Relative efficiency of European stock markets

Alexandru TODEA\textsuperscript{a,*}
\textsuperscript{a}Department of Finance, Faculty of Economics and Business Administration, Babes-Bolyai University, Teodor Mihali 58-60, 400591 Cluj-Napoca, Romania

Mircea GHERMAN\textsuperscript{b}
\textsuperscript{b}Department of Communication, Faculty of Electronics, Telecommunication and Information Technology, Technical University of Cluj-Napoca, Bariţiu 26-28, 400027 Cluj-Napoca, Romania

Abstract
We applied the Generalized Spectral test of Escanciano and Velasco (2006) in a rolling window approach to measure and rank the informational efficiency of European stock markets, from February 2001 to December 2009.

Keywords: European stock markets; relative efficiency; martingale; generalized spectral test

JEL Classification: C12; G14.

1. Introduction
Based on the argument that a financial market can’t be informationally perfectly efficient, Campbell et al. (1997) introduced the concept of relative efficiency, that is the efficiency of one market measured against another. The main feature of most studies regarding absolute efficiency is represented by the fact that conclusions are drawn upon the entire studied sample, without taking into account the possible alternation of the efficiency subperiods with those of inefficiency. This kind of behaviour is supported by the Adaptive Markets Hypothesis of Lo (2004) which aims at reconciling the Efficient Market Hypothesis

\textsuperscript{*} Permanent address: Alexandru Todea, Faculty of Economics and Business Administration, Babes-Bolyai University, Teodor Mihali 58-60, 400591 Cluj-Napoca, Romania. Tel.: +40723918369, Fax: +40264412570, Email: alexandru.todea@econ.ubbcluj.ro
with behavioral alternatives by applying the principles of evolution to financial interactions. This relatively new theory postulates that market efficiency evolves over time and across markets.

Identifying subperiods of efficiency/inefficiency and ranking the relative market efficiency are most often accomplished using the time-varying or rolling window approach. Thus, Cajueiro and Tabak (2004) estimate Hurst exponents in each window to test for long-range dependence and use the median as a statistical measure when ranking the markets. Lim (2007) and Lim and Brooks (2010) used the rolling bicorrelation test statistic that focuses on nonlinear dependence, arguing that a more appropriate indicator for relative efficiency would be the percentage of time windows in which the market exhibits significant nonlinear dependence. Recent studies use other methodologies such as the algorithmic complexity theory by Giglio et al. (2008) or the Shannon entropy by Risso (2009).

This study applies the Generalized Spectral (GS) test of Escanciano and Velasco (2006) in the rolling window approach for ranking the European stock markets. This test, which has never been used to evaluate the relative efficiency, has the null hypothesis of martingale with the alternative of nonmartingale, being able to detect a wide range of linear and non-linear dependence in conditional mean, allowing for a general form of unknown conditional heteroscedasticity. In a recent article, Charles et al. (2010) compares the power properties of this test with other competitors and highlights its superiority especially under nonlinear dependence. Moreover, its good asymptotic properties recommend it in a rolling window approach. The asymptotic null distribution of GS test depends on the data generating process, so a wild bootstrap procedure is used to simulate the critical values for the test statistic.

2. Methodology

2.1 Generalized spectral test: a brief description

Considering \( \{Y_t\}_{t=1}^{\infty} \), a stationary time series of returns, the null hypothesis of martingale difference sequence (MDS) which should be verified by using GS test, can be expressed as: \( H_0: m_j(y) = 0, j \geq 1 \), where \( m_j(y) = E[Y_t - \mu | Y_{t-j} = y] \) and \( \mu \) is a real number. In order to test if a sequence is a MDS, a measure for conditional mean dependence is considered: \( \gamma_{0-j}^{\infty} \). By using the exponential weighing function, this more general expression of the autocovariance measures the conditional mean dependencies
of time series in a non-linear framework. Thus, the null hypothesis can be verified by testing the following condition $\gamma_0(x) = 0$.

