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Testing for predictability in equity returns for European transition markets

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Abstract

This paper presents empirical evidence of short and long-run predictability in stock returns for European transition economies. We employ variance ratios with a bootstrap methodology to test for short-run predictability, which is present in most countries. We also estimate Hurst exponents to test for long-range dependence, and find evidence of such. Furthermore, we find evidence of strong time-varying long-range dependence in these economies stock returns, which is in line with evidence of multifractality of equity returns.

JEL classification: G14; G15

Keywords: European transition economies; Hurst exponents; Long memory; Predictability; Variance ratio; Multifractality

1. Introduction

The debate regarding predictability in developed and emerging markets continues to be an issue of central concern in the financial literature. Various empirical studies have documented substantial evidence of predictability in asset returns (Fama and French, 1988; Lo and Mackinlay, 1988; Poterba and Summers, 1988; Brock et al., 1992; Cochran et al., 1993; Chan et al., 1996; Gencay, 1998; Bessembinder and Chan, 1998; Allen and Karjalain, 1999; Lo et al., 2000; Chang et al., 2004; Patro and Wu, 2004).

Predictability is generally attributed to fads, overreaction, other types of irrationality, or it may be attributed to time-varying risk within an equilibrium framework. It is important to notice, however, that predictability does not imply profitability.

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The economic significance of predictability is controversial in the literature. Makiel (2005) presents evidence suggesting that active management is a ‘‘loser’s game’’, as it increases transaction costs reducing performance. Therefore, even if markets are predictable to some extent, it is very difficult to transform this predictability into superior performance.[1] Chang et al. (2004), who employ technical analysis, are not able to find significant strategies when comparing active management with a buy and hold strategy, taking into consideration transaction costs. On the other hand, in a recent paper, Xu (2004) found that the performance of a market timing strategy that uses small-return predictability yields high returns and is even less risky (assuming a fat tail distribution). Therefore, in the light of his paper, predictability is economically significant.[2]

Despite the controversy that arises from whether or not predictability is economically significant and economic profits can be made from predictable patterns, predictability is a major concern for both academics and practitioners. Most financial models are based on the assumption of absence of predictability, when empirical evidence of it suggests that such models need major improvements. Most financial models assume that asset prices follow a random walk. For example, this is a crucial assumption in the widely used Black and Scholes (1973) option-pricing model.

A recent strand of the financial literature that studies predictability has brought attention to some features of financial data, such as long-range dependence and multifractality. Various recent empirical studies have found evidence of long-range dependence in asset returns and multifractality (Cajueiro and Tabak, 2004a,b; Sun et al., 2001; Calvet and Fisher, 2001; Fillol, 2003; Limam, 2003; Xu and Gencay, 2003; Wei and Huang, 2005).

Although the research on predictability for developed markets has been extensively studied, there is a gap in the literature. There is scarce research on predictability for European transition economies.[3] Very little is known on the degree of predictability of such equity markets and whether they are converging to more mature and efficient markets. Furthermore, to the best of our knowledge, there is no prior research on multifractality for these countries. The main purpose of this paper is to fill this gap in financial literature, and study the degree of predictability and whether these countries exhibit multifractality.

Studying emerging European transition economies is quite important as they are increasing their degree of integration with global equity markets, while becoming an important source of diversification for global portfolios and the fund industry. Furthermore, due to their characteristics, it is expected that a higher degree of predictability may be found for these countries, which makes these equity markets interesting investing opportunities.

In the year 2000, the European Union (EU) accepted as full candidates for accession Bulgaria, the Czech Republic, Hungary, Latvia and Poland. These countries have to meet a broad set of political, economic and institutional requirements, as summarized in the EU Copenhagen criteria. One of the main criteria is that these countries must guarantee the existence of a fully functioning market economy. Therefore, one should expect convergence towards more efficient and mature stock markets.[4]

[1] Makiel (2004) tested market timing strategies and was not able to produce returns that are superior to a buy and hold strategy.

[2] The author employs a Monte Carlo simulation to test for robustness under different return distributions and transaction costs.

[3] See Li (2003), Rockinger and Urga (2000) and Zalewska-Mitura and Hall (1999) for research on predictability in transition economies.

[4] These countries have been enhancing investor protection and developing their domestic stock markets (IMF, 2000).

