Time-varying stock market efficiency on the Balkan refugee route

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Abstract: - Five German states will hold elections this year in preparation for federal elections in 2017. These votes will be a referendum on Merkel and her Christian Democratic Union, which has opened the doors to large masses of unassimilable foreigners. The German Federal Minister of Economic Cooperation and Development Gerd Müller warned that only 10% of Syrian and Iraqi migrants have made it to Europe so far, and that “8 to 10 million are still on the way.” And, he warns, millions more are coming from Africa. This study focuses on one facet of this complex issue, the stock market efficiency reflection to the surge in asylum seekers in the European Union (EU). Market efficiency is investigated for a period of 7 years, between April 2009 and April 2016. A wavelet-based technique is utilized to the daily return series of the major stock indices of the eight stock markets on the Balkan refugee route (Greece, Turkey, Bulgaria, Serbia, Croatia, Hungary, Austria and Germany) in order to track the dynamics of the long-range dependence (LRD) parameter, since its value is closely related to the degree of returns predictability.

Key-Words: - Long-range dependence; wavelet transform; European Union; refugee crisis

1 Introduction

Five German states will hold elections this year in preparation for federal elections in 2017. These votes will be a referendum on Merkel and her Christian Democratic Union, which has opened the doors to large masses of unassimilable foreigners. The German Federal Minister of Economic Cooperation and Development Gerd Müller warned that only 10% of Syrian and Iraqi migrants have made it to Europe so far, and that “8 to 10 million are still on the way.” And, he warns, millions more are coming from Africa. This study focuses on one facet of this complex issue, the stock market efficiency reflection to the surge in asylum seekers in the European Union (EU).

The weak-form of efficient market hypothesis (EMH) is built based on the assumption that newly generated information is immediately and completely reflected in stock prices (Fama, 1970). In support of this hypothesis, stock price follows a “random walk” or a process with no memory.

The random walk model, as noted above, hypothesizes that successive price changes are independent and suggests that price increments are independently and identically distributed (i.i.d.), in which case the process of y_t is given by:

$$y_t = C + y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim i.i.d.(0, \sigma^2) \qquad (1)$$

where *C* is the expected price change or drift.

In the recent finance literature, several studies have been interested in examining the statistical properties of returns and the volatility of stock markets focused on investigating the long memory and/or structural break properties.

2 Time-varying long term memory

M. Liu [1] constructed a model, which he called the regime switching stochastic volatility (RSSV) model, to model the long memory pattern in stock market volatility. Using RSSV model for the S&P composite return series, the paper presents evidence in support of the assumption of a heavy-tail distribution with a duration of a regime. The model is found to fit the dynamics of the stock prices extremely well and the estimated tail index is highly significant. Daniel Cajueiro and Benjamin Tabak [2] have studied the short and long-term predictability in emerging European transition equity markets. They also have estimated Hurst exponents to test for long-range dependence, and have found evidence of such. In addition, the same authors have developed a formal test for long-range dependence using the R/S and V/S methodologies for 41 equity indices for world markets [3].

In a recent paper [4] Sang Hoon Kang has estimated the long memory property in the volatility of Chinese stock markets and has found that the volatility in four Chinese stock markets reveals a long memory feature. In addition, the suggested assumption of non-normality has provided better specifications when modelling long memory volatility processes and the FIGARCH model is better equipped to capture the long memory volatility process than the GARCH and IGARCH models.

In their paper from 2015 Ahmet Sensoy and Benjamin M. Tabak proposed a new efficiency index to model time-varying inefficiency in stock markets [5]. They have focused on European stock markets and have shown that these markets have different degrees of time-varying efficiency. The authors observed that the 2008 global financial crisis has an adverse effect on almost all EU stock markets. However, the Eurozone sovereign debt crisis has a significant adverse effect only on the markets in France, Spain and Greece. For the late members, joining EU does not have a uniform effect on stock market efficiency.