Escanciano and Velasco (2006) also suggest that the generalized spectral distribution function should be used in order to test the null of MDS. Hence, by applying the Fourier transformation, one has to estimate the following process:

$$\lambda \in [0;1]$$

Since $\{Y_i\}_{i=1}^n$ is a sample with a finite size, the estimation of the previous expression becomes:

$$\frac{1}{n} \sum_{j=1}^{n} \frac{1}{w_j}$$

where $\left(1 - \frac{j}{n}\right)^{1/2}$ is a finite sample correction factor, and $Y_{i,j} \frac{1}{1-n+j}$.

The major advantage of this test is that, by using a pairwise approach, it can turn into account all existing lags, whereas other tests omit some lags. Therefore, the null hypothesis is equivalent to $H(\lambda, x) = \gamma_0(x) \lambda$ and a new statistic for testing the MDS null hypothesis is considered:

$$\sqrt{\frac{1}{n} \sum_{j=1}^{n} \sum_{i=j+1}^{n} (Y_i - \bar{Y}_{n-j})(Y_i - \bar{Y}_{n-j}) \exp(-0.5(Y_{i,j} - Y_{i,j})^2)}.$$ 

As the GS test statistic has not a standard asymptotic distribution, $D_n^2$ is evaluated by using a wild bootstrap technique. This approach involves the usage of a random variable $w$. Therefore, when implementing this statistic one has to estimate the value for $S_n^*(w)$ instead of $S_n^*(\lambda, x)$ and then the asymptotic distribution of the $S_n^*(w)$ process. The acceptance probability of the null hypothesis ($p$-value of the GS test) is computed by performing the following steps:
1). An independent random variable \( \{w\}_{i=1}^{n} \) is generated from the original sample \( \{Y_{i}\}_{i=1}^{n} \) with zero mean and variance equals to one.

2). Using the \( \{w\}_{i=1}^{n} \) variable, the sequences \( \hat{\gamma}_{j}(x) \) and \( S_{n}(w) \) are calculated and are then used for computation of the \( D_{n}^{2} \) statistic.

3). The last two steps 1) and 2) are repeated sufficiently many times, say \( B \) times, to form a bootstrap distribution of the test statistic \( \{D_{n}^{2}\}_{j=1}^{B} \) (in our study we chose \( B = 1000 \)).

The bootstrap distribution \( \{D_{n}^{2}\}_{j=1}^{B} \) is used to approximate the sampling distribution of the \( D_{n}^{2} \) statistic. The \( p \)-value of the test is estimated as the proportion of \( \{D_{n}^{2}\}_{j=1}^{B} \) higher than the \( D_{n}^{2} \) statistic calculated from the original data.

\[ \text{2.2 Statistical indicators of relative efficiency} \]

In the rolling window approach, the acceptance probability of the null hypothesis (\( p \)) is computed for a window of 300 observations, and then the sample is rolled one point forward eliminating the first observation and including the next one for re-estimation of the \( p \). Because the distributions of \( p \) statistics are not normally, for each index is determined, as statistical indicators of relative efficiency, the median of \( p \) statistics and the percentage of windows for which \( p \) is less than 0.05. The two indicators are the most frequently used in drawing up the efficiency rankings but, as Lim (2009) noted, the research to find the best statistical measure should continue.

3. Data and Empirical Results

3.1 Data

This study uses market value-weighted equity indices at daily frequency for sixteen European stock markets, comprising eleven developed markets – Austria (ATX), France (CAC 40), Germany (DAX 30), Italy (MIBTEL), Netherlands (AEX), Norway (OSEAX), Portugal (PSI 20), Spain (IBEX), Sweden (OMXS), Switzerland (SMI) and the United Kingdom (FTSE 100) – and five emerging markets – Czech Republic (PX 50), Hungary (BUX), Poland (WIG), Romania (BET) and Russia (RTS). At these markets is added also the US (S&P 500) to see how the European markets are positioned compared to the main world market in terms of degree of efficiency. All the closing values of these indices collected from Datastream are denominated in their respective local currency units for the sample period 1
February 2001 to 29 December 2009, with the exception of Italy MIBTEL index that finished on 29 May 2009. The data is transformed into a series of continuously compounded percentage returns, \( Y_t = 100 \cdot \ln(P_t / P_{t-1}) \), where \( P_t \) and \( P_{t-1} \) denote two consecutive trading days.