This paper presents empirical evidence of short-term predictability, using variance ratio (VR) tests (with a bootstrap procedure) and also long-term predictability, employing a variation of the range over standard deviation (*R*/*S*) analysis (with a shuffle procedure to account for short-term autocorrelation). Furthermore, it is shown similarly to what has been found in developed economies, that asset prices exhibit multifractal characteristics.[5] Additionally, with the use of time-varying Hurst exponents, we present evidence that only a few countries have been exhibiting convergence towards more efficient markets.

This paper proceeds as follows. In Section 2 we present a brief literature review. In Section 3 we present the methodology that will be used to ascertain the degree of short and long-term predictability. Section 4 describes the data set that is used in the paper. Section 5 presents empirical results. Finally, Section 6 concludes the paper.

2. Brief literature review

The literature on market efficiency and stock market predictability is vast, as researchers have been discussing this theme in depth for the past decades.[6]

One of the main topics in the research agenda has been testing whether asset prices follow a random walk. Many implications emerge from the rejection of the random walk hypothesis (RWH). On one hand, asset prices may be predictable using information on the history of past prices. On the other hand, current financial models need to suffer adjustments as this is an assumption widely used. Finally, it suggests that searching for forecasting models may be worthwhile.[7]

Three seminal works have provided the foundation for testing for short-term predictability in stock returns. These seminal works are due to Lo and Mackinlay (1988, 1989) and Poterba and Summers (1988), who suggest that the VR is a more robust methodology to test for predictability than usual unit root tests. They have also found evidence of mean reversion in stock prices for the US. Since then, many researchers have employed VR statistics to test the validity of the RWH for different countries.[8]

A lot of research focusing on different countries has considered these seminal works as a basis for testing the validity of the RWH. Blasco et al. (1997) have presented evidence of strong serial correlation for stocks traded on the Madrid stock exchange using VR statistics. Furthermore, the authors have discovered non-linear dependencies in their sample. Mookerjee and Yu (1999) have been able to reject the RWH for both the Shanghai and Shenzhen stock exchanges. Lima and Tabak (2004) have tested the RWH for China, Hong Kong and Singapore presenting evidence that liquidity and market capitalization play a significant role in explaining results from VR (weak form efficiency) tests.

Richards (1995) has studied developed economies and has presented evidence of relative return predictability, which implies the existence of a transitory, mean-reverting, country-specific component. Mean reverting behavior in stock returns is a commonly cited long-run form of

[5] Multifractal models may be seen as competitors for ARCH/GARCH models and others.

[6] See Balvers et al. (2000), Fama (1970, 1991), Fama and French (1988), Frennberg and Hansson (1993), Harvey (1995), Kandel and Stambaugh (1996), Keim and Stambaugh (1986), Lo and Mackinlay (1988), Pesaran and Timmermann (1995) and Richards (1997).

[7] For example, Fama and French (1988) find that 25–45% of the variation of 3–5 years stock returns is predictable from past returns.

[8] See for example Chang et al. (2004), Dockery and Vergari (1993), Frennberg and Hansson (1993), Lima and Tabak (2004), Malliaropulos and Priestley (1999) and Patro and Wu (2004).

dependence. Mean reversion holds that firms that did poorly in the past tend to exhibit higher returns than those which enjoyed a better than average performance, this being considered over a long-investment horizon. Richards (1997) has also reported evidence of reversals in indices returns for 16 national markets. Malliaropulos and Priestley (1999) have found comparable results in a sample of Asian markets, as do Frennberg and Hansson (1993) for the Swedish market. Pesaran and Timmermann (1995) reported evidence of predictability in both US and UK stock markets, which could have been exploited by investors.

Recently, Chang et al. (2004) studied emerging equity markets and found that we can reject the RWH. Patro and Wu (2004) studied 18 developed markets and also rejected the random walk hypothesis for many countries, suggesting that equity returns are predictable.

Recently, Mateus (2004) has investigated the importance of global risk factors and the predictability of returns for the 13 EU accession countries. The author has found evidence of predictability of stock markets using both unconditional and conditional multifactor models of returns. Moreover, the author has found that local information, market inefficiency and/or investor irrationality may explain most predictability of returns during the turbulent period of 1997–2002.