The primary aim of this paper is to examine the time-varying long term memory property in the volatility of eight stock markets on the Balkan refugee route (Greece, Turkey, Bulgaria, Serbia, Croatia, Hungary, Austria and Germany) employing wavelet-based technique in the period after 2008 global financial crisis.

2.1 Long-Range Dependence and FARIMA (p, d, q)

The presence of a short-term dependency in a given data set could be modeled very well by the classical ARIMA processes however the covariance between the observations X_i and X_{i+h} decreases fast with the increase of h. More precisely – the autocorrelation function of the process $\rho(k)$ is geometrically restricted:

$$|\rho(k)| \le Cr^k, \quad k = 1,2,\ldots, \tag{2}$$

where C>0 и 0< r <1.

A class of models where the covariance between distant observations decreases like power function, are suggested simultaneously by [6] and [7]. A main feature of these models is the usage of fractional differentiation. The operator for fractional differentiation is formally defined by the following binomial decomposition:

$$\nabla^d = (1-B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-B)^j = \tag{3}$$

$$= 1 - dB - \frac{1}{2}d(1-d)B^2 - \frac{1}{6}d(1-d)B^3 \ldots$$

where B is the lag operator $Bx_i = x_{i-1}$, and d takes fractional values. To calculate the binomial coefficients it is technically more convenient to use the Gama function $\Gamma(.)$:

$$\nabla^d = (1-B)^d = \sum_{j=0}^{\infty} \pi_j B^j \, (-B)^j \tag{4}$$

where

$$\pi_j = \prod_{0<k\le j} \frac{k-1-d}{k} = \frac{\Gamma(j-d)}{\Gamma(j+1)\Gamma(-d)}, \quad j = 0,1,2,\ldots; \tag{5}$$

The ARIMA (0, d, 0) process could be defined when the operator for fractional differentiation is used (in the case of Gaussian innovations): $\nabla^d X_t = Z_t$,

where Z_t is a process of discrete white noise – for simplicity it is taken to have one as a dispersion and d takes values in the (-0.5,0.5) interval.

The main features of one ARIMA (0, d, 0) process could be listed without a detailed exposition as follows:

- when d<0.5 $\{X_t\}$ is a stationary process with infinite moving average representation:

$$X_t = \sum_{j=0}^{\infty} \psi_j Z_{t-j} = \nabla^{-d} Z_t, \text{ where} \tag{6}$$

$$\psi_j = \frac{(j-1+d)!}{j!(-1+d)} = \frac{\Gamma(j+d)}{\Gamma(j+1)\Gamma(d)} \tag{7}$$

when $j \to \infty, \quad \psi_j \sim j^{d-1} \big/ (d-1)!$.

- when d>-0.5 {Xt} is a invertible process and has the following infinite autoregression representation:

  $$\nabla^d X_t = Z_t = \sum_{j=0}^{\infty} \pi_j X_{t-j},$$

  where the coefficients π_j are defined in (4)

  when $j \to \infty, \quad \pi_j \sim j^{-d-1} \big/ (-d-1)!$
- when -0.5<d<0.5 the spectral density of $\{X_t\}$ is $s(\omega) = \left(2\sin\frac{1}{2}\omega\right)^{-2d}, 0 < \omega \le \pi$, and in case of $\omega \to \infty$ we have that $s(\omega) \to \omega^{-2d}$.
- when -0.5<d<0.5 the autocovariance function, autocorrelation function and the partial autocorrelation function are:

