail dependence between two time series through a joint distribution. Intuitively, the tail dependence reflects the tendency of jointly experiencing the extreme up or down comovements, and thus helps to measure the tendency of stock markets to crash or boom together. Such dependence is usually evaluated through upper- and lower-tail dependence coefficients denoted by U and L, respectively, and is defined as:

$$\lambda_U = \lim_{u \to 1} Pr\left[X \geq F_X^{-1}(u) | Y \geq F_Y^{-1}(u)\right] = \lim_{u \to 1} \frac{1 - 2u + C(u, u)}{1 - u} \tag{16}$$

$$\lambda_L = \lim_{u \to 0} Pr\left[X \leq F_X^{-1}(u) | Y \leq F_Y^{-1}(u)\right] = \lim_{u \to 0} \frac{C(u, u)}{u} \tag{17}$$

where $F_X^{-1}(u)$ and $F_Y^{-1}(u)$ are the marginal quantile functions and $\lambda_U, \lambda_L \in [0, 1]$. The two variables exhibit lower (upper) tail dependence if $\lambda_L > 0 (\lambda_U > 0)$. The larger values of $\lambda_L(\lambda_U)$ indicate clustering of data in the lower (upper) tail of the joint distribution, and thus the stock markets are said to be upper (lower) tail dependent.

The Symmetrized Joe–Clayton (SJC) copula, a modification of the original Joe–Clayton (JC) copula, developed by Patton [55] allows gauging both upper and lower tail dependence as:

$$C_{SJC}(u, v; \lambda_U, \lambda_L) = 0.5\left(C_{JC}(u, v; \lambda_U, \lambda_L) + C_{JC}(1 - u, 1 - v; \lambda_U, \lambda_L) + u + v + 1\right) \tag{18}$$

where $C_{JC}(u, v; \lambda_U, \lambda_L)$ denotes the Joe–Clayton copula defined as:

$$C_{JC}(u, v; \lambda_U, \lambda_L) = 1 - \left(1 - \left\{\left[1 - (1 - u)^k\right]^{-\gamma} + \left[1 - (1 - u)^k\right]^{-\gamma} - 1\right\}^{-1/\gamma}\right)^{1/k} \tag{19}$$

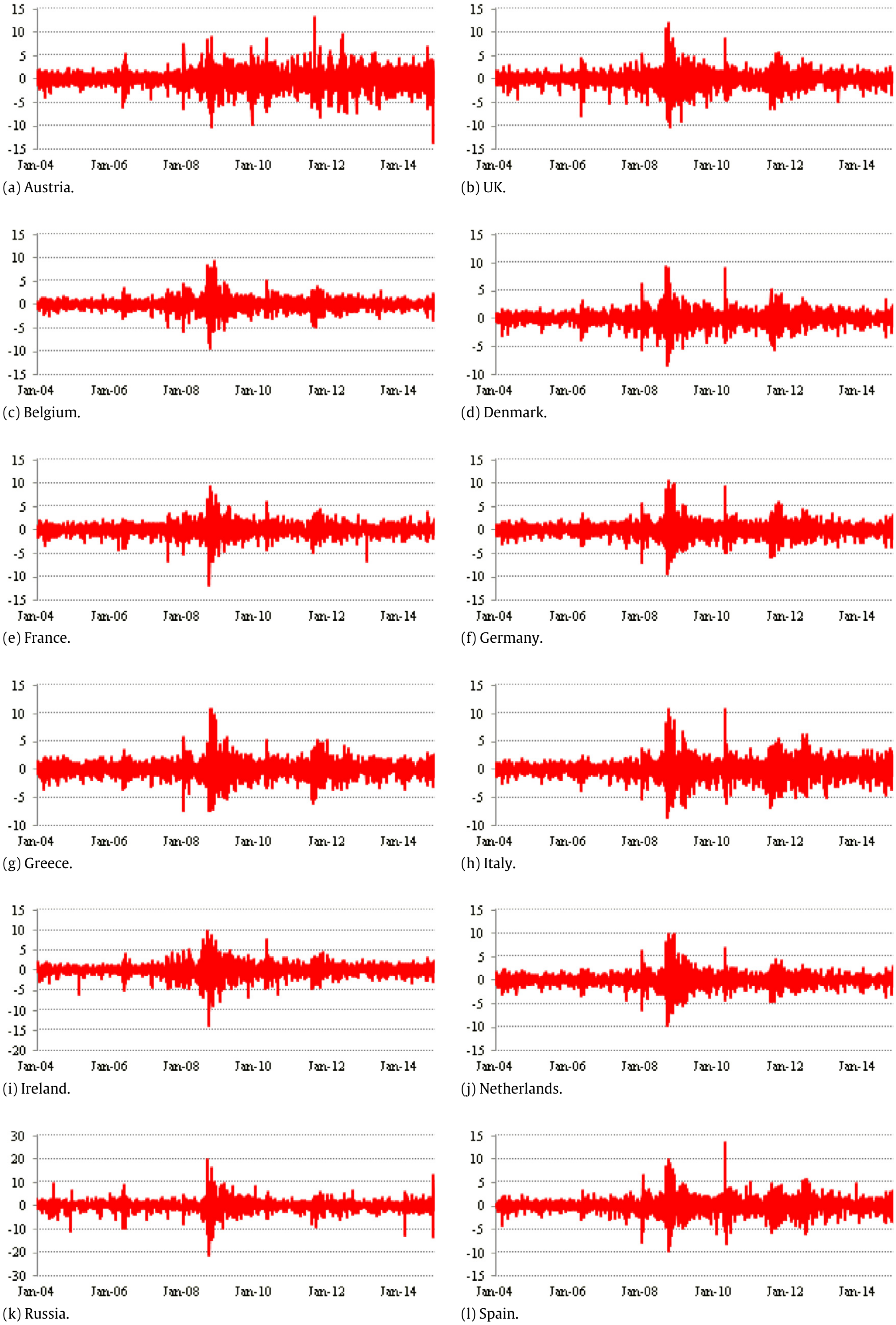
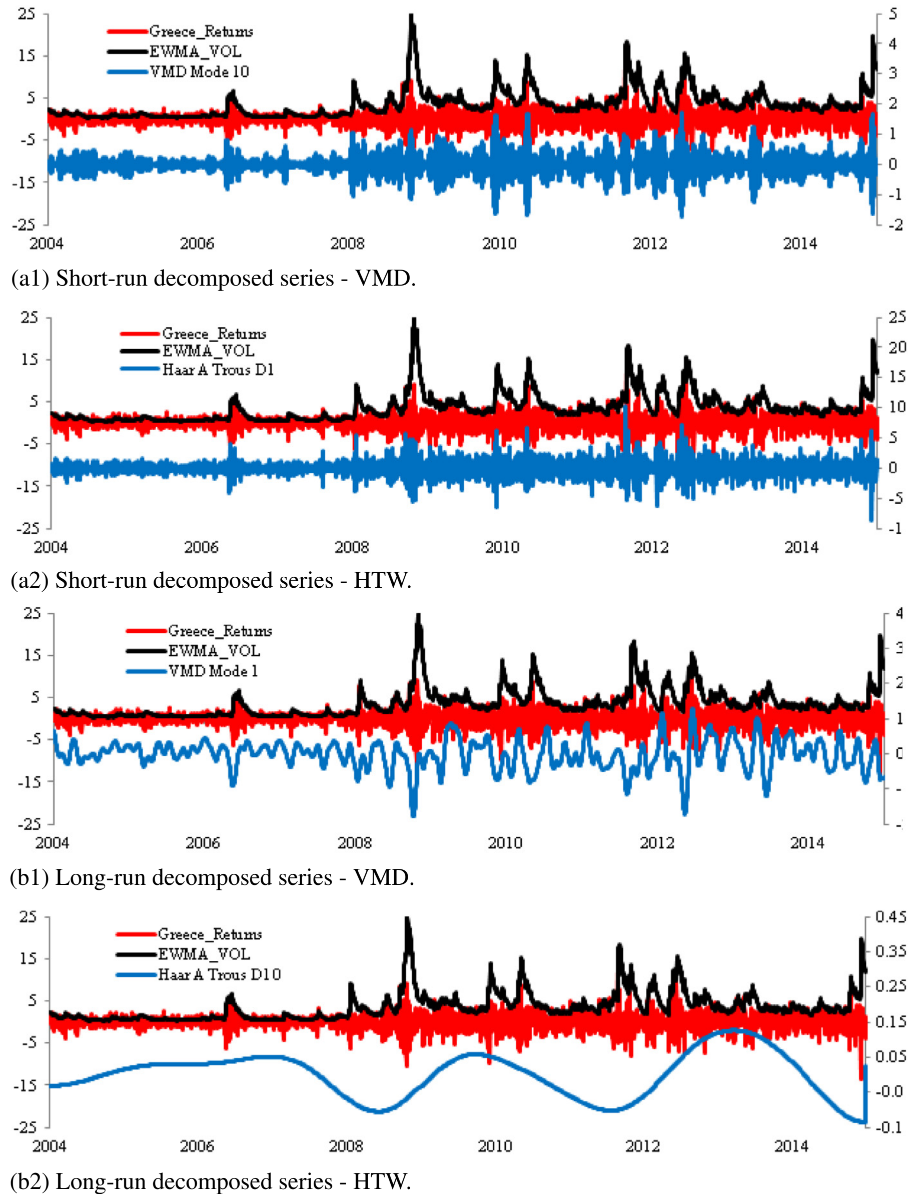


Fig. 3. European stock markets' returns.



(a1) Short-run decomposed series - VMD.

(a2) Short-run decomposed series - HTW.

(b1) Long-run decomposed series - VMD.

(b2) Long-run decomposed series - HTW.

Fig. 4. Comparison of decomposed short- and long periodicity series through VMD and HTW.

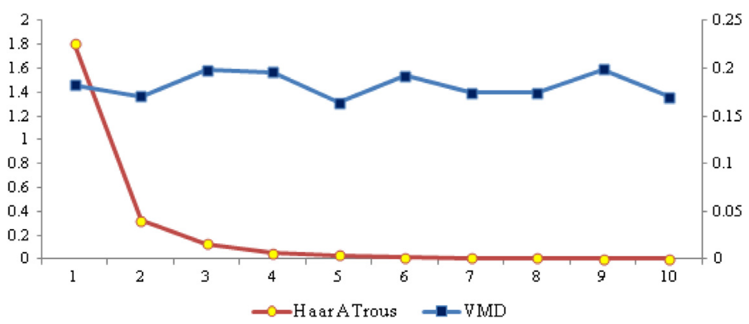
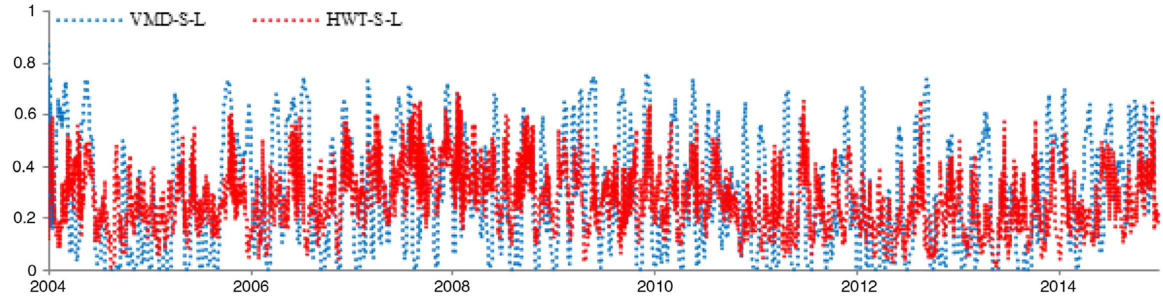
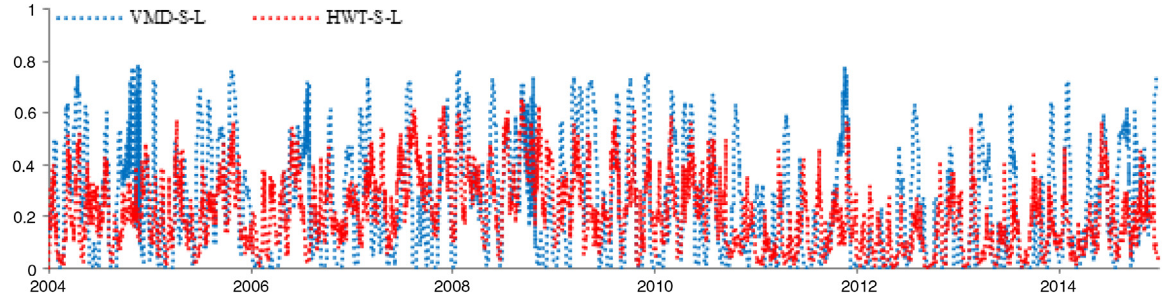


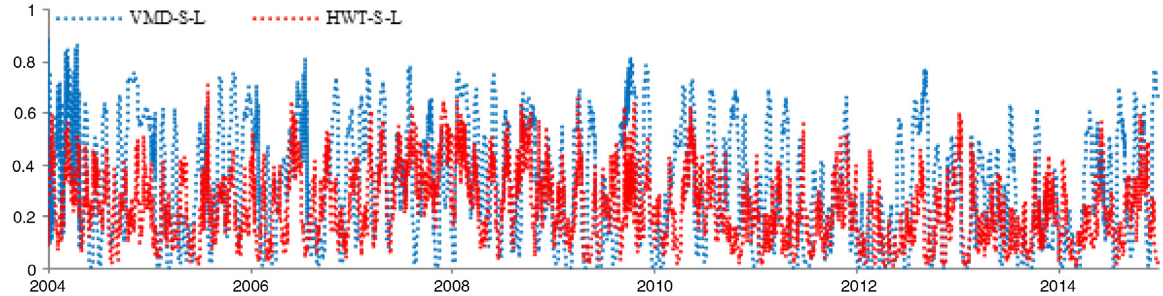
Fig. 5. VMD and HTW variances.