Evidence of mean reversion (or aversion) in stock returns has led researchers to investigate the presence of long-range dependence. Evidence of such dependence is controversial in the financial literature. Barkoulas et al. (1999) have found evidence of long-range positive dependence in futures prices for commodities and currencies. Barkoulas et al. (2000) have presented significant and robust evidence of positive long-term persistence in the Greek stock market, using a spectral regression method. Beveridge and Oickle (1997) have presented evidence of long memory for Canadian daily stock returns, using fractional ARIMA models. Henry (2002) has provided evidence of long memory in German, Japanese, South Korean and Taiwanese stock markets, using a semi-parametric estimation method. Mulligan (2004) and Mulligan and Lombardo (2004) have examined a variety of equity indices and have found evidence supporting a multifractal model of stock returns and the presence of long-range dependence. Cajueiro and Tabak (2004a,b) have presented evidence of long-range dependence in a variety of emerging market indices. However, Lo (1991) and Cheung and Lai (1995) have not found evidence of long-range dependence in stock returns.[9]

Calvet and Fisher (2001) have shown that a multifractal model of asset returns fits well both Deutsche mark/US dollar exchange rates and several equity series, presenting empirical evidence of multifractality for developed equity markets. Sun et al. (2001), Xu and Gencay (2003) and Wei and Huang (2005) have also provided evidence of multifractality for stock returns and foreign exchanges.

Very little research has been undertaken for emerging European transition economies. Dockery and Vergari (1993) have tested the random walk hypothesis for the Budapest stock exchange using VR tests and conclude that it follows a random walk. The authors employed asymptotic theory for inference purposes. Rockinger and Urga (2000) have considered aggregate stock indices of the Czech Republic, Hungary, Poland and Russia. Chelley-Steeley (2005) have shown that Eastern European stock markets have become more integrated over time with developed markets. Hungary is the country which is becoming integrated most quickly.

[9] These authors have used the modified *R/S* method, which is known to have a strong bias toward accepting the null hypothesis (i.e., no long-range dependence), even in ideal situations of purely long-range dependent data (see Teverovsky et al., 1999).

The goal of this paper is to focus on European transition economies by studying short and long-term predictability, using robust methods. To the best of our knowledge, this is the first paper that studies long-range dependence in a variety of emerging European transition economies. Furthermore, it studies multifractality for these stock markets. Multifractality has many implications for asset modeling and risk and portfolio management. Therefore, empirical tests for different financial markets are important to build stylized facts and provide directions for financial modeling developments.

3. Methodology

In this section the methodology is presented. We will briefly introduce the VR statistic and its multiple version with a bootstrap procedure. The *R/S* test for long-range dependence and multifractality will also be commented. Both tests are non-parametric and robust to non-normality, which is a feature of all stock indices studied in this paper.

3.1. The VR methodology

If a time series of returns follows a random walk, then in a finite sample, the increments in variance are linear, inside the observation interval, i.e., the variance of returns should be proportional to the sample interval. Thus, the variance of monthly returns should be four times the variance of weekly returns. In order to test the RWH, we can use the VR defined as

$$\mathrm{VR}(q) = \frac{\sigma_q^2}{q\sigma^2} \tag{1}$$

where σ_q^2 and σ^2 are the variance for q and one-period increments, respectively. The test relies on checking whether the VR is statistically indistinguishable from one. VR(q) satisfies the relation

$$\mathrm{VR}(q) \approx 1 + 2\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\hat{\rho}(k) \tag{2}$$

where $\hat{\rho}(k)$ is the estimated kth order autocorrelation coefficient of returns.

One of the problems with this method is that we have to examine the VR statistic for different values of q, and we only fail to reject the RWH if it is not rejected for all of the q selected. In a multiple comparison framework this method fails to control the test size, which causes an inappropriate large probability of type I error. Chow and Denning (1993) have suggested an extension of the VR methodology that circumvents these problems, as it takes into account multiple VR(q).

Lo and Mackinlay (1988, 1989) and Chow and Denning (1993) have derived the limiting distribution of these statistics, and they have been used in many empirical applications.[10] However, Ceccheti and Lam (1994) have shown that VR tests based on asymptotic approximations are often misleading, especially when the sample is small. To overcome these difficulties, we employ a bootstrap method in order to derive the actual distribution of the VR. We used a weighted bootstrap method which is robust to the presence of heteroscedasticity following Wu (1986) and Malliaropulos and Priestley (1999), which is done by resampling normalized

[10] See for example Dockery and Vergari (1993), Frennberg and Hansson (1993) and Lima and Tabak (2004).

returns instead of actual returns. This is done due to empirical evidence in favor of ARCH/GARCH terms in European transition indices returns, i.e., there seems to be squared returns serial dependence. Furthermore, we employ a Wald statistic to test for a joint VR test, following Ceccheti and Lam (1994) and Malliaropulos and Priestley (1999).