$\gamma(h) = E(X_t X_{t-h}) = \frac{(-1)^h(-2d)!}{(h-d)!(-h-d)!}$;
$\rho(h) = \frac{\gamma(h)}{\gamma(0)} = \frac{\Gamma(h+d)\Gamma(1-d)}{\Gamma(h-d+1)\Gamma(d)}$,
and in case $h \to \infty$ we have that $\rho(h) \sim \frac{d!}{(d-1)!} h^{2d-1}$; $\alpha(h) = \frac{d}{(h-d)}$;
The listed features reveal that when -0.5<d<0.5 the ARIMA (0, d, 0) process is stationary and invertible, with coefficients ψ_j, π_j that decrease like a power function with the increase of j. We should note the difference from the exponential decrease in the case of a standard ARIMA (p, 0, q) process. When d>0 there is a long-term dependency, as could be seen from the formulas for $s(\omega)$ if $\omega \to 0$ and $\rho(h)$ if $h \to \infty$.
On the basis of the results received for ARIMA (0, d, 0) could be defined a significantly broader class of ARIMA (p, d, q) processes with fractional d.
The process $\{X_t\}$ is a fractional ARIMA (p, d, q) process with -0.5<d<0.5 and if it is stationary and satisfies a difference equation of the form:

$$\Phi(B)\nabla^d X_t = \Theta(B) Z_t \tag{8}$$

where

$$\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p,$$
$$\Theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q, \tag{9}$$

B is the lag operator, and Z_t is a discrete white noise.
If the polynomials $\Phi(B), \Theta(B)$ do not have common roots then in case of $\Phi(z) \neq 0$ when $|z| = 1$ then a single stationary solution of (7) exists and it is given by:

$$X_t = \sum_{j=-\infty}^{\infty} \psi_j \nabla^{-d} Z_{t-j} \tag{10}$$

where $\Psi(z) = \sum_{j=-\infty}^{\infty} \psi_j z^j = \Theta(z)/\Phi(z)$ (11)

2.2 Wavelet-based estimator of the LRD parameter

The wavelet regression relies on the Mallat decomposition [8] and Bogdanova & Ivanov algorithm [9]. The Mallat wavelet regression filters the original data series X = $(X_0, X_1, \ldots, X_{N-1})$ using a pair of high-pass and low-pass filters denoted, respectively, as $h = (h_0, h_1, \ldots, h_{L-1})$ and $g = (g_0, g_1, \ldots, g_{L-1})$, each of length L, $L < N$. The wavelet and the scaling coefficients corresponding to the j^{th} level of decomposition, j = 1, 2, . . , j. J is an integer, are obtained via Equations (12) and (13), respectively:

$$w_{j,t} = \sum_{l=0}^{L-1} h_l c_{j-1}, 2t + 1 - l \bmod N \tag{12}$$

$$c_{j,t} = \sum_{l=0}^{L-1} g_l c_{j-1}, 2t + 1 - l \bmod N \tag{13}$$

for t = 0, 1,…, $N/2j - 1$.
Mallat decomposition utilizes the fact that there is a linear relationship between the variable $s_j = \log_2(\mathrm{var}(w_j))$ and the octave j, $j \in [j_1, j_2]$, j_1 and j_2 are integers, referred to as upper and lower cut-off, respectively. Intuitively, one would run linear regression in order to estimate the slope coefficient γ, where the fractional differencing parameter is expressed as $d = \gamma/2$. Bogdanova & Ivanov adopt the weighted linear regression proposed in [10] and derive the estimator of the slope coefficient expressed in Equation (14):

$$\hat{\gamma} = \frac{\sum_{j=j_1}^{j_2} y_j (jS - S_1)/\sigma_j^2}{SS_2 - S_1^2}, \tag{14}$$

where $y_j = log_2(\left(\frac{1}{N_j}\right)\sum_{t=0}^{N_j-1} |w_{j,t}|^2) - g(j)$,

$$g(j)\left(-\frac{1}{N_j Ln2}\right), \quad \sigma_j^2 \sim \frac{2}{N_j ln^2 2},$$
$$S = \sum_{j=j_1}^{j_2} \frac{1}{\sigma_j^2}, \; S_1 = \sum_{j=j_1}^{j_2} \frac{j}{\sigma_j^2}, \; S = \sum_{j=j_1}^{j_2} \frac{j^2}{\sigma_j^2},$$