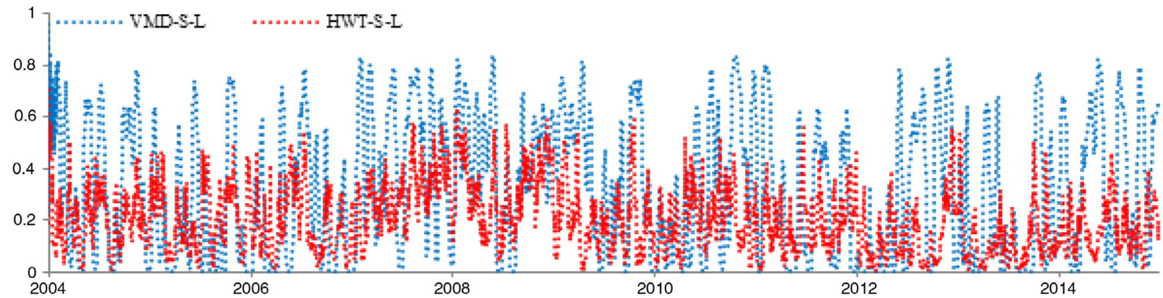
(a) Greece–Austria.



(b) Greece–UK.



(c) Greece–Belgium.

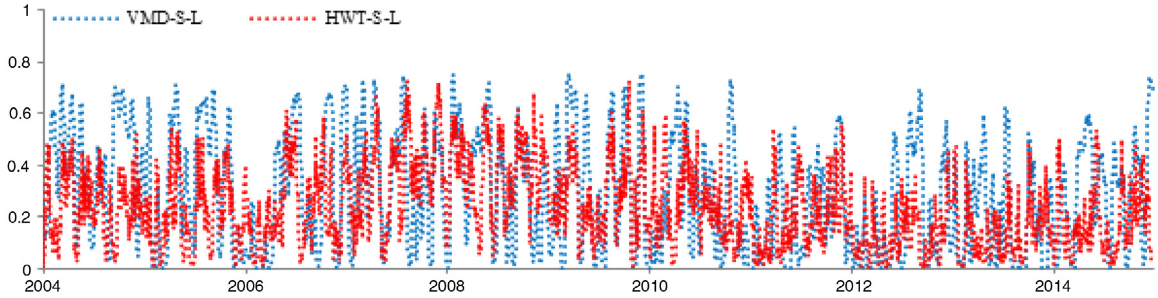


(d) Greece–Denmark.

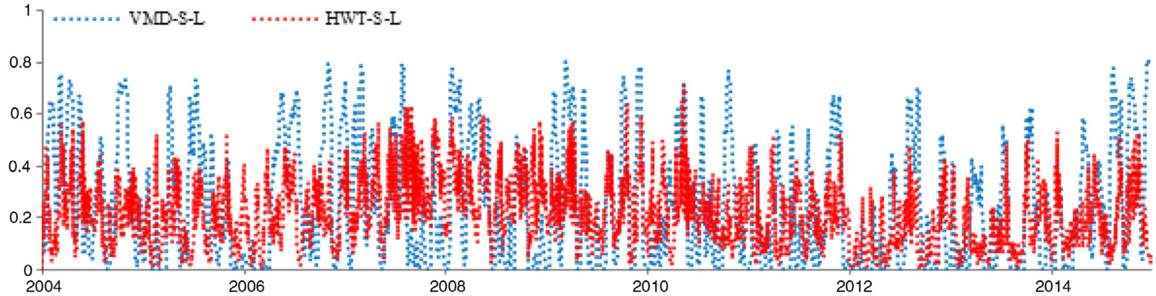
Fig. 6. Short-term lower tail dependence time path—TVP SJC copula.

where $k = 1/\log_2(2 - \lambda_U)$, $\gamma = -1/\log_2(\lambda_L)$, $\lambda_U \in (0, 1)$ and $\lambda_L \in (0, 1)$. Notably, both static and dynamic copula functions can be used to examine the tail dependence between the time series. However, the dynamic or conditional copulas introduced by Patton [55] take into account the time variations in the dependence structure. For the conditional SJC copula, the evolution equations for the tail dependence parameters are:

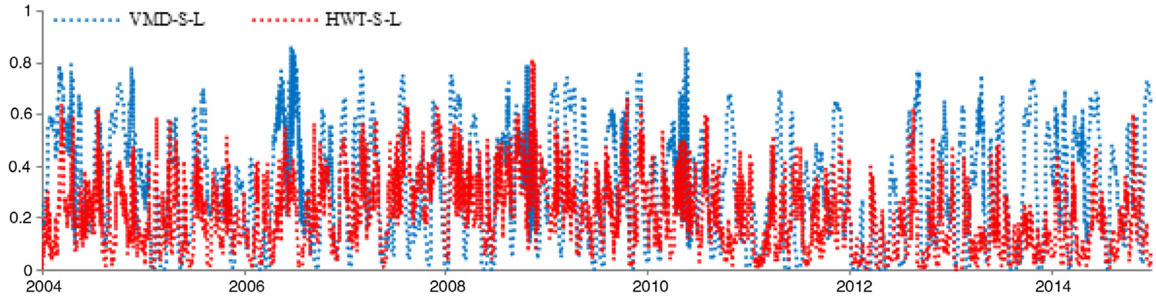
$$\lambda_t^U = \Delta\left(\omega_U + \beta_U \lambda_{t-1}^U + \alpha_U \frac{1}{q}\sum_{j=1}^{q} |u_{t-j} - v_{t-j}|\right) \tag{20}$$



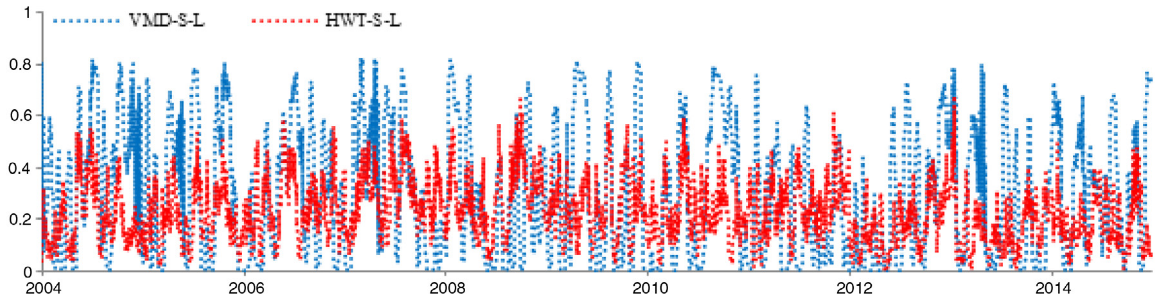
(e) Greece–France.



(f) Greece–Germany.



(g) Greece–Italy.

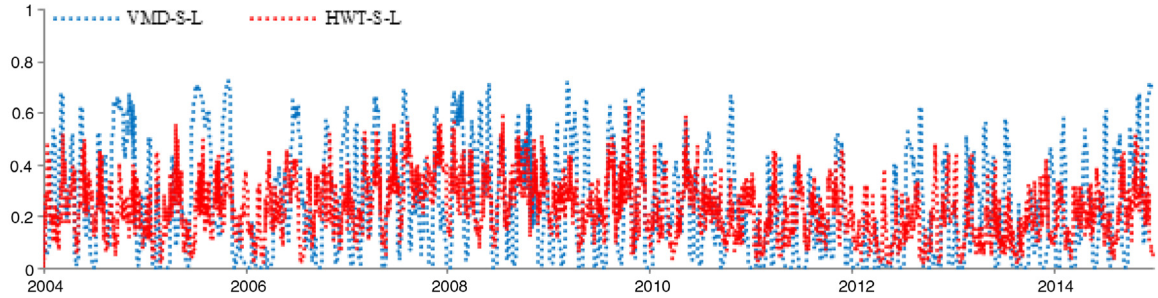


(h) Greece–Ireland.

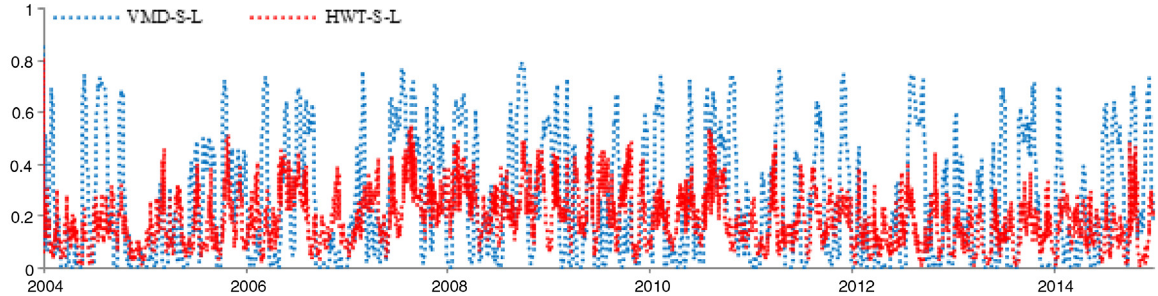
Fig. 6. (*continued*)

$$\lambda_t^L = \Delta\left(\omega_L + \beta_L \lambda_{t-1}^L + \alpha_L \frac{1}{q}\sum_{j=1}^{q} |u_{t-j} - v_{t-j}|\right) \tag{21}$$

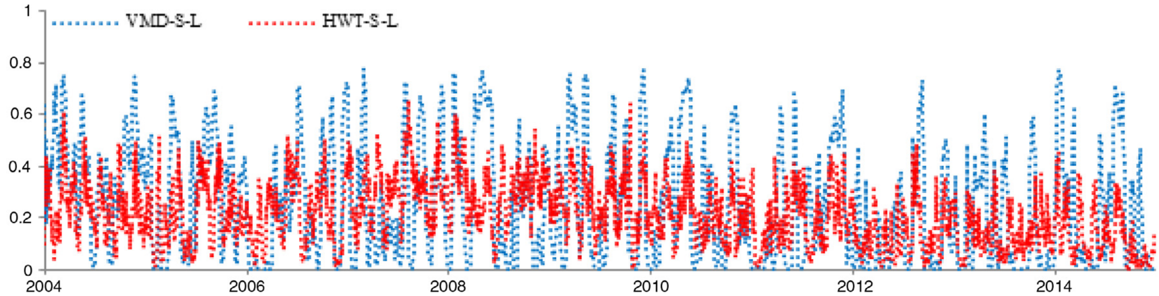
where $\Delta(x) = (1 + \mathrm{e}^{-x})^{-1}$ is the logistic transformation used to keep λ_t^U and λ_t^L within the interval (0, 1) at all times. These equations indicate that both upper and lower tail dependence parameters follow an ARMA(1, q)-type process with an autoregressive term, $\beta_U \lambda_{t-1}^U$ and $\beta_L \lambda_{t-1}^L$, designed to capture persistence in dependence, and a forcing variable, which is the mean absolute difference between u_t and u_t over the last q observations and captures the variation effect in dependence.



(i) Greece–Netherlands.



(j) Greece–Russia.



(k) Greece–Spain.

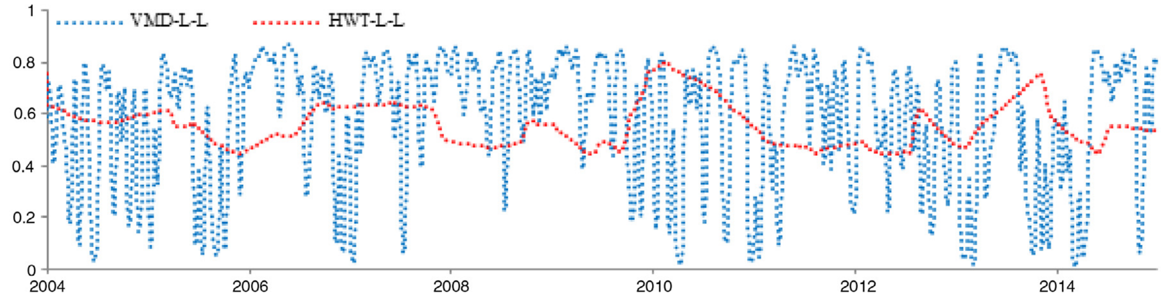
Fig. 6. (*continued*)

3. Data and findings

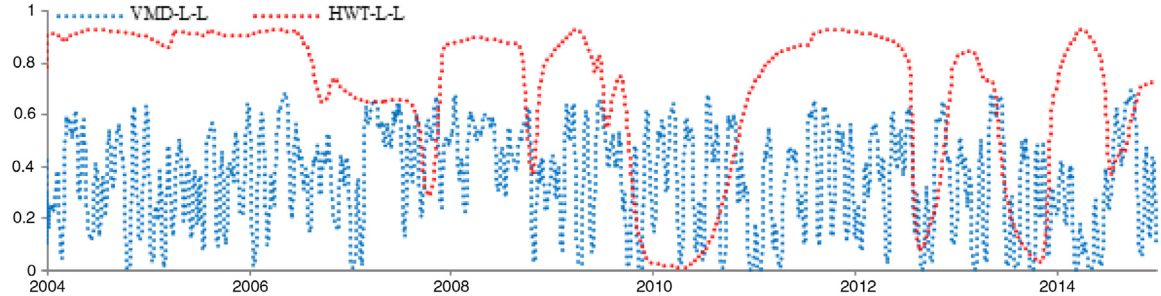
3.1. Data

The data for this study comprises of 12 European daily stock market exchanges from 1.1.2004 till 30.4.2015 and is extracted from DataSteam International (Thomson Financial). The market indices representing each stock market are as follows: Greece (ACI), Russia (RTSI), Austria (ATX), United Kingdom (FTSE 100), Belgium (BEL 20), Denmark (OMXC 20), France (CAC 40), Germany (DAX), Italy (FTSE MIB Index), Ireland (ISEQ), Netherlands (AEX) and Spain (IBEX 35). The price series are converted into returns using natural logarithmic difference of prices as: $r_t = \ln(p_t/p_{t-1}) * 100$. The total observations are 2728 for each selected stock market. Since the Greek GDP decreased by nearly 20% from 2008 to 2010 and economy suffered from the financial crisis of 2007–08, our data represents both stable and turbulence market conditions. For comparison, standardized prices of European stock markets are shown in Fig. 2 and we note that all the stock markets significantly dropped around onset of the global financial crises of 2007–08 (GFC). The stock market returns are shown in Fig. 3(a)–(l) which also shows that stock markets' return variations (volatility) increased during the GFC. Further, the temporal dynamics of the returns series show change during 2011–12.