The methodology in Wu (1986) was originally designed to build confidence intervals for parameters estimated in linear regressions with heteroskedastic errors. Wu (1986) assumes the linear regression model:

$$y = X\beta + u \tag{3}$$

where y is a n-vector of dependent observations, X a matrix of covariates, β a vector of unknown parameters and u is a vector of errors with zero mean and variance given by σ^2. Estimates of β are given by $\hat{\beta}$ with $\hat{u}$ being the OLS vector of residuals.

In order to provide more accurate estimates of the variance of the estimated parameters, Wu (1986) suggested a simple bootstrap scheme that can be summarized with the following algorithm:

1. Draw a random sample from $u^* = (u_1^*, u_2^*, \ldots, u_n^*)$ from $\hat{u}$.
2. Form a bootstrap sample: $y^* = X\hat{\beta} + u^*$.
3. Compute OLS estimates from the regression model in step 2.
4. Repeat 1–3 a large number of times.
5. Compute the variance of the estimated parameters.

However, since in many empirical applications one should take into account heteroskedasticity, Wu (1986) has proposed a modification to this simple scheme. The author has suggested replacing 1 and 2 by 1b and 2b, in the previous algorithm:

1b. For each i, draw a value t_i from a distribution with zero mean and unit variance.
2b. Form a bootstrap sample: $y^* = X\hat{\beta} + t_i\hat{u}_i^*(1-\omega_{ii})^{-1}$, $i = 1, n$, with ω_{ii} being the ith diagonal element of $X(X'X)^{-1}X'$.

Cribari-Neto and Zarkos (1999) evaluated the performance of this bootstrap methodology by comparing the weighted with the unweighted bootstrap. Their results suggested that weighted bootstrap estimators perform very well, outperforming other estimators, even in the case of homoskedastic errors and non-normality (fat tails).

The bootstrap is a distribution-free randomization technique, which can be used to estimate the sampling distribution of the VR statistic, when the distribution of the original population is unknown. The strongest difficulty with resampling schemes, such as bootstrap, is that they may generate data that is less dependent than the original data. The main idea of the weighted bootstrap scheme is to overcome this difficulty.

To estimate empirical quantiles for the VR, the bootstrap procedure can be carried out in three steps:

(1) Draw a bootstrap sample of N observations r_t^*, $t = 1, \ldots, N$, with replacement from the empirical distribution of one-period returns, r_t.
(2) Calculate the VR(q) from the pseudo data r_t^* for $k = 1, \ldots, K$.
(3) Repeat steps 1 and 2M times obtaining VR(q, m), $m = 1, \ldots, M$.

The non-parametric implementation of Wu's (1986) method can be carried out by replacing (1) by (1a) and (1b):

(1a) For each t, draw a weighting factor z_t^*, $t = 1, \ldots, N$, with replacement from the empirical distribution of normalized returns $z_t = (r_t - \bar{r})(\mathrm{SE}(r))^{-1}$, where $\bar{r}$ is the mean return and $\mathrm{SE}(r)$ is the standard deviation of returns.

(1b) Form the bootstrap sample of N observations $r_t^* = z_t^* r_t$, $t = 1, \ldots, N$, by multiplying each observation of actual returns with its corresponding random weighting factor. Using this procedure, resampling from normalized returns instead from actual returns, the weighted bootstrap method accounts for the possible non-constancy of the variance of returns.

This bootstrap procedure is robust to heteroscedasticity and can be found in Malliaropulos and Priestley (1999). Basically, we normalize returns by multiplying each observation of actual returns, for each one of the time series of returns, by a corresponding random factor and resample from these normalized returns.

However, we then employ a multivariate version of the VR statistic (due to Ceccheti and Lam, 1994) to test the RWH, in order to control the investment horizon with this bootstrap methodology. Ceccheti and Lam (1994) suggest the following Wald statistic:

$$S(q) = [\mathbf{VR}(q) - E[\mathbf{VR}(q)]'\Sigma^{-1}(q)[\mathbf{VR}(q) - E[\mathbf{VR}(q)], \tag{4}$$

where E is the expectation operator, **VR** a column vector sequence of VR statistics $\mathbf{VR}(q) = [\mathrm{VR}(2), \mathrm{VR}(3), \ldots, \mathrm{VR}(q)]$, $E[\mathbf{VR}(q)]$ is the expected value of $\mathbf{VR}(q)$, and $\Sigma(q)$ is a measure of the covariance matrix of $\mathbf{VR}(q)$.