For computing the time-varying long term memory property in the volatility of the researched stock markets we have applied the following algorithm:
Step 1: The Stephane Mallat algorithm is applied over a window of the first 512 observations;
Step 2: An estimate of the slope coefficient $\hat{\gamma}$ is obtained through application of Equation (14) and an estimate of d is derived as $\hat{d} = \frac{\hat{\gamma}}{2}$;
Step 3: The window is slid forward by one day ahead (i.e. the first observation is dropped and the 513^{-th} observation is included). The first two steps are performed again, thus obtaining another estimate $\hat{d}$. The estimating procedure is repeated until the last observation is included in the window.

2.3 Data

All analysis undertaken in this paper is based on a data set that consists of the daily closing prices of eight stock markets on the Balkan refugee route (Greece, Turkey, Bulgaria, Serbia, Croatia, Hungary, Austria and Germany) in the period Q2 2009 – Q2 2015. The results that were obtained concern the most important indices that were surveyed - 'XU100', 'ASE100', 'BELEX15', 'BUX', 'CROBEX', 'ATX', 'DAX' and 'SOFIX' measured as the daily logarithmic stock returns. The data that consists of daily quotes is transformed into logarithmic returns according the following formula:

$$R_t = \log \frac{P_t}{P_{t-1}}, \quad t = 2,3,\ldots,N \tag{15}$$

3 Empirical analysis

We use a rolling sample approach, therefore we do not have to use a strict cutoff date which is usually subject to criticism. Recent papers using rolling window approach shown that long term memory property evolves over time. In order to verify if this is the case, we choose a 2 year (512 observations) time-window (that shift a day at a time). Even when an important event occurs such as a refugee crisis, it may take a long time for its full effect to take place.
Following the algorithm, proposed in Section 2.2, dynamical estimate of the long memory in stock market volatility parameter measured as fractional differencing parameter d is delivered for the investigated return series. The following findings might be outlined with regard to the wavelet regression results, Fig. 1.

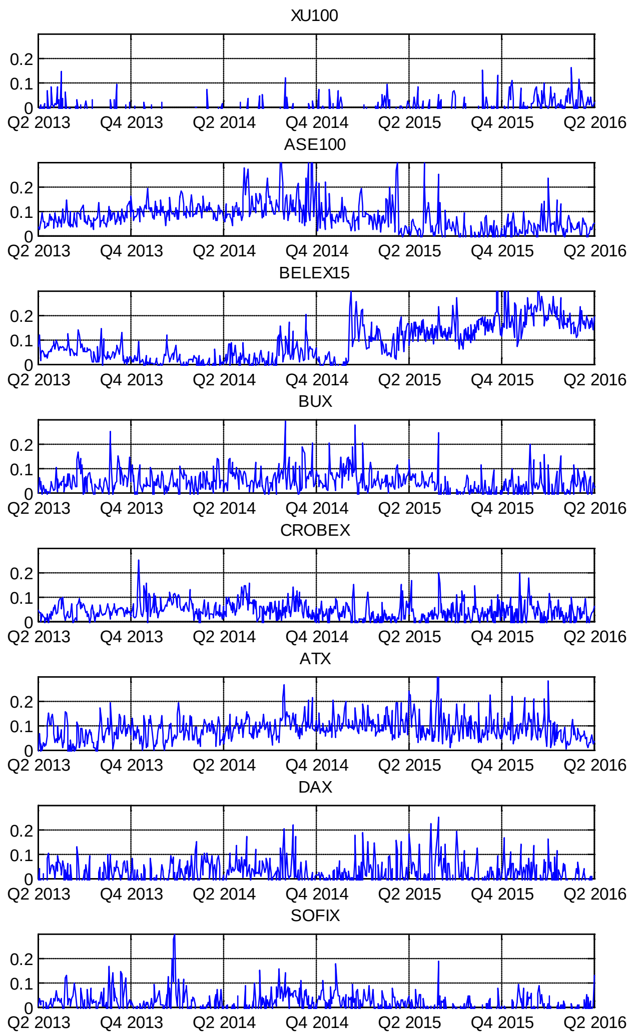

Fig. 1- Blue curves are the time-varying fractional differencing parameter d for the logarithmic return series of the studied stock markets