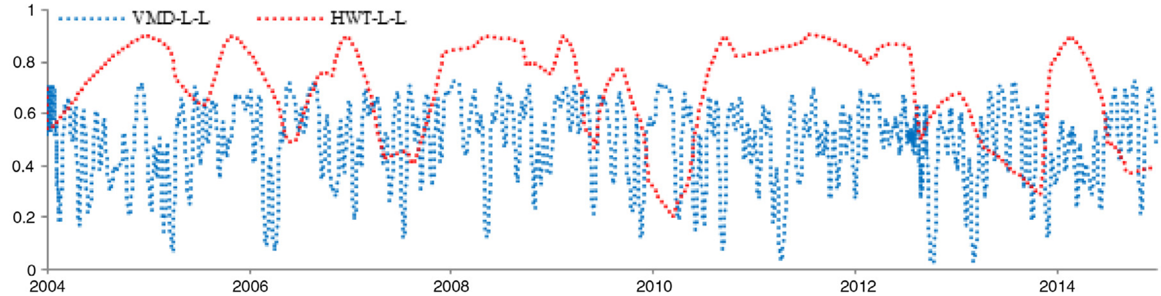
Descriptive statistics of the European stock market returns are provided in Table 1. The average returns (volatility measured by the standard deviation) of Greece stock market is lowest at −0.0377% (highest at 1.9142%) over the sample period. The stock market of Italy has the second lowest average daily returns (−0.0134%). The average daily returns are highest for Denmark stock market at 0.0396%. The Jarque–Bera statistics rejects the normality of the daily log returns for all stock markets and confirm that most of the stock markets are negatively skewed and leptokurtic—a feature specific



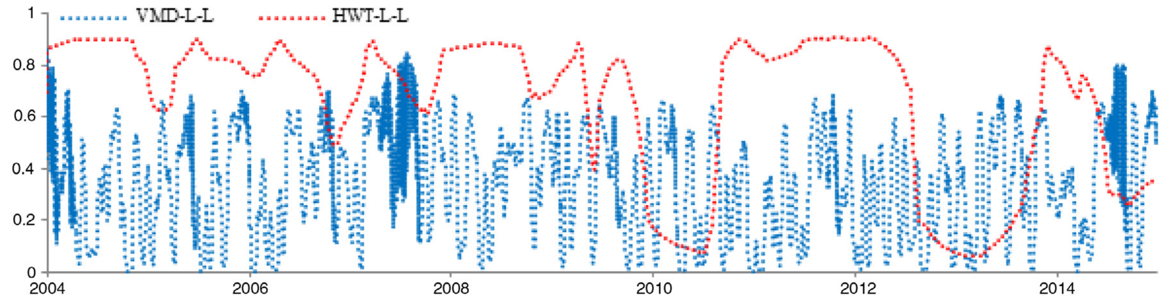
(a) Greece–Austria.



(b) Greece–UK.



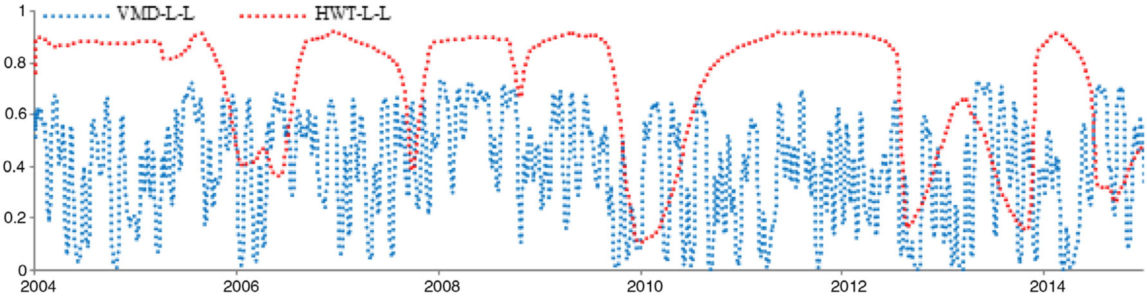
(c) Greece–Belgium.



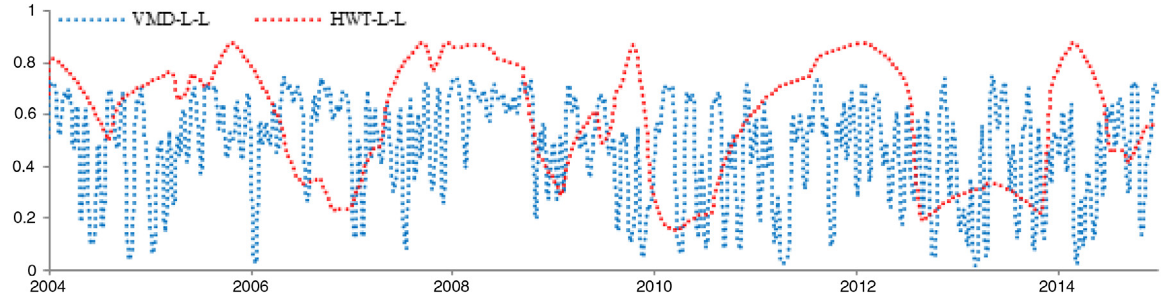
(d) Greece–Denmark.

Fig. 7. Long-term lower tail dependence time path—TVP SJC copula.

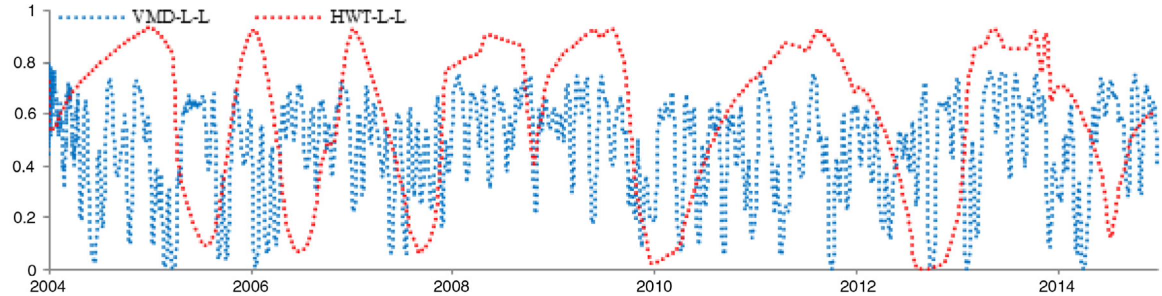
to stock markets. France, Germany and Spain stock market returns exhibit positive skewness. The null hypothesis of no autocorrelation in returns and squared returns is examined through Ljung–Box Q-statistics. The order 12 statistics show presence of autocorrelation in the return series within conventional levels of significance. Further, the presence of significant ARCH effects is confirmed through autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) test statistics. The non-normality, serial correlation and heteroskedasticity in stock market returns clearly support our selection of ARMA–GARCH specification for marginal estimates.



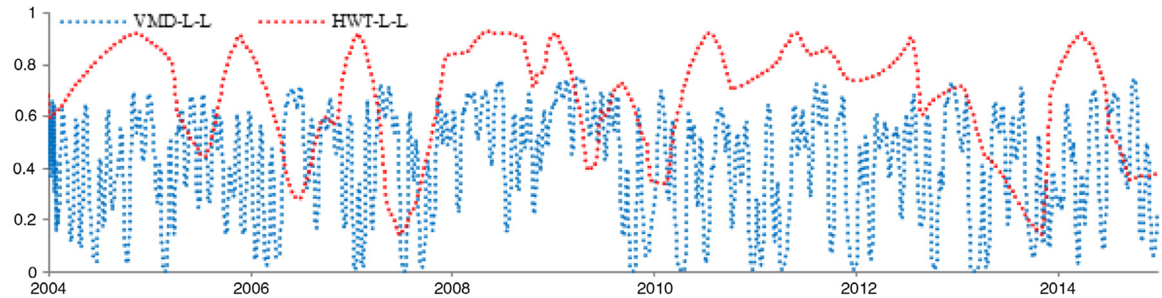
(e) Greece–France.



(f) Greece–Germany.



(g) Greece–Italy.



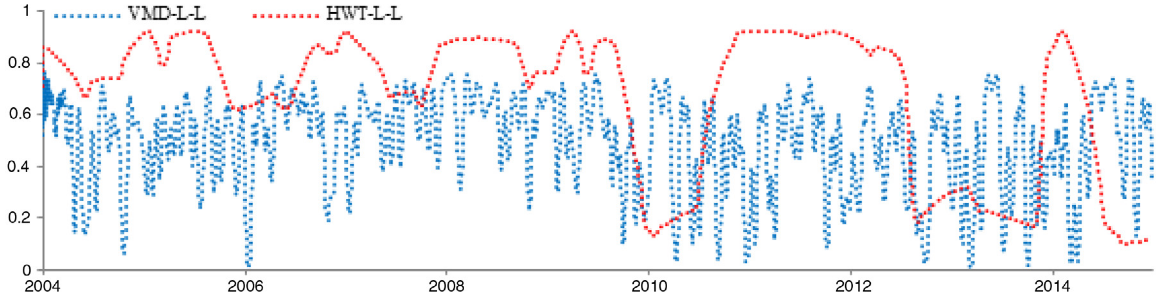
(h) Greece–Ireland.

Fig. 7. (*continued*)

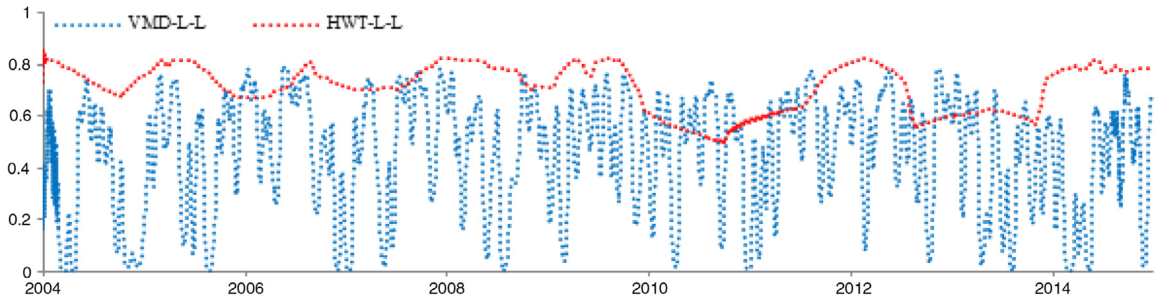
3.2. Estimation of ARMA–GARCH models

The estimated marginal model for 12 selected stock market returns using Eqs. (1)–(3) are reported in Table 2. The lag order *p*- and *q*- values for conditional returns and *r*- and *m*- values for conditional variance equation are selected from a range between zero and two in order to minimize the log likelihood values.

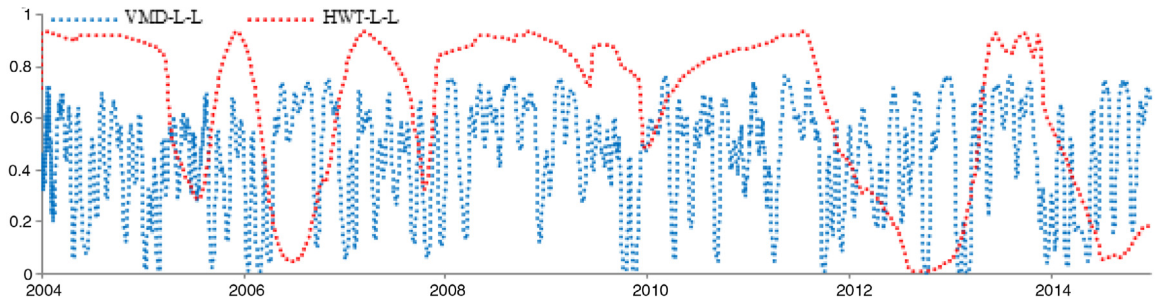
In general, serial correlation is observed for eight stock markets returns. However, the stock market returns of Belgium, Greece, Italy and Russia show no serial correlation. The persistence of volatility across all stock market returns is confirmed as shown by the volatility estimates. The leverage effects are also observed for all countries except for France, Italy and Russia.