The joint VR $S(q)$ statistic follows a χ^2 distribution with q degrees of freedom. However, as suggested in Ceccheti and Lam (1994), the empirical distributions of the VR have large positive skewness, suggesting that inference based on the χ^2 distribution will be misleading. Therefore, we estimate the Wald statistic $S(q)$ for each bootstrapped **VR** estimator vector. Finally, we use the bootstrapped distribution of Wald statistics for hypothesis testing.

3.2. Measures of long-range dependence

In order to estimate the long memory parameter, we employ the usual and most popular methodology, which is the R/S method (see Hurst, 1951; Feder, 1988). The R/S method is applied to the log return time series to evaluate the Hurst exponent.

Let $X(t)$ be the price of a stock on a time t and $r(t)$ be the logarithmic return denoted by $r(t) = \ln((X(t+1))/(X(t)))$. The R/S statistic is the range of partial sums of deviations of times series from its mean, rescaled by its standard deviation. Therefore, consider a sample of continuously compounded asset returns $\{r_1, r_2, \ldots, r_\tau\}$ and let $\bar{r}_\tau$ denote the sample mean $(1/\tau)\Sigma_\tau r_\tau$ where τ is the time span considered. Then the R/S statistic is given by

$$\left(\frac{R}{S}\right)_\tau \equiv \frac{1}{s_\tau}\left[\max_{1\le t\le\tau}\sum_{k=1}^{t}(r_k - \bar{r}_\tau) - \min_{1\le t\le\tau}\sum_{k=1}^{t}(r_k - \bar{r}_\tau)\right] \tag{5}$$

where S_τ is the usual standard deviation estimator

$$s_\tau \equiv \left[\frac{1}{\tau}\sum_t (r_t - \bar{r}_\tau)^2\right]^{1/2} \tag{6}$$

Hurst found that the rescaled range, *R*/*S*, for many records in time, is very well described by the following empirical relation:

$$\left(\frac{R}{S}\right)_{\tau} = \left(\frac{\tau}{2}\right)^{H} \tag{7}$$

The major problem with such methodology is that the *R*/*S* is sensitive to short-term memory. Therefore, in order to correct for short-range dependence, we have applied the *R*/*S* analysis to blocks of shuffled data, i.e., one picks a random permutation of the data series within blocks of predetermined size (in general, blocks of small size) and applies the *R*/*S* analysis to this shuffled data.[11] In this work, we use blocks of size 20.[12]

A number of empirical studies have found evidence of multifractality in equity returns for a variety of countries. For example, Calvet and Fisher (2001) have shown that a multifractal model is able to replicate asset returns and found evidence of multifractatility for the Deutsche mark/US dollar exchange rates and for the CRSP index and five major stocks in the US. Fillol (2003) finds similar evidence for the French stock market (CAC40). Sun et al. (2001) and Wei and Huang (2005) show that multifractal analysis can reveal useful information about the market trend, and present evidence of multifractality for stock indices in Hong Kong. They have also shown that it is possible to employ technical trading strategies using such information, which is profitable.

Therefore, it is an important issue to test for evidence of multifractality in European emerging equity returns. These countries are accessing the EU and will be natural candidates to form global equity portfolios in the future. Studying their properties may enhance portfolio and risk management.

Multifractality can also be tested by checking whether the long-range dependence parameter (Hurst exponent) is time-varying. This is done by using fixed-length moving windows with 504 daily observations (approximately 2 years of data), which should be enough to capture long-term trends and long-range dependence.[13] Therefore, besides testing for long-range dependence for time series, we check whether the dynamics of these time series change substantially over time and whether they are time-varying. If Hurst exponents change over time, then the time series are said to be multifractal.

It is worth mentioning that Bouchaud et al. (2000) present a model that, by construction, is monofractal, but it shows apparent multifractality due to a slow crossover phenomenon on finite time. Here, in this paper, the phenomenon of multifractality arises from the variation, over time, of the dynamic properties of financial time series. Therefore, we believe that our results are robust to Bouchaud et al.'s (2000) critique.

4. Data

This paper studies European transition countries such as Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Poland, Russia and Ukraine. Our database contains daily closing prices of nine countries and nine equity indices that were obtained from Bloomberg.

[11] This is justified due to Lo's critique (Lo, 1991) that the *R*/*S* statistic is sensitive to the presence of short-range dependence and the effect of random permutations in these small blocks destroys any particular structure of auto-correlation within them. See Teverovsky et al. (1999) for a discussion on problems with the modified *R*/*S* methodology.

[12] Qualitative results remain robust if we employ blocks of sizes 10 or 30.

[13] See Cajueiro and Tabak (2004a,b).