For all eight stock markets, Fig. 1 presents the time-varying fractional differencing parameter d for the logarithmic return series.
The period Q2 2009 – Q2 2015of our study includes the 2010 global refugee crisis. The time-varying long memory pattern in stock market measured as fractional differencing parameter d tell us that stock market efficiency reacts to the global refugee crisis basically in one of the next ways:

(1) Market efficiency is not affected;

(2) Market efficiency is adversely affected but recovers within the study period;

(3) Market efficiency is adversely affected and a recovery is not observed.

The first group of stock markets consists of Bulgaria and Turkey. The results for the XU100 return series indicate the lack of LRD for the returns of the

Turkish stock index and decreasing values of the fractional differencing parameter *d* for the SOFIX.

	XU100	SOFIX
Count	768	768
Mean	0.0156	0.0177
Standard Error	0.0018	0.0015
Median	0.0201	0.0140
Standard Deviation	0.0499	0.0417
Kurtosis	2.2786	5.8367
Skewness	1.0375	1.4026
Conf. Level (95.0%)	0.0035	0.0030

Tab. 1Descriptive statistics of the investigated fractional differencing parameter d for Turkey and Bulgaria

The second group of stock markets consists of (Greece, Croatia, Hungary, Austria and Germany). The results for the ASE100 and ATX return series are adversely affected but recovers within the study period. DAX and CROBEX are affected lower than could be expected but recovers within the same short period.

	ASE100	ATX
Count	768	768
Mean	0.0655	0.0702
Standard Error	0.0021	0.0020
Median	0.0571	0.0670
Standard Deviation	0.0581	0.0556
Kurtosis	3.2475	1.2963
Skewness	1.2735	0.5480
Conf. Level (95.0%)	0.0041	0.0039

Tab. 2-Descriptive statistics of the investigated fractional differencing parameter d for Greece and Austria

	CROBEX	*DAX*
Count	768	768
Mean	0.0361	0.0185
Standard Error	0.0014	0.0018
Median	0.0319	0.0133
Standard Deviation	0.0386	0.0506
Kurtosis	1.9680	1.5865
Skewness	0.9606	0.8930
Conf. Level (95.0%)	0.0027	0.0036

Tab. 3-Descriptive statistics of the investigated fractional differencing parameter *d* for Hungary and Germany

In the third group of markets comes only Serbia. Empirical results for BELEX15 show strong evidence for the presence of long memory in the original volatility series, and the applied wavelet empirical tool suggests that time-varying fractional differencing parameter *d* is adversely affected by the global refugee crisis.

	BELEX15'
Count	768
Mean	0.0813
Standard Error	0.0026
Median	0.0682
Standard Deviation	0.0723
Kurtosis	0.1415
Skewness	0.7699
Confidence Level (95.0%)	0.0051

Tab. 4-Descriptive statistics of the investigated fractional differencing parameter *d* for Serbia

4 Conclusion

In our study, we apply wavelet-based tool for analysis and modelling of financial time series exhibiting strong long-range dependence and rolling sample approach to analyze time-varying stock market efficiency on the Balkan refugee route. Our dynamic approach reveals that while the refugee crisis has an adverse effect on most of the studied stock markets, the Balkan refugee route stock markets reflection to the surge in asylum seekers in the European Union (EU) is not clear. One of the major conclusions is that the Serbian stock market is characterized by a distinguished level of LRD, adversely affected by the global refugee crisis which is not diminishing over time. On the odder side most of the established European stock markets in group two are affected lower than could be expected and converge to efficiency in a short time with a permanent characteristic, including Greece.

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