(i) Greece–Netherlands.



(j) Greece–Russia.



(k) Greece–Spain.

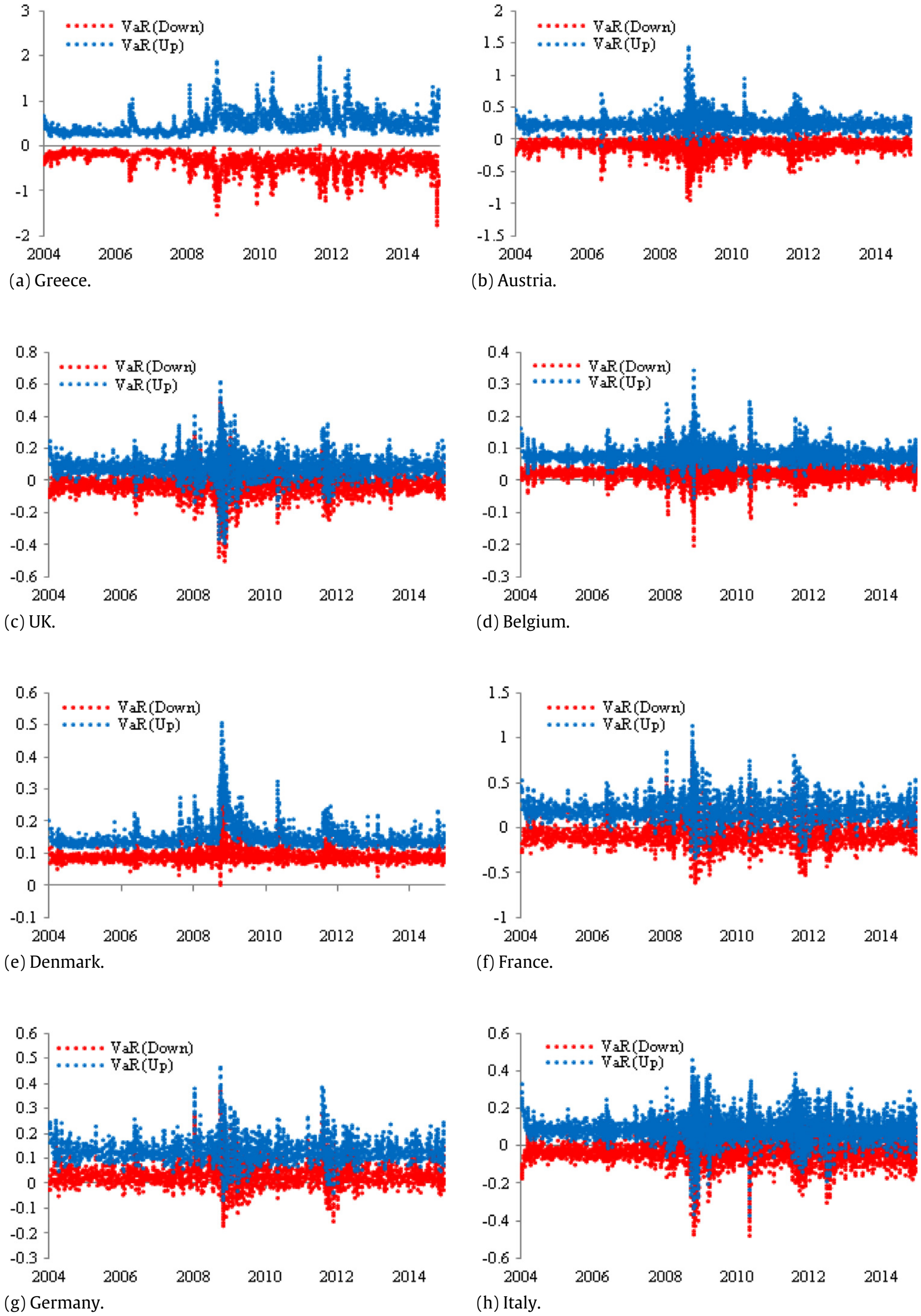
Fig. 7. (*continued*)

A similar pattern is observed in the case of distribution asymmetry estimates. The asymmetry parameters are negative and significant for all markets, except for Italy and Russia. However, the degrees of freedom estimates confirm the error terms are non-normal and fat tailed for all stock markets. The results of different goodness-of-fit tests are reported in the last rows of Table 2 for each model, respectively. The tests results show that selected marginal models adequately reflect the stock market returns' serial correlation and ARCH effects, and that neither serial correlation nor ARCH effects are present.

3.3. *Decomposition analysis*

Next, we apply HTW and VMD to decompose the stock market return into ten different modes (levels). In HTW, the decomposed scales correspond to 2–4 days (D1), 4–8 days (D2), 8–16 days (D3), 16–32 days and so on up to tenth level. Consistent with HTW, the decomposition modes using VMD approach are arbitrarily set to ten. The mode-by-mode decomposition through VMD enables us to distinguish between short- and long-run return dynamics [51]. An objective of the study is to analyze the short- and long-term dependence structure between the stock market returns. Subsequently, we present the variations in original return series, short- and long-run decomposed series, and the exponentially weighted moving average (EWMA) volatility for Greece (Fig. 4).[4] The short-term decomposed series via VMD and HTW are presented in Fig. 4(a1) and (a2), respectively. Fig. 4(b1) and (b2) show the long-run dynamics captured by VMD and HTW, respectively. With the help of these figures, we can examine the strength of the two distinct approaches in capturing the time-scale nature of stock market returns.

[4] The decomposed series and the decomposition results for the other countries are not presented here to conserve the space however, they can be made available upon request.



(a) Greece. (b) Austria.

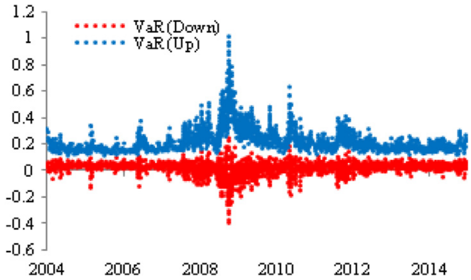
(c) UK. (d) Belgium.

(e) Denmark. (f) France.

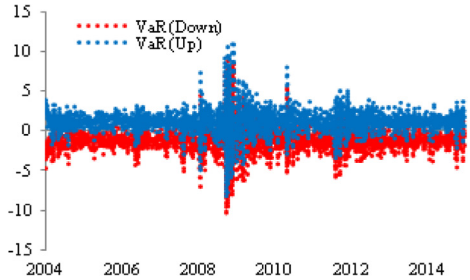
(g) Germany. (h) Italy.

Fig. 8. Upside and downside value-at-risk (VaR) for stock market returns.

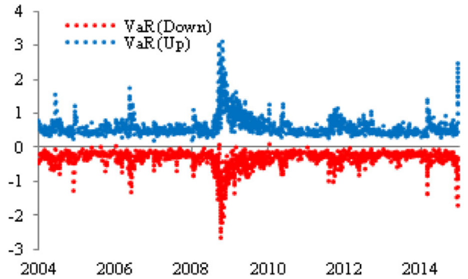
We can observe three general characteristics of decomposed series: (a) the short-run decomposed series through both methods closely trace the variations in the original series that also coincide with the EWMA volatility; (b) the long-run decomposition mode (level) results in smooth series; and (c) the short-term (long-term) variations of HTW series is higher (lower) in comparison with VMD based decomposition. The decomposition methods also provide the variance level of each decomposed series [52], which we present in Fig. 5. The results for Greece stock market return series indicate that the decomposed series have different variances over time on a lowest to highest scale and a significant difference in the variation magnitudes is observed. The first (short-run) decomposed component of HTW displays maximum variations (1.8). However,



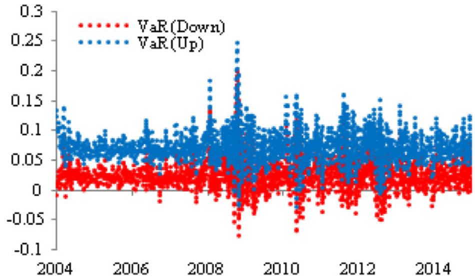
(i) Ireland.



(j) Netherlands.



(k) Russia.



(l) Spain.

Fig. 8. (*continued*)

Table 1
Descriptive statistics of daily stock market returns.

Country	Mean	Std. Dev.	Skew	Kurt	JB-Stat	$Q(12)$	$Q^2(12)$	ARCH(12)
Austria	0.0117	1.6337	−0.2832	9.0010	4129.7***	20.194*	561.51***	612.62***
UK	0.0138	1.1892	−0.0885	12.240	9707.9***	49.797***	2202.0***	782.12***
Belgium	0.0135	1.2648	−0.2031	9.5551	4902.9***	27.522***	2450.6***	690.94***
Denmark	0.0396	1.3087	−0.2877	10.533	6487.5***	27.458***	2177.0***	768.44***
France	0.0063	1.4261	0.0970	10.129	5781.0***	48.533***	1563.2***	656.05***
Germany	0.0327	1.3742	0.0669	10.018	5600.7***	19.6494*	1511.7***	590.73***
Greece	−0.0377	1.9142	−0.1815	7.3843	2199.9***	20.1947*	561.51***	522.43***
Italy	−0.0134	1.5527	−0.0254	8.3239	3222.0***	25.558**	1517.8***	594.26***
Ireland	0.0018	1.5233	−0.5629	10.743	6959.0***	18.224***	2265.0***	693.61***
Netherlands	0.0078	1.3470	−0.1340	12.643	10 578.2***	42.620***	2506.5***	850.90***
Russia	0.0122	2.2374	−0.4305	14.687	15 608.7***	73.247***	1398.0***	632.76***
Spain	0.0087	1.5101	0.0810	9.8203	5290.31***	27.197***	1116.5***	512.43***

Note: This table displays descriptive statistics for daily stock market returns for the period from 1 January 2004 to December 31, 2014. Std. Dev., Skew., Kurt., and JB stands for standard deviation, Skewness, Kurtosis and Jarque–Bera test for normality, respectively. $Q(12)$ and $Q^2(12)$ represent the Ljung–Box statistics for serial correlation of order 12 in returns and squared returns, respectively. Finally, ARCH(12) is the Lagrange multiplier test for autoregressive conditional heteroscedasticity of order 12.

* Shows statistical significance at the 10% level.
** Shows statistical significance at the 5% level.
*** Shows statistical significance at the 1% level.

as the decomposition level increases, HTW components approaches zero after the third level. The variations in VMD modes are relatively stable over time and their values range between 0.15 and 0.20. Hence, the two methods produce distinct outcomes and therefore a further comparison is justified.[5]

3.4. Copula models estimation

After the decomposition of short- and long-run components of stock markets returns, we measure the dynamics dependence between them using a battery of copula functions. We consider static copulas, i.e. the Gaussian, Clayton, Rotated Clayton, Plackett, Gumbel, Rotated Gumbel, Student's t, SJC and time varying copulas which includes TVP Gaussian, TVP Rotated Gumbel, and TVP SJC.[6] The choice of best fitted copula function is based on the log likelihood test statistics (Table 3).

[5] We are thankful to the anonymous reviewers for highlighting this point and asking for a comparative analysis using both methods.

[6] A detailed discussion on these copulas can be found in Ref. [52].

Table 2
Parameter estimates for marginal models of stock market returns.