Table 1
Descriptive information on indices

Bloomberg code	Country	Index name	Begin	End	Number of obs.
SOFIX Index	Bulgaria	Bulgaria Stock Exchange Index SOFIX	23.10.00	26.05.04	872
ZSICI Index	Croatia	Croatia Zagreb Stock Exchange	01.01.98	13.04.04	1370
PX50 Index	Czech Republic	Prague Stock Exchange PX 50 Index	05.04.94	27.05.04	2448
TALSE Index	Estonia	Tallinn Stock Exchange Main Index	31.12.98	27.05.04	1368
RICI Index	Latvia	Latvia RICI Equity Index	05.01.98	27.05.04	1545
BUX Index	Hungary	Budapest Stock Exchange Index	17.06.93	27.05.04	2732
WIG Index	Poland	WSE WIG Index	21.06.93	27.05.04	2592
RTSI$ Index	Russia	Russian RTSI$ Index	01.09.95	27.05.04	2172
UKASW Index	Ukraine	Ukraine KAC-20 Liquid Index	10.01.97	27.05.04	1766

Indices were selected on an availability of historical data basis. The last column presents the number of observations.

All indices are in US dollar terms. The indices were chosen due to availability of the historical time series. Furthermore, they comprise the bulk of emerging transition European economies.

Table 1 presents descriptive information on the indices that are being currently employed. The length of the time series depends on the availability of data, ranging from 872 to 2732 observations. All samples end in 27 May 2004. Therefore, we include a very recent period in our analysis.

The history of the Bulgarian equity market dates back almost a century ago. After World War II the Stock Exchange ceased its operations, and the equity market was re-established in 1991 with the introduction of the Commercial Act. On 21 October 2000 the Bulgarian Stock Exchange launched its official index, the SOFIX. The SOFIX is a price index, market capitalization weighted, with base value of 100 points, consisting of the top domestic stocks. The shares account for 54.48% of total market capitalization.[14]

There are two organized securities exchanges in Croatia: The Varazdin Stock Exchange (VSE) and The Zagreb Stock Exchange (ZSE). The ZSE was founded in 1991, while the VSE started its operations in 1993 as an over-the-counter market. Liquidity in the VSE is much lower than in the ZSE. Therefore, we decided to focus on the Croatian Zagreb Stock Exchange Index (ZSICI), which includes the most liquid shares traded on the Zagreb exchange, and accounts for a large share of market capitalization (more than 50%).

The Prague stock exchange was formed in November 24, 1992, while in 5 April 1994, the calculation of the Exchange's official PX-50 Index was opened. The PX-50 is a capitalization-weighted index, which comprises 50 companies listed on the Prague stock exchange. This index accounts for more than 90% of total market capitalization. We will use this index as a benchmark for the Czech Republic.

The Tallinn Stock Exchange is the only regulated securities market in Estonia. It was founded in April 1995 by 10 commercial banks, nine brokerage firms and state players. Licensed by the Ministry of Finance, Tallinn Stock Exchange opened for trading on 31 May 1996 with 11 securities listed. For Estonia, we study the Tallinn Stock Exchange Index (TALSE). This index shows changes in the prices of shares listed in the main and investor lists of the Tallinn stock

[14] For all indices, figures for market capitalization of the index were provided for December 2004.

exchange. It is a capitalization-weighted index, and it accounts for more than 95% of the market capitalization of the Estonian stock market.

For Latvia, we study the Riga stock exchange price index (RICI), which is an equally weighted index. On 2 February 1998, the Riga Stock Exchange price index RICI was launched. It is calculated according to an equally weighted principle after each deal during continuous trading. Thus, it represents the price changes at all times during trading. The shares account for more than 85% of market capitalization. This index was discontinued by the exchange effective 09/27/04.

In Hungary, the Budapest Stock Exchange (BSE) opened in 1864, and around the beginning of this century it became the fourth largest stock exchange in Europe. The BSE was reestablished in June 1990. Securities trading is entirely electronic. Since 1 April 1997 the index (BUX) has been calculated and recorded continuously with a time resolution of 5 s during the main trading hours. This index is a capitalization-weighted index that tracks the daily price performance of large, actively traded shares on the Budapest Stock Exchange. The shares account for 58% of domestic market capitalization. The BUX Index will be employed as the benchmark for Hungary.

In this study, we use the Warszawski Indeks Gieldowy (WIG) as our market index for Poland. The WIG includes all companies listed on the main market of the Warsaw Stock Exchange (WSE), with the exclusion of foreign companies and investment funds. The WSE uses three types of quotation systems, the single-price auction system with one auction, the single-price auction system with two auctions, and a continuous trading system. This index accounts for more than 80% of total domestic market capitalization.