3.2. Empirical Results

The \( p \)-value for each time window is computed using a routine implemented in MATLAB software. By analysing these values there was found, for each stock market, an alternation of martingale subperiods with those of nonmartingale, thus confirming the time varying market inefficiency. The frequency and intensity of subperiods of efficiency/inefficiency differs from one market to another and thus their relative efficiency is different. For example, it is clear from Fig. 1 and Fig. 2 that the degree of return predictability is substantially higher in case of the Portuguese PSI index compared to the FTSE 100 index.

![Fig.1. p-values of GS test: the FTSE 100 index](image1.png)

![Fig.2. p-values of GS test: the case of PSI index](image2.png)
From Table 1 it is observed that regardless of the statistical indicator used - the median or the proportion of windows - the ranking order of the markets remains almost the same. In the ranking it may be observed that in first position is the FTSE 100 index, followed by the CAC 40 index and ahead of US market index S&P 500. Furthermore, until the tenth position, the ranking order is somewhat expected, given the tradition and the level of development of the markets in Western Europe. Surprising is the fact that the indices from Central Europe BUX, PX 50 and WIG occupy a better position than the Swiss index SMI, as well as the last position occupied by the Portuguese index PSI 20. Except for the two indices, the results are consistent with those obtained by Risso (2009), according to which the difference among the Western and Eastern Europe markets is clear.

<table>
<thead>
<tr>
<th>Statistical indicator of relative efficiency</th>
<th>Median of $p$-values</th>
<th>% of windows for which $p &lt; 0.05$</th>
</tr>
</thead>
<tbody>
<tr>
<td>FTSE 100</td>
<td>0.089</td>
<td>FTSE 100 41.72</td>
</tr>
<tr>
<td>CAC40</td>
<td>0.074</td>
<td>CAC40 43.50</td>
</tr>
<tr>
<td>S&amp;P500</td>
<td>0.057</td>
<td>S&amp;P500 47.58</td>
</tr>
<tr>
<td>DAX 30</td>
<td>0.0525</td>
<td>DAX 30 49.55</td>
</tr>
<tr>
<td>IBEX</td>
<td>0.0425</td>
<td>IBEX 52.72</td>
</tr>
<tr>
<td>ATX</td>
<td>0.041</td>
<td>ATX 53.07</td>
</tr>
<tr>
<td>AEX</td>
<td>0.037</td>
<td>AEX 54.86</td>
</tr>
<tr>
<td>MIBTEL</td>
<td>0.035</td>
<td>MIBTEL 56.46</td>
</tr>
<tr>
<td>OMXS</td>
<td>0.03</td>
<td>OMXS 58.94</td>
</tr>
<tr>
<td>PX 50</td>
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<td>PX 50 59.71</td>
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<tr>
<td>BUX</td>
<td>0.0295</td>
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<tr>
<td>OSEAX</td>
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<td>OSEAX 60.42</td>
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<tr>
<td>WIG</td>
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<td>WIG 61.74</td>
</tr>
<tr>
<td>SMI</td>
<td>0.022</td>
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</tr>
<tr>
<td>RTS</td>
<td>0.014</td>
<td>RTS 72.65</td>
</tr>
<tr>
<td>BET</td>
<td>0.014</td>
<td>BET 71.01</td>
</tr>
<tr>
<td>PSI 20</td>
<td>0.004</td>
<td>PSI 20 77.27</td>
</tr>
</tbody>
</table>

4. Conclusions

Our results suggest that the degree of markets inefficiency varies through time and confirms the expected differences between the developed and the emerging stock markets in
Europe. Also, there is no clear trend towards higher efficiency as postulated by the classical Efficient Market Hypothesis because the statistical features of data plead rather in favor of the Adaptive Market Hypothesis. According to the evolutionist principles of this theory, profit opportunities in the European stock markets manifest themselves in an episodic way and do not disappear definitively.

References
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