	Austria	UK	Belgium	Denmark	France	Germany
Mean						
$\emptyset_0$	0.0528* (0.0311)	0.0154 (0.0155)	0.0607 (0.0529)	0.0750*** (0.0223)	0.0116 (0.0208)	0.0175** (0.0072)
$\emptyset_1$	−0.1145 (0.0864)	0.1361 (0.1369)		−0.1594** (0.0736)	0.5247** (0.2222)	0.6236*** (0.0430)
θ_1	0.1782** (0.0848)	−0.1923* (0.1232)		0.1724** (0.0693)	−0.6011*** (0.2348)	−0.6502*** (0.0449)
Variance						
ω	0.0407*** (0.0114)	0.0170*** (0.0039)	0.0274*** (0.0067)	0.0488*** (0.0093)	0.0310 (0.0200)	0.0278*** (0.0070)
α_1	0.0125 (0.0217)	0.0000 (0.0525)	0.0083 (0.0384)	0.0433*** (0.0141)	0.0000 (0.4220)	0.0000 (0.0173)
β_1	0.9000*** (0.0255)	0.9031*** (0.0335)	0.8793*** (0.0262)	0.8532*** (0.0228)	0.8907*** (0.2441)	0.9019*** (0.0153)
λ	0.1285*** (0.0216)	0.1626*** (0.0491)	0.1862*** (0.0378)	0.1411*** (0.0338)		0.1617*** (0.0261)
Asymmetry	−0.1393*** (0.0252)	−00.1381*** (0.0337)	−0.1071** (0.0487)	−0.0631*** (0.0207)	−0.1401** (0.0689)	−0.1312*** (0.0250)
Tail	12.604*** (2.3034)	11.311*** (1.1927)	8.8324** (3.4922)	7.3235*** (0.8692)	10.591*** (2.8913)	8.6515*** (0.9169)
LL	−4559	−3608	−3864	−4051	−4221	−4172
Q (24)	22.710	24.965	17.027	24.204	15.511	14.953
Q^2(24)	24.341	25.286	11.584	15.681	28.293	23.248
ARCH(24)	22.091	27.239	17.765	22.002	16.645	15.966
	Greece	**Italy**	**Ireland**	**Netherlands**	**Russia**	**Spain**
Mean						
$\emptyset_0$	0.0430 (0.0296)	0.0174 (0.2472)	0.0938*** (0.0321)	0.0087 (0.0095)	0.0679 (0.0547)	0.0107 (0.0078)
$\emptyset_1$			−0.5215*** (0.1795)	0.5482* (0.3015)		0.6362*** (0.1616)
θ_1			0.5459*** (0.1752)	−0.5514* (0.3002)		−0.6481*** (0.1606)
Variance						
ω	0.0232*** (0.0072)	0.0116*** (0.0033)	0.0200*** (0.0057)	0.0205*** (0.0049)	0.0782*** (0.0188)	0.0194*** (0.0052)
α_1	0.0611*** (0.0152)	0.0000 (0.0089)	0.0454*** (0.0136)	0.0000 (0.0158)	0.0439*** (0.0113)	0.0000 (0.0200)
β_1	0.9097*** (0.0147)	0.9292*** (0.1503)	0.9019*** (0.0147)	0.8993*** (0.0178)	0.8973*** (0.0243)	0.9167*** (0.0173)
λ	0.0515*** (0.0180)		0.0821*** (0.0202)	0.1729*** (0.0245)		0.1490*** (0.0251)
Asymmetry	−0.0610* (0.0331)	−0.1625 (0.2907)	−0.0591** (0.0273)	−0.1320*** (0.0266)	−0.0552 (0.0864)	−0.1100*** (0.0263)
Tail	7.3075*** (1.1292)	8.7511* (4.8541)	8.5431*** (0.9253)	12.794*** (2.8794)	4.8635*** (0.3807)	8.0706*** (0.9193)
LL	−5148	−4401	−4297	−3937	−5353	−4381
Q (24)	10.558	9.581	11.510	19.439	28.440	26.296
Q^2(24)	18.538	15.932	21.860	21.371	10.568	15.866
ARCH(24)	10.370	35.936	11.760	20.348	28.022	26.537

Note: The table shows parameter estimates and standard errors (in parentheses). LogLik is the log-likelihood value; Q (Q^2) denotes the Ljung–Box statistics for serial correlation in the residual (squared residual) model calculated with 24 lags. ARCH is Engle's LM test for the ARCH effect in residuals up to 24th order.
* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.

Compared with static copulas, time-varying copulas have relatively lower values of log likelihood statistics and hence better characterize the stock markets returns' dependence. In terms of the log likelihood statistics,[7] the time-varying SJC copula is the best fitted model to describe the dependence structure between all the stock markets.

[7] The AIC and BIC criteria provide same conclusion and are available from author on request.

Table 3
Log likelihood for copulas.

Greece with	Austria	UK	Belgium	Denmark	France	Germany	Italy	Ireland	Netherlands	Russia	Spain
Panel A: Short run (VMD)											
Gaussian	−261.33	−232.77	−352.41	−271.95	−301.67	−208.00	−255.25	−286.39	−305.58	−179.90	−243.21
Clayton's	−214.26	−181.19	−264.68	−210.86	−234.37	−164.56	−198.02	−210.08	−227.64	−135.94	−190.44
Rotated Clayton	−214.49	−180.97	−264.32	−211.36	−233.88	−164.21	−197.79	−210.17	−227.51	−136.32	−190.36
Plackett	−259.51	−204.86	−318.60	−287.56	−267.76	−184.36	−230.00	−252.24	−262.30	−176.94	−215.01
Gumbel	−258.07	−212.22	−312.20	−257.73	−276.70	−197.12	−235.15	−245.92	−264.92	−160.65	−225.35
Rotated Gumbel	−257.61	−212.47	−312.55	−257.53	−277.02	−197.40	−235.43	−246.00	−265.00	−160.26	−225.40
Student's *t*	−297.97	−239.29	−353.45	−288.89	−308.64	−216.54	−261.56	−286.00	−305.27	−183.97	−250.46
SJC	−281.06	−239.07	−336.40	−269.20	−306.71	−221.51	−260.12	−267.37	−292.69	−174.64	−253.11
TVP Gaussian	−421.18	−386.80	−470.49	−482.96	−465.90	−398.54	−443.96	−403.72	−411.52	−323.79	−359.74
TVP Rotated Gumbel	−471.76	−442.81	−530.75	−586.28	−514.05	−448.10	−478.93	−516.65	−486.38	−402.22	−449.43
TVP SJC	**−550.39**	**−495.76**	**−599.51**	**−696.38**	**−580.82**	**−548.76**	**−566.96**	**−588.98**	**−534.15**	**−484.66**	**−512.78**
Panel B: Short run (HTW)											
Gaussian	−308.19	−209.67	−275.47	−226.20	−266.30	−230.96	−250.63	−222.28	−259.36	−186.68	−226.70
Clayton's	−245.44	−164.57	−205.46	−172.74	−201.36	−172.21	−181.91	−184.64	−195.35	−143.88	−174.49
Rotated Clayton	−250.01	−179.25	−232.17	−181.31	−220.14	−192.94	−211.31	−182.68	−217.31	−143.44	−190.42
Plackett	−297.57	−204.57	−255.77	−225.13	−257.26	−220.85	−239.37	−222.88	−252.06	−175.87	−218.62
Gumbel	−299.75	−211.90	−268.18	−218.18	−255.48	−225.11	−242.53	−221.12	−252.52	−172.21	−225.42
Rotated Gumbel	−299.23	−202.98	−253.45	−206.62	−248.27	−210.43	−227.03	−225.30	−240.01	−169.13	−214.67
Student's *t*	−331.33	−235.97	−289.62	−238.74	−282.25	−244.14	−261.86	−255.63	−277.42	−191.62	−246.78
SJC	−326.99	−231.69	−289.54	−230.82	−276.29	−241.17	−258.14	−245.97	−271.03	−188.42	−243.75
TVP Gaussian	−350.90	−263.97	−306.98	−264.97	−308.69	−262.92	−290.76	−273.50	−291.52	−227.40	−281.85
TVP Rotated Gumbel	−352.23	−270.70	−298.35	−248.81	−305.96	−255.97	−276.53	−263.31	−275.55	−219.06	−270.07
TVP SJC	**−375.21**	**−297.87**	**−335.36**	**−272.46**	**−332.09**	**−280.99**	**−310.79**	**−286.87**	**−302.54**	**−242.22**	**−292.63**
Panel C: Long run (VMD)											
Gaussian	−723.04	−361.60	−755.71	−335.40	−653.58	−647.44	−828.32	−411.18	−487.17	−439.69	−663.89
Clayton's	−736.63	−373.84	−657.88	−383.47	−599.59	−599.07	−601.82	−393.91	−540.50	−401.16	−547.51
Rotated Clayton	−381.69	−175.02	−443.09	−140.20	−365.87	−386.04	−620.57	−216.58	−210.53	−278.98	−427.18
Plackett	−721.87	−352.87	−673.39	−330.91	−606.74	−619.15	−821.10	−418.42	−485.62	−446.16	−658.97
Gumbel	−540.53	−252.18	−577.39	−220.43	−496.51	−510.79	−757.50	−297.53	−323.81	−361.38	−557.61
Rotated Gumbel	−782.31	−382.16	−727.47	−376.80	−647.12	−660.07	−749.00	−419.39	−536.18	−449.68	−623.89
Student's *t*	−724.01	−362.31	−754.53	−336.40	−653.64	−648.81	−832.24	−412.05	−488.95	−450.93	−667.07
SJC	−754.77	−374.65	−698.77	−375.64	−621.53	−643.30	−751.06	−396.89	−530.50	−436.20	−601.71
TVP Gaussian	−847.01	−465.76	−803.88	−467.66	−733.06	−743.69	−862.27	−577.19	−620.89	−661.97	−748.47
TVP Rotated Gumbel	−1164.48	−617.31	−852.83	−656.00	−812.68	−877.97	−1013.35	−739.67	−757.72	−821.67	−955.97
TVP SJC	**−1248.12**	**−626.35**	**−981.89**	**−718.02**	**−991.83**	**−909.00**	**−1073.45**	**−763.34**	**−794.65**	**−886.18**	**−961.84**
Panel D: Long run (HTW)											
Gaussian	−1562.75	−1652.07	−1074.43	−810.50	−1415.70	−913.80	−1150.87	−1153.97	−1047.99	−1151.43	−1461.62
Clayton's	−1440.07	−1573.56	−1006.45	−1012.40	−1353.43	−991.69	−1559.67	−981.43	−1067.89	−1276.20	−1214.34
Rotated Clayton	−806.62	−816.14	−488.14	−284.57	−647.55	−327.07	−1383.14	−549.78	−486.81	−448.36	−840.29
Plackett	−1739.47	−1121.17	−1209.83	−1079.77	−1742.01	−982.43	−1236.97	−1254.71	−1328.37	−1176.95	−1760.80
Gumbel	−826.62	−516.14	−716.80	−521.64	−1003.34	−533.90	−1234.10	−780.12	−747.61	−726.34	−692.32
Rotated Gumbel	−739.47	−721.17	−1105.59	−987.28	−931.21	−982.37	−1139.27	−1119.28	−1161.63	−1257.91	−1312.43
Student's *t*	−1574.72	−1670.23	−1084.13	−815.73	−1433.03	−919.59	−1163.78	−1162.61	−1050.69	−1157.50	−1462.60
SJC	−1440.06	−1581.99	−1004.70	−1015.87	−1362.08	−983.46	−1718.60	−975.36	−1067.74	−1267.01	−1244.42
TVP Gaussian	−1679.07	−1815.12	−1169.30	−830.56	−1745.10	−950.48	−1265.69	−1321.59	−1077.46	−1170.56	−1530.49
TVP Rotated Gumbel	−1671.32	−1810.13	−1590.50	−1640.32	−1733.23	−1213.07	−1843.18	−1502.60	−1125.25	−1345.52	−1863.16
TVP SJC	**−1939.04**	**−1929.33**	**−1870.33**	**−1825.47**	**−1924.57**	**−1519.27**	**−1939.76**	**−1825.61**	**−1665.78**	**−1640.28**	**−1958.39**

The parameters of the time-varying SJC copula using both the short- and long-run series are presented in Table 4. Since the dependence between Greece stock market with other European stock markets is the primary interest of our analysis, we report the estimates of dependence parameters of Greece with other markets, pair-wise respectively. For TVP Copula, the upper tail dependence, persistence, and adjustment is captured by ω_u, β_u and α_u, respectively; and the lower tail parameters are denoted by ω_L, β_L and α_L, respectively. The panels A and B show the TVP SJC estimates for short-term dependence dynamics for both VMD and HTW decomposed series, respectively. Similarly, panels C and D present the long-term dependence dynamics. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) for the respective estimated models are reported in the last row for each pair.

The TVP SJC copula suggests significant upper and lower tail dependence between Greece and European stock markets, which duly confirms that the time-varying copulas characterize the dynamic dependence structure between European stock markets. In short-run, the VMD based lower and upper dependence estimates are higher than the HTW. All the upper and lower tail dependence parameters are significant (at the conventional levels) for VMD based decomposition. The highest

Table 4
TVP Symmetrized Joe–Clayton copula parameter estimates.