We also study the Russian Trading System Index (RTSI$), which is a capitalization-weighted index. This index is the official RTS stock exchange benchmark. The RTS stock exchange was established in 1995 to consolidate separate regional securities trading floors into a unified securities market. This index accounts for more than 90% of market capitalization of all stocks traded in the RTS.

In Ukraine, a massive privatization of state-owned firms was undertaken in the 1990s, which boosted the stock market. The infrastructure of the stock market has been developing rapidly, with market capitalization growing accordingly. For this country, we study the KAC-20 (UKASW), which is a liquid market index and was designed to reflect the performance of the most liquid stocks in the Ukrainian market. It accounts for more than 65% of domestic market capitalization.

It is important to notice that most of these indices emphasize the use of liquid and relatively important (as measured by market capitalization) stocks.[15] This is essential since the lack of liquidity is a major characteristic of these markets and of general emerging markets.

5. Empirical results

5.1. VR statistics

In this section, we report the VR test results. Table 2 shows the VR test results using daily closing returns in US dollar terms, for 12 indices of 9 different countries. We provide estimates for the VR and two normalized test statistics, $Z_1(q)$ and $Z_2(q)$. The first statistic assumes homoskedasticity, and has a limiting normal distribution. The second statistic is hetero-

[15] The stock indices that were selected account for more than 50% of domestic market capitalization.

Table 2
VR statistics – Chow and Denning (1993)

	Investment horizon in days, q							
	2	4	8	16	32	64	128	Conclusion
SOFIX Index								
VR(q)	0.875	0.836	0.781	0.75	0.814	0.89	0.919	
z_1	−1.838	−0.648	−0.273	−0.105	−0.027	−0.006	−0.001	Accept RWH
z_2	−1.509	−1.255	−1.311	−1.143	−0.614	−0.271	−0.147	Accept RWH
ZSICI Index								
VR(q)	1.073	1.169	1.246	1.449	1.763	2.265	2.811	
z_1	1.354	0.833	0.385	0.236	0.138	0.08	0.04	Accept RWH
z_2	1.889	2.364	2.242	2.865	3.51	4.164	4.352	Reject RWH
PX50 Index								
VR(q)	1.13	1.232	1.289	1.411	1.551	1.635	1.686	
z_1	3.208	1.534	0.605	0.288	0.134	0.054	0.02	Reject RWH
z_2	4.863	4.783	3.864	3.751	3.556	2.974	2.362	Reject RWH
TALSE Index								
VR(q)	1.08	1.103	1.203	1.294	1.442	1.683	1.616	
z_1	1.473	0.51	0.317	0.154	0.08	0.043	0.014	Accept RWH
z_2	2.524	1.716	2.212	2.202	2.348	2.573	1.68	Reject RWH
RICI Index								
VR(q)	1.132	1.244	1.49	2.011	2.567	3.524	5.215	
z_1	2.602	1.279	0.813	0.564	0.302	0.17	0.1	Reject RWH
z_2	4.048	4.072	5.374	7.667	8.431	9.636	11.555	Reject RWH
BUX Index								
VR(q)	1.09	1.142	1.139	1.335	1.577	1.476	1.379	
z_1	2.344	0.988	0.307	0.249	0.148	0.043	0.012	Accept RWH
z_2	2.167	1.964	1.331	2.293	2.869	1.791	1.101	Reject RWH
WIG Index								
VR(q)	1.182	1.213	1.265	1.388	1.48	1.483	0.956	
z_1	4.62	1.447	0.569	0.281	0.12	0.042	−0.001	Reject RWH
z_2	4.606	2.978	2.41	2.504	2.281	1.705	−0.115	Reject RWH
RTSI$ Index								
VR(q)	1.163	1.271	1.358	1.587	1.81	2.103	2.6	
z_1	3.801	1.685	0.705	0.388	0.185	0.088	0.045	Reject RWH
z_2	4.301	4.093	3.672	4.273	4.274	4.251	4.589	Reject RWH
UKASW Index								
VR(q)	0.517	0.276	0.164	0.115	0.106	0.112	0.121	
z_1	−10.142	−4.067	−1.485	−0.528	−0.184	−0.064	−0.022	Reject RWH
z_2	−1.233	−1.234	−1.221	−1.205	−1.167	−1.098	−1.049	Accept RWH