Greece with	Austria	UK	Belgium	Denmark	France	Germany	Italy	Ireland	Netherlands	Russia	Spain
Panel A: Short run (VMD)											
ω_u	1.780***	1.645***	1.784***	1.839***	1.735***	1.708***	1.782***	1.733***	1.600***	1.705***	1.588***
	(0.123)	(0.135)	(0.138)	(0.233)	(0.128)	(0.275)	(0.262)	(0.290)	(0.355)	(0.313)	(0.309)
β_u	−12.26***	−10.32***	−11.40***	−9.324***	−14.56***	−13.02***	−8.298***	−10.03***	−11.31***	−10.08***	−12.43***
	(0.000)	(0.000)	(0.000)	(0.798)	(0.000)	(0.958)	(0.917)	(1.026)	(1.149)	(1.093)	(1.092)
α_u	−0.031	0.017	0.000	0.222***	0.008	0.170***	0.084	0.171*	−0.106	0.195***	0.061
	(0.077)	(0.073)	(0.088)	(0.058)	(0.079)	(0.063)	(0.057)	(0.090)	(0.065)	(0.073)	(0.093)
ω_L	1.763***	1.647***	1.784***	1.847***	1.733***	1.707***	1.785***	1.741***	1.609***	1.703***	1.593***
	(0.125)	(0.133)	(0.138)	(0.240)	(0.128)	(0.278)	(0.264)	(0.303)	(0.346)	(0.325)	(0.288)
β_L	−11.32***	−14.16***	−10.60***	−11.35***	−9.976***	−8.207***	−12.13***	−13.21***	−7.535***	−15.57***	−9.998***
	(0.000)	(0.000)	(0.000)	(0.831)	(0.000)	(0.974)	(0.911)	(1.052)	(1.121)	(1.142)	(1.007)
α_L	−0.039	0.027	−0.001	0.226***	0.005	0.1676**	0.081	0.177	−0.098	0.1903**	0.068
	(0.079)	(0.072)	(0.088)	(0.062)	(0.079)	(0.067)	(0.063)	(0.113)	(0.066)	(0.077)	(0.075)
AIC	−994.953	−900.001	−1084.217	−1203.389	−1058.425	−944.660	−1007.974	−1027.476	−961.865	−840.930	−914.959
BIC	−959.487	−864.536	−1048.751	−1167.923	−1022.959	−909.194	−972.508	−992.010	−926.399	−805.464	−879.494
Panel B: Short run (HWT)											
ω_u	1.2904*	1.4053**	1.427***	1.009***	1.4047**	1.159**	1.3751**	0.985	1.2499*	1.448*	1.177***
	(0.712)	(0.636)	(0.236)	(0.340)	(0.679)	(0.785)	(0.650)	(0.916)	(0.718)	(1.684)	(0.253)
β_u	−16.12***	−11.32***	−11.12***	−16.32***	−15.23***	−6.235***	−8.245***	−13.26***	−11.36***	−13.12	−12.11***
	(2.639)	(3.352)	(0.004)	(0.041)	(2.574)	(3.023)	(2.502)	(3.316)	(2.752)	(17.027)	(0.000)
α_u	−0.829***	−0.284	−0.648***	−0.672***	−0.489***	−0.643***	−0.639***	−0.695***	−0.674***	0.112	−0.787***
	(0.073)	(0.524)	(0.219)	(0.218)	(0.190)	(0.094)	(0.211)	(0.105)	(0.102)	(19.893)	(0.090)
ω_L	1.4962**	1.419***	1.352***	1.311***	1.533***	0.473	1.3061**	0.952	0.637	1.005*	1.284***
	(0.699)	(0.451)	(0.358)	(0.208)	(0.572)	(0.945)	(0.629)	(0.881)	(1.165)	(1.625)	(0.278)
β_L	−11.23***	−10.00***	−10.00***	−10.00***	−10.00***	−12.12***	−13.01***	−11.45**	−9.999**	−9.976	−9.213***
	(2.740)	(1.838)	(0.002)	(0.018)	(2.545)	(3.002)	(2.807)	(3.028)	(3.982)	(14.981)	(0.001)
α_L	−0.503**	0.020	−0.227	−0.079	0.0365**	−0.980***	−0.200	−0.921***	−0.981***	−0.387	−0.131
	(0.208)	(0.033)	(0.647)	(0.196)	(0.015)	(0.011)	(0.335)	(0.041)	(0.009)	(248.104)	(0.370)
AIC	−724.333	−564.893	−644.304	−524.036	−636.065	−537.898	−592.566	−550.832	−592.895	−454.521	−563.253
BIC	−688.867	−529.427	−608.839	−488.570	−600.599	−502.432	−557.100	−515.366	−557.429	−419.055	−527.787
Panel C: Long run (VMD)											
ω_u	0.941***	1.428***	1.476***	1.276***	1.277***	1.412***	2.017***	1.235**	1.309***	1.406***	1.692***
	(0.059)	(0.374)	(0.178)	(0.184)	(0.315)	(0.150)	(0.400)	(0.520)	(0.227)	(0.190)	(0.240)
β_u	−10.26***	−10.11***	−10.67***	−10.56***	−11.07***	−11.92***	−10.34***	−10.49*	−10.06***	−10.10***	−10.22***
	(0.000)	(1.554)	(0.001)	(0.940)	(1.516)	(0.000)	(1.788)	(5.192)	(1.025)	(0.000)	(1.249)
α_u	0.797***	0.355***	−0.016	0.599***	0.342***	0.138	−0.027	0.776***	0.525***	0.230***	0.309
	(0.030)	(0.095)	(0.099)	(0.054)	(0.119)	(0.125)	(0.034)	(0.207)	(0.064)	(0.072)	(0.083)
ω_L	3.028***	2.296***	3.035***	2.442***	2.810***	2.730***	2.479***	2.748***	2.943***	2.687***	2.436***
	(0.119)	(0.362)	(0.170)	(0.291)	(0.233)	(0.168)	(0.472)	(0.257)	(0.353)	(0.104)	(0.574)
β_L	−11.50***	−10.02***	−10.02***	−10.19***	−10.11***	−13.23***	−12.47***	−10.08***	−10.02***	−10.22***	−11.60***
	(0.000)	(1.061)	(0.000)	(0.907)	(0.796)	(0.000)	(1.626)	(0.775)	(1.164)	(0.000)	(1.221)
α_L	0.211***	−0.329***	−0.355***	−0.156**	−0.157***	−0.019	0.037	−0.172***	−0.309***	0.093***	0.000
	(0.047)	(0.060)	(0.095)	(0.066)	(0.044)	(0.085)	(0.033)	(0.036)	(0.050)	(0.049)	(0.098)
AIC	−2237.526	−1155.927	−1716.375	−1247.406	−1664.146	−1768.950	−1957.844	−1399.035	−1491.688	−1590.079	1783.182
BIC	−2202.060	−1120.462	−1680.909	−1211.940	−1628.680	−1733.485	−1922.378	−1363.569	−1456.222	−1554.613	−1747.716

(continued on next page)

parameters are found for Greece–Denmark stock market pair, and the HWT based dependence estimates provide no sign of upper or lower tail dependence for Greece–Ireland pair. Similarly, non-significant lower tail dependence is noted for Greece–Germany stock market pair.

The results for the long-term dependence dynamics for VMD and HTW decomposition are presented in panels C and D (Table 4). Notably, the values of long-run upper and lower tail dependence in case of HTW are higher than those reported by VMD. This result supports our previous analysis of decomposition where the variance of long-run series through HTW is close to zero. Thus, smoothness of the trend series obtained through wavelet decomposition results in higher estimates of the long-run dependence. We argue that decrease in variance of higher frequency series using wavelet methods may result in over-estimation of the statistical estimates.

Further, the dominance of TVP copula over other copula functions indicates that the link between Greece stock market with the other European countries is characterized by the tail and/or asymmetric dependence. These findings imply that

Table 4 (*continued*)

Greece with	Austria	UK	Belgium	Denmark	France	Germany	Italy	Ireland	Netherlands	Russia	Spain
Panel D: Long run (HWT)											
ω_u	9.097***	8.231**	5.00**	1.455***	1.796	2.228***	1.400***	2.00***	2.00***	1.967***	5.087***
	(2.238)	(4.467)	(2.571)	(0.072)	(8.012)	(0.105)	(0.059)	(0.004)	(0.096)	(0.011)	(0.809)
β_u	−1.588	−0.274	−10.22**	−11.15***	−12.41***	−9.994***	−9.021***	−10.12	−13.21***	−8.288***	−1.063
	(1.354)	(24.036)	(3.139)	(0.607)	(0.000)	(0.448)	(1.991)	(10.027)	(2.247)	(2.035)	(1.992)
α_u	−1.000***	−5.230***	10.00***	0.831***	8.324	0.856***	0.853***	9.995***	9.999***	8.117***	−1.666***
	(0.000)	(1.552)	(0.942)	(0.011)	(10.172)	(0.011)	(0.481)	(0.221)	(0.901)	(0.995)	(0.340)
ω_L	1.491	3.138	2.369***	2.254***	4.053***	1.482***	4.00***	2.155***	3.045***	3.193***	−0.116
	(5.434)	(32.653)	(0.412)	(0.371)	(1.466)	(0.075)	(1.175)	(0.247)	(0.410)	(0.444)	(3.645)
β_L	−0.207	−0.321	−11.08***	−9.979***	−0.156	−12.05***	−9.997***	−8.072	−10.00*	−9.552***	−0.448
	(30.297)	(24.757)	(0.377)	(1.560)	(2.175)	(0.577)	(2.007)	(2.020)	(0.713)	(1.333)	(3.866)
α_L	−1.039***	−3.510	0.871	0.894***	0.796**	0.885***	−0.721***	0.871	0.866***	0.625***	−2.328**
	(0.015)	(18.390)	(1.073)	(0.013)	(0.383)	(0.010)	(3.216)	(1.093)	(0.074)	(0.055)	(0.938)
AIC	−2153.156	−2238.123	−2858.315	−3268.928	−2703.104	−2697.805	−676.169	−2687.463	−3155.960	−2644.428	−1918.640
BIC	−2117.691	−2202.657	−2822.849	−3233.462	−2667.638	−2662.340	−640.703	−2651.997	−3120.495	−2608.962	−1883.174

Note: The table shows parameter estimates and standard errors (in parentheses). AIC and BIC denote Akaike and Bayesian information criteria, respectively.
* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

although the dependence occurs during most of the sample period, it (the dependence) varies with the extreme market events. The stock markets have the tendency to boom or crash together.

3.5. SJC copula dependence paths

In our view TVP SJC copula is superior to other copula functions and hence we exclusively focus on the lower tail dependence between Greece and European stock markets.[8] The lower tail dependence time paths for short-term return series are presented in Fig. 6(a)–(k), pair wise. We show the results of both HTW and VMD decomposition on a single figure for comparison. Notably, the short-term lower tail dependence of Greece stock market with other European stock markets varies between 0–0.6 and 0–0.8 using HTW and VMD decomposition, respectively. Considering the time-varying lower tail dependence, the graphs in Fig. 2 indicate two common features of the countries. First, the conditional dependence between the stock markets shows substantial time variations during the full sample period which supports the appropriateness of dynamic copulas over constant copulas. Second, the dependence of Greece stock market with all other countries' exhibits similarity in dependence structure over time. The lower tail dependence before 2007 crises varies between 0 and 0.4. This short-term comovement increases during early periods of 2007 and reaches a maximum of 0.6 for HTW and 0.8 for VMD series. More specifically, an increase in lower tail dependence between Greece and European stock markets is apparent during financial crises of 2007–08 which decrease to general level towards the end of 2011. These two short-term dependence regimes are consistent with the earlier findings of stock markets co-movement [56,3], Graham et al. (2013), [57]. We also note a difference of variations in dependence based on HTW and VMD decomposition methods. Although, the magnitude of variations is higher with VMD based series, there is an overall consistency in detecting the two different dependence regimes.

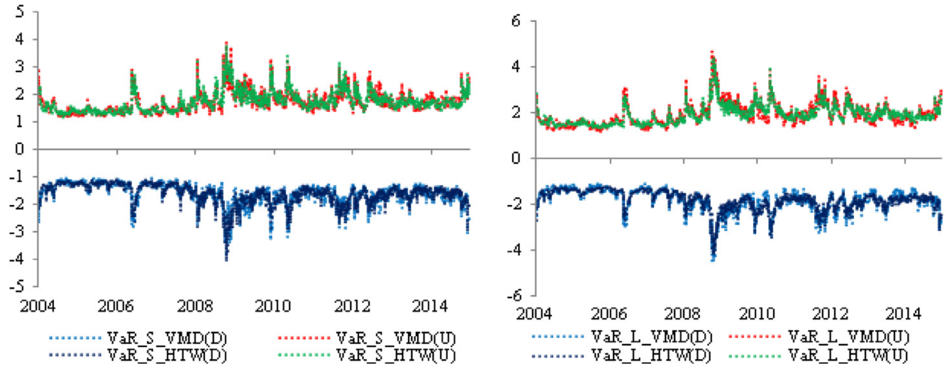
Next, the long-term lower tail dependence time paths of Greece stock markets with other stock markets are shown in Fig. 7(a)–(k). The long-term dynamics does not indicate any substantial change in dependence between the stock markets especially during the financial crises. The overall dependence depicted by both decomposition methods is higher. The VMD methods suggest highest dependence between the Greece–Austrian stock market pair (0.8). The long-term dependence of Greece with other markets has maximum at 0.6. As expected, the long-term dependence exhibits less fluctuation compared to the short-run. Notably, there is a difference in the peaks and troughs of both decompositions methods and the variations are higher for HTW series. In conclusion, both decomposition methods depict that the short-term lower tail dependence of Greece increased during financial crises and long-run dependence between the markets is generally higher.

3.6. Risk management application

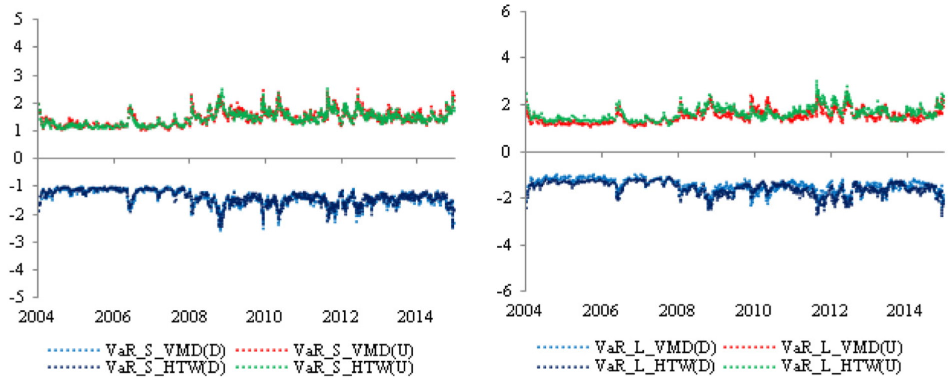
We first quantify the risk of individual stock markets by calculating down and upside Value atRisk (VaR).[9] Following Reboredo et al. [60], the VaR of a single asset shows the maximum possible loss within a specific time interval and at a given

[8] The upper tail dependence figures are not presented here as our primary focus is on lower tail dependence and its dynamics during financial crises. The upper tail dependence figures nevertheless can be made available upon request.

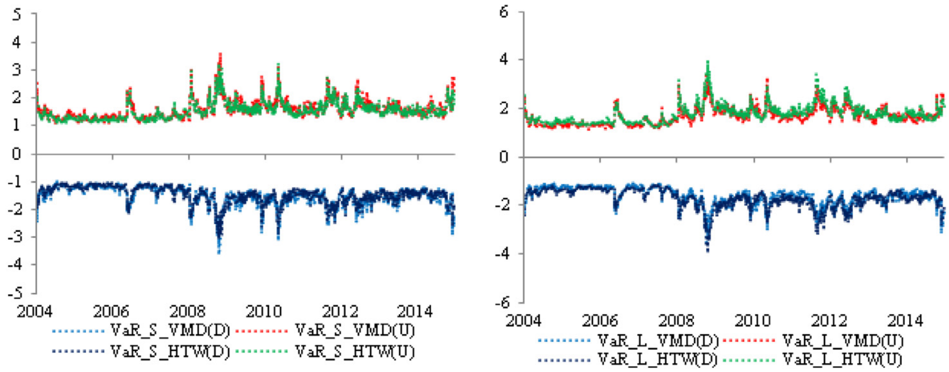
[9] A detailed exposition in regards to the performance of the extreme value theory in Value-at-Risk calculations relative to other modeling techniques is provided in Ref. [58] and in regards to the application of VaR in emerging markets, see Ref. [59].



(a) Greece–Austria.



(b) Greece–UK.



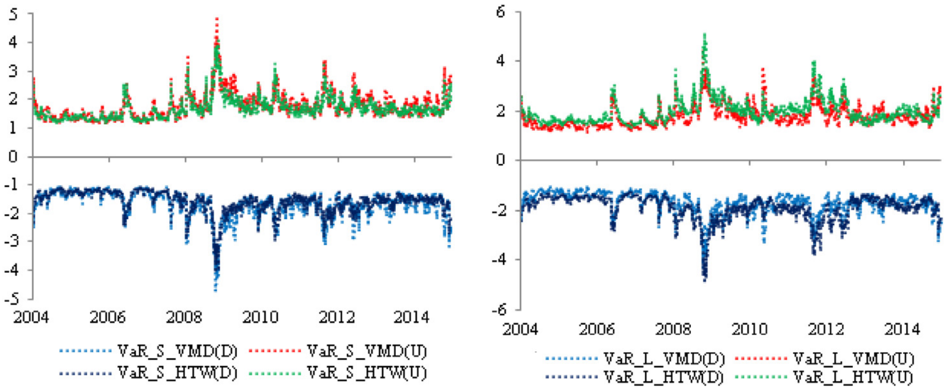
(c) Greece–Belgium.

Fig. 9. Upside and downside portfolio short run VaR (left) and long run VaR (right).

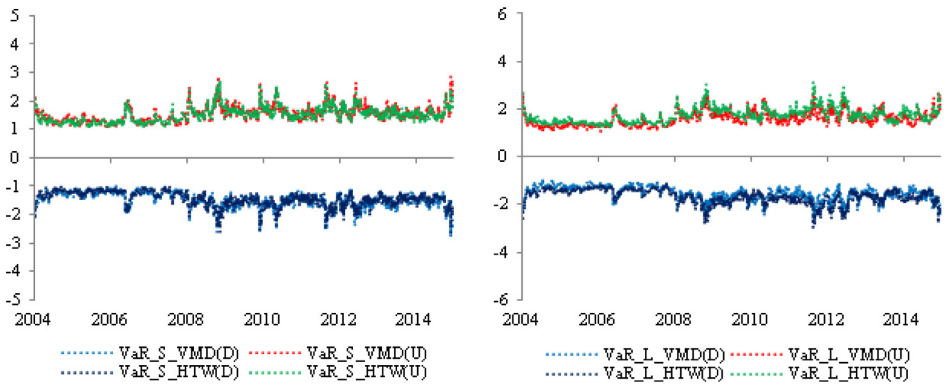
level of confidence. Hence, the upside and downside VaR quantifies the possibility of losses of a buy side (long position) and a sell side (short position) investor. These two risk measures are of equal importance for safety-first investors in an effort to minimize the probable extreme losses (Poon et al. 2004).

The downside VaR for a time period t with a significance level α (confidence level $1-\alpha$) can be quantified as $Pr\left(r_t \le VaR_{a,t}\right) = \alpha$. With the marginal model estimates, this can be calculated as $VaR_{a,t} = \mu_t + t_{\nu,\eta}^{-1}(\alpha)\sigma_t$. Here, the conditional mean μ_t and conditional variance σ_t of stock market returns are calculated using Eqs. (1)–(2) and the α-quantile i.e. $t_{\nu,\eta}^{-1}(\alpha)$ derives it values from the skewed Student-t distribution as in Eq. (3). Similarly, the upside VaR can be computed by $Pr\left(r_t \le VaR_{1-\alpha,t}\right) = \alpha$ and with the marginal model estimates it can be represented as: $VaR_{1-\alpha,t} = \mu_t + t_{\nu,\eta}^{-1}(1-\alpha)\sigma_t$.

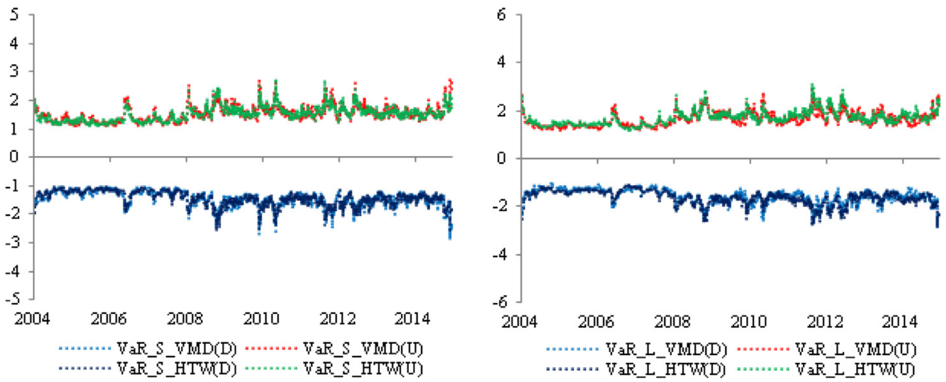
The resulting temporal dynamics of downside and upside VaR of individual stock markets are shown in Fig. 8(a)–(l). All figures depict a similar trend of both risk measures for all countries with slight differences in the magnitudes. Although the



(d) Greece–Denmark.



(e) Greece–France.

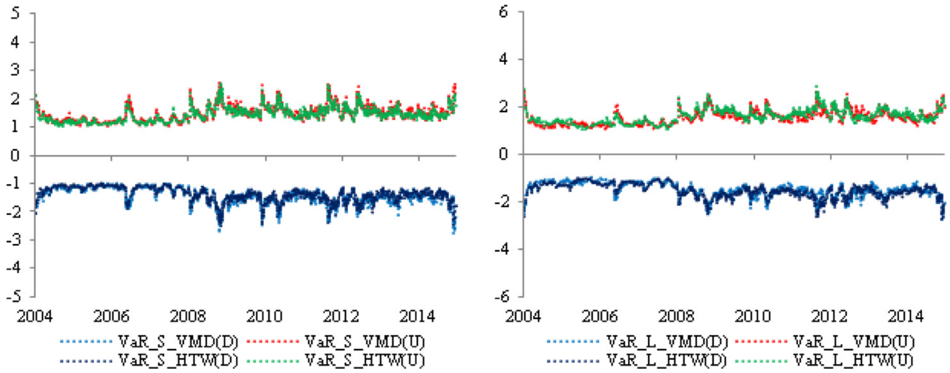


(f) Greece–Germany. .

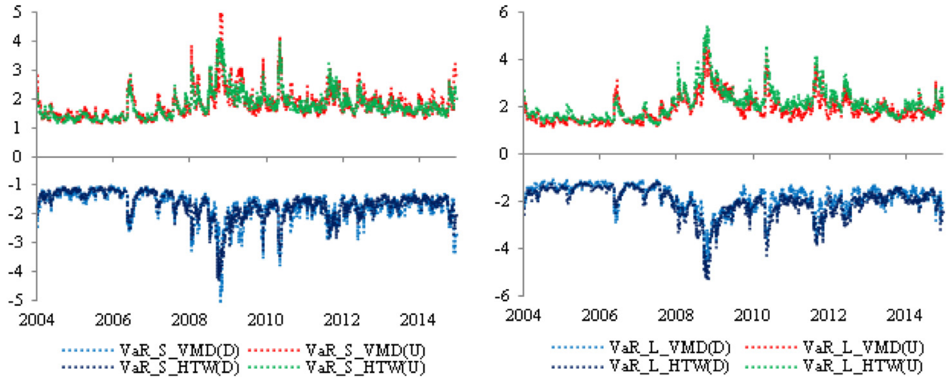
Fig. 9. (*continued*)

impact of the global financial crisis of 2007–08 is marked with sudden high values of down and upside VaRs, this is common for all selected stock markets. However, we can divide the stock markets into two distinct groups. The first group which includes Austria, Belgium, Denmark, Germany, Ireland, Netherlands, and Russia, shows that up and down VaRs decreased to their normal levels after global financial crises and experienced a sudden marginal increase during 2011–2012 periods. Notably, this time period corresponds to the downgrade of the Greece's credit rating by several rating agencies and the fall of the Athens Stock Exchange general index below 1000 points on 8th August, 2011. The other group comprises of Greece, UK, France, Italy and Spain. The down- and up-side VaR of these stock markets have remained vibrant after 2012 with a number of peaks.

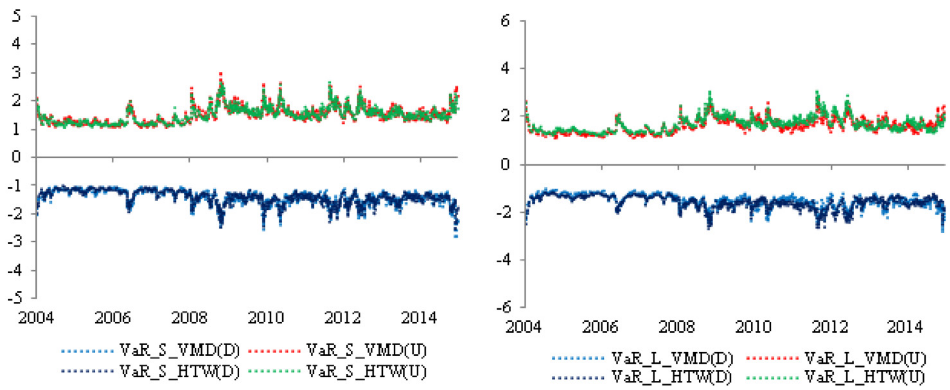
Next, we formulate a two-asset portfolio by combining Greece stock market with other European stock markets. For portfolio risk, we consider the comovement between the markets pairs which is obtained from the best copula function.



(g) Greece–Italy.



(h) Greece–Ireland.

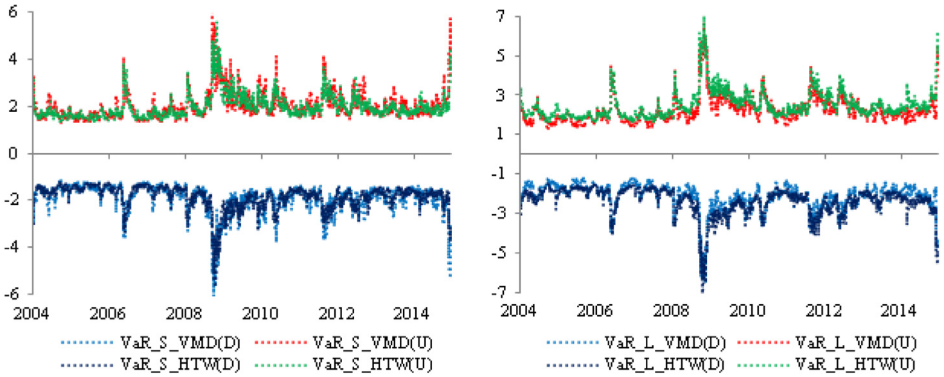


(i) Greece–Netherlands.

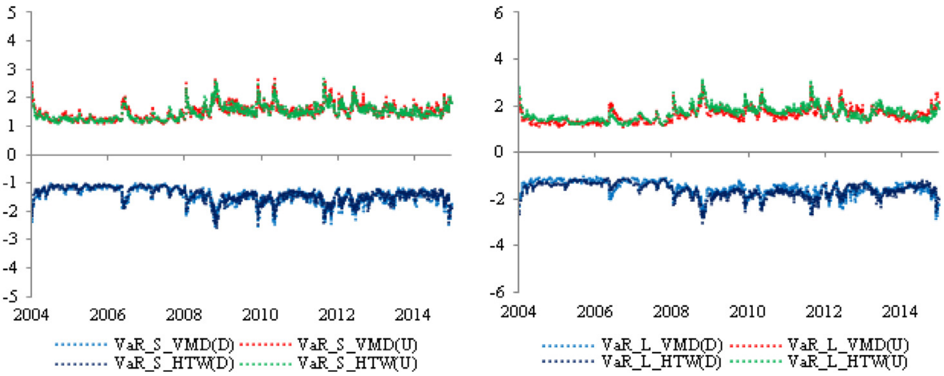
Fig. 9. (*continued*)

Notably, TVP SJC provides dependence series for both lower and upper tails and considers the two different methods of decomposition. Hence, first we compute the two assets up (upper tail) and down (lower tail) VaRs using the short-term dependence through HTW and VMD. Similarly, the long-term down and up portfolio VaRs are computed using long-run lower and upper tail dependence, respectively. Now, the portfolio VaR shows the maximum possible loss that a two-asset portfolio can incur over short or long time period at the 95% confidence level. The graphic representation for stock market pairs is provided in Fig. 9(a)–(k) where the figures on the left (right) show the short (long) term portfolio VaRs.

Notably, less comovement between stock market pairs results in lower VaRs. Thus dependence regimes have implications for portfolio diversification in both the short- and long-run. When we add UK, France, Germany, Italy, Netherlands, and Spain to Greece, we note a significant difference in portfolio VaRs in comparison with individual VaR patterns (Fig. 8(a)–(l)). Further, the portfolio of Greece stock market with Austria, Belgium, Denmark, Ireland and Russia indicates higher up and



(j) Greece–Russia.



(k) Greece–Spain.

Fig. 9. (*continued*)

down (for both the short- and long-run dependence) VaR during global financial crises of 2007–08. These market pairs also show an increase in VaR during 2011–12.

It is worth noting that Greece, UK, France, Italy and Spain stock markets show a permanent increase in VaR after 2011–12 but when combined with Greece as a portfolio, both short and long-term VaR values become smooth. These findings suggest that portfolio implications, which are mainly driven by the co-movement between the assets, of a financial crisis can be seen in at least two dimension: (a) the diversification benefits may not always decrease but the new investment avenues may arise after the crisis episode; and (b) the co-movement of asset is time dependent and hence investment time horizon plays a vital role. Therefore, the (institutional) investors like hedge funds, insurance companies, banks and pension funds, among others can influence and/or drive the portfolio implication based on their specific investment time horizon.

4. Conclusion

In this study, we examined the interdependence of European stock markets and their portfolio implications in wavelet and variational mode decomposition domain. Both decomposition techniques enabled us to analyze the structural properties of data while distinguishing between short and long term dynamics of stock market returns. First, the standardized residuals were obtained through GARCH-type models. Next, different copula functions were evaluated based on the conventional information criteria and hence the TVP SJC copula was chosen to model the tail dependence between the stock markets. The short-run lower tail dependence time paths showed a sudden increase in comovement during the global financial crises. The results of long-run dependence suggested that European stock markets have higher interdependence with Greece stock market.

Next, we apply the extreme value theory and calculate individual country as well as the upside and downside portfolio VaRs. It is worth noting that the possibility of losses differs in a buy side (long position) and a sell side (short position) investor. These two risk measures are of equal importance for safety-first investors in an effort to minimize the probable extreme losses. Further, the market expectations and investment implications of stock markets' dependence differ for short-term and long-term investors. Hence, first we compute the two assets up (upper tail) and down (lower tail) VaRs using the short-term dependence through HTW and VMD. Similarly, the long-term down and up portfolio VaRs are computed using long-run lower and upper tail dependence, respectively. The individual country Value at Risk (VaR) separated the countries into two distinct groups. A two-asset portfolio VaR measures highlighted the potential markets for Greece stock market investment diversification.

The findings provide a useful input for regional and international investors when assigning optimal weightage of different assets in portfolio formulation. The investors should also consider that diversification benefits of European stock markets are lesser for long-term investments and vanish during the financial (debt) crisis. Additionally, the study contributed to the literature in understanding the decomposed financial time series and its application in portfolio management. Further application of decomposed time series to evaluate different portfolio strategies viz. individual utility functions can be an area worth exploring for future research.

References

[1] R. Aloui, M.S.B. Aïssa, D.K. Nguyen, Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? J. Bank. Finance 35 (1) (2011) 130–141.
[2] G. Dewandaru, S.A.R. Rizvi, R. Masih, M. Masih, S.O. Alhabshi, Stock market co-movements: Islamic versus conventional equity indices with multi-timescales analysis, Econ. Syst. 38 (4) (2014) 553–571.
[3] M. Gallegati, A wavelet-based approach to test for financial market contagion, Comput. Statist. Data Anal. 56 (11) (2012) 3491–3497.
[4] L. Loh, Co-movement of Asia-Pacific with European and US stock market returns: A cross-time–frequency analysis, Res. Int. Bus. Finance 29 (2013) 1–13.
[5] K.J. Forbes, R. Rigobon, No contagion, only interdependence: measuring stock market comovements, J. Finance 57 (5) (2002) 2223–2261.
[6] S.R. Das, R. Uppal, Systemic risk and international portfolio choice, J. Finance 59 (6) (2004) 2809–2834.
[7] F. Longin, B. Solnik, Extreme correlation of international equity markets, J. Finance 56 (2001) 649–676.
[8] A.J. Patton, On the out-of-sample importance of skewness and asymmetric dependence for asset allocation, J. Bank. Finance 2 (1) (2004) 130–168.
[9] P. Embrechts, A. McNeil, D. Straumann, Correlation and dependence in risk management: properties and pitfalls, in: Risk Management: Value at Risk and Beyond, Cambridge University Press, 2002, pp. 176–223.
[10] T. Berger, Forecasting value-at-risk using time varying copulas and EVT return distributions, Int. Econ. 133 (2013) 93–106.
[11] C.P. Hsu, C.W. Huang, W.J.P. Chiou, Effectiveness of copula-extreme value theory in estimating value-at-risk: empirical evidence from Asian emerging markets, Rev. Quant. Financ. Account. 39 (4) (2012) 447–468.
[12] T. Berger, A wavelet based approach to measure and manage contagion at different time scales, Physica A 436 (2015) 338–350.
[13] F. Caramazza, L. Ricci, R. Salgado, International financial contagion in currency crises, J. Int. Money Finance 23 (1) (2004) 51–70.
[14] I. Goldstein, A. Pauzner, Contagion of self-fulfilling financial crises due to diversification of investment portfolios, J. Econom. Theory 119 (1) (2004) 151–183.
[15] F. Allen, D. Gale, Financial contagion, J. Polit. Econ. 108 (1) (2000) 1–33.
[16] T. Adrian, H.S. Shin, Financial intermediaries, financial stability, and monetary policy. FRB of New York staff report, (346), 2008.
[17] G.A. Calvo, Contagion in emerging markets: when Wall Street is a carrier, 1999. http://drum.lib.umd.edu/handle/1903/4036.
[18] A.S. Kyle, W. Xiong, Contagion as a wealth effect, J. Finance 56 (4) (2001) 1401–1440.
[19] D. Gromb, D. Vayanos, Limits of arbitrage: The state of the theory (No. w15821). National Bureau of Economic Research, 2010.
[20] W. Xiong, Convergence trading with wealth effects: an amplification mechanism in financial markets, J. Financ. Econ. 62 (2) (2001) 247–292.
[21] I. Schnabel, H.S. Shin, Liquidity and contagion: The crisis of 1763, J. Eur. Econ. Assoc. (2004) 929–968.
[22] M.S. Kumar, A. Persaud, Pure contagion and investors' shifting risk appetite: analytical issues and empirical evidence, Int. Finance 5 (3) (2002) 401–436.
[23] R.J. Caballero, A. Krishnamurthy, Flight to quality and collective risk management (No. w12136). National Bureau of Economic Research, 2006.
[24] V. Coudert, M. Gex, Does risk aversion drive financial crises? Testing the predictive power of empirical indicators, J. Empir. Finance 15 (2) (2008) 167–184.
[25] D. Vayanos, Flight to quality, flight to liquidity, and the pricing of risk (No. w10327). National Bureau of Economic Research, 2004.
[26] J. Annaert, M. De Ceuster, P. Van Roy, C. Vespro, What determines euro area bank CDS spreads? J. Int. Money Finance 32 (2013) 444–461.
[27] L.E. Kodres, M. Pritsker, A rational expectations model of financial contagion, J. Finance 57 (2) (2002) 769–799.
[28] S. Bikhchandani, S. Sharma, Herd behavior in financial markets, IMF Staff Pap. (2000) 279–310.
[29] G.A. Calvo, E.G. Mendoza, Rational contagion and the globalization of securities markets, J. Int. Econ. 51 (1) (2000) 79–113.
[30] S. Chakravorti, S. Lall, Managerial incentives and financial contagion. Federal Reserve Bank of Chicago Research Paper Series, 2003.
[31] R.A. Jarrow, F. Yu, Counterparty risk and the pricing of defaultable securities, J. Finance 56 (5) (2001) 1765–1799.
[32] P. Jorion, G. Zhang, Credit contagion from counterparty risk, J. Finance 64 (5) (2009) 2053–2087.
[33] V. Coudert, M. Gex, Contagion inside the credit default swaps market: The case of the GM and Ford crisis in 2005, J. Int. Financ. Markets Inst. Money 20 (2) (2010) 109–134.
[34] G. Dewandaru, R. Masih, A.M.M. Masih, Why is no financial crisis a dress rehearsal for the next? Exploring contagious heterogeneities across major Asian stock markets, Physica A 419 (2015) 241–259.
[35] K. Dragomiretskiy, D. Zosso, Variational mode decomposition, IEEE Trans. Signal Process. 62 (3) (2014) 531–544.
[36] Y. Fan, R. Gençay, Unit root tests with wavelets, Econometric Theory 26 (05) (2010) 1305–1331.
[37] R. Gençay, F. Selçuk, B. Whitcher, Differentiating intraday seasonalities through wavelet multi-scaling, Physica A 289 (3) (2001) 543–556.
[38] R. Gençay, F. Selçuk, B. Whitcher, Scaling properties of foreign exchange volatility, Physica A 289 (1) (2001) 249–266.
[39] R. Gencay, D. Signori, Multi-scale tests for serial correlation, J. Econometrics 184 (1) (2015) 62–80.
[40] F. In, S. Kim, R. Gençay, Investment horizon effect on asset allocation between value and growth strategies, Ecol. Modell. 28 (4) (2011) 1489–1497.
[41] Y. Xue, R. Gençay, S. Fagan, Jump detection with wavelets for high-frequency financial time series, Quant. Finance 14 (8) (2014) 1427–1444.
[42] F. Murtagh, J.L. Starck, O. Renaud, On neuro-wavelet modeling, Decis. Support Syst. 37 (4) (2004) 475–484.
[43] H. Boubaker, N. Sghaier, Portfolio optimization in the presence of dependent financial returns with long memory: A copula based approach, J. Bank. Finance 37 (2) (2013) 361–377.
[44] R.B. Nelsen, An Introduction to Copulas, Springer-Verlag, New York, 1999.
[45] F.X. Diebold, T.A. Gunther, A.S. Tay, Evaluating density forecasts with applications to financial risk management, Internat. Econom. Rev. 39 (1998) 863–883.
[46] J.M. Zakoian, Threshold heteroskedastic models, J. Econom. Dynam. Control 18 (5) (1994) 931–955.
[47] B.E. Hansen, Autoregressive conditional density estimation, Internat. Econom. Rev. (1994) 705–730.
[48] D.L. Donoho, Denoising by soft-thresholding, IEEE Trans. Inform. Theory 41 (1995) 613–627.
[49] R. Jammazi, Cross dynamics of oil-stock interactions: A redundant wavelet analysis, Energy 44 (1) (2012) 750–777.
[50] E. Haven, X. Liu, L. Shen, De-noising option prices with the wavelet method, European J. Oper. Res. 222 (1) (2012) 104–112.
[51] S. Lahmiri, Long memory in international financial markets trends and short movements during 2008 financial crisis based on variational mode decomposition and detrended fluctuation analysis, Physica A 437 (2015) 130–138.
[52] R. Jammazi, A.K. Tiwari, R. Ferrer, P. Moya, Time-varying dependence between stock and government bond returns: International evidence with dynamic copulas, N. Am. J. Econ. Finance 33 (2015) 74–93.
[53] T. Berger, M. Missong, Copulas and portfolio strategies: an applied risk management perspective, J. Risk 17 (2) (2014) 51.

[54] C. Aloui, R. Jammazi, Dependence and risk assessment for oil prices and exchange rate portfolios: A wavelet based approach, Physica A 436 (2015) 62–86.
[55] A.J. Patton, Modelling asymmetric exchange rate dependence, Internat. Econom. Rev. 47 (2) (2006) 527–556.
[56] C. Aloui, B. Hkiri, Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis, Ecol. Modell. 36 (2014) 421–431.
[57] X. Huang, H. An, X. Gao, X. Hao, P. Liu, Multiresolution transmission of the correlation modes between bivariate time series based on complex network theory, Physica A 428 (2015) 493–506.
[58] R. Gençay, F. Selçuk, A. Ulugülyagci, High volatility, thick tails and extreme value theory in value-at-risk estimation, Insurance Math. Econom. 33 (2) (2003) 337–356.
[59] R. Gencay, F. Selcuk, Extreme value theory and Value-at-Risk: Relative performance in emerging markets, Int. J. Forecast. 20 (2) (2004) 287–303.
[60] J.C. Reboredo, M.A. Rivera-Castro, A. Ugolini, Downside and upside risk spillovers between exchange rates and stock prices, J. Bank. Finance 62 (2016) 76–96.
[61] M. Sklar, Fonctions de Répartition à n Dimensions et Leurs Marges, Université Paris 8, 1959, pp. 229–231.