The VR(q) estimates are given in the main rows, with homocedastic and heterocedastic test statistics given below. The conclusion in the last column is made using the multiple VR(q) test of Chow and Denning (1993), with a critical value of 2.491.

skedasticity-robust and also has a limiting normal distribution under the null hypothesis of unpredictability of returns.[16] We implement the tests for different horizons, q = 2, 4, 8, 16, 32, 64

[16] There seems to be strong evidence of heteroskedasticity in these indices and therefore we will focus on the heteroskedastic-robust statistic in our analysis. These results are not reported here to conserve space, and are available upon request. Other researchers have found similar results. See Kasch-Haroutounian and Price (2001), who study stock indices for Hungary, Poland, the Czech Republic and Slovakia and find that they possess strong GARCH effects.

Table 3
VR Statistics using bootstrapped empirical distribution

	Investment horizon in days, q								
	2	4	8	16	32	64	128	Wald statistic	Conclusion
SOFIX Index									
VR	0.875	0.835	0.786	0.75	0.776	0.777	0.773	5.846	
p-Value	0.023	0.043	0.043	0.076	0.2	0.33	0.462	0.49	Accept RWH
ZSICI Index									
VR	1.072	1.165	1.236	1.438	1.705	2.098	2.539	25.281	
p-Value	0.03	0.014	0.017	0.003	0.003	0.001	0.002	0.013	Reject RWH
PX50 Index									
VR	1.129	1.231	1.292	1.424	1.639	1.703	1.796	36.804	
p-Value	0	0	0	0	0	0	0.007	0	Reject RWH
TALSE Index									
VR	1.079	1.111	1.207	1.278	1.4	1.58	1.379	16.282	
p-Value	0.004	0.037	0.013	0.028	0.023	0.022	0.095	0.035	Reject RWH
RICI Index									
VR	1.131	1.239	1.477	1.977	2.475	3.298	4.957	197.103	
p-Value	0.001	0	0	0	0	0	0	0	Reject RWH
BUX Index									
VR	1.089	1.14	1.135	1.325	1.546	1.443	1.327	25.32	
p-Value	0.011	0.018	0.077	0.021	0.007	0.05	0.11	0.012	Reject RWH
WIG Index									
VR	1.181	1.212	1.263	1.392	1.514	1.607	1.498	30.73	
p-Value	0	0.007	0.01	0.008	0.01	0.018	0.052	0.009	Reject RWH
RTSI$ Index									
VR	1.162	1.267	1.348	1.563	1.776	2.025	2.35	33.237	
p-Value	0.002	0.004	0.006	0	0.001	0.001	0.002	0.004	Reject RWH
UKASW Index									
VR	0.517	0.276	0.164	0.114	0.101	0.104	0.114	12.897	
p-Value	0	0	0	0	0.001	0.001	0.001	0.107	Accept RWH

The VR(q) estimates are given in the main rows, with bootstrapped p-value below. The p-value report the probability that the VR from the bootstrap distribution is less (larger) than the sample VR if the sample value is less (larger) than the median of the bootstrap distribution in 1000 iterations. The conclusion in the last column is made using the Wald statistic and the p-value below reports the probability that the Wald statistic from the bootstrap distribution is larger than the sample statistic.

and 128. The conclusion in the last column of the table is drawn by using Chow and Denning's (1993) result of multiple VR.[17]

Rejection of the RWH is striking in Table 2 for most indices, even when accounting for heteroskedasticity. For all indices, except the Bulgarian Stock Exchange Index

[17] Chow and Denning (1993) suggest testing the RWH by comparing all selected VR estimates with unity. They suggest using the absolute largest value of the $Z_i(q)$ statistics for $i = 1,2$. Such statistics have a Student Maximum Modulus distribution asymptotically, and the limiting critical value is 2.491 (higher than its normal counterpart of 1.96) for a 5% test.

Table 4
Hurst exponents

	H	Standard error	Wald statistic	p-Value
SOFIX Index	0.561	0.016	13.715	0
ZSICI Index	0.604	0.009	138.558	0
PX50 Index	0.624	0.009	211.205	0
TALSE Index	0.583	0.014	36.689	0
RICI Index	0.682	0.014	158.947	0
BUX Index	0.654	0.011	206.664	0
WIG Index	0.582	0.011	50.43	0
RTSI$ Index	0.64	0.008	343.318	0
UKASW Index	0.641	0.012	136.226	0

Static Hurst exponents for each index were calculated with their associated standard errors. The Wald statistics tests the hypothesis $H = 0.5$, and the last column presents it's associated p-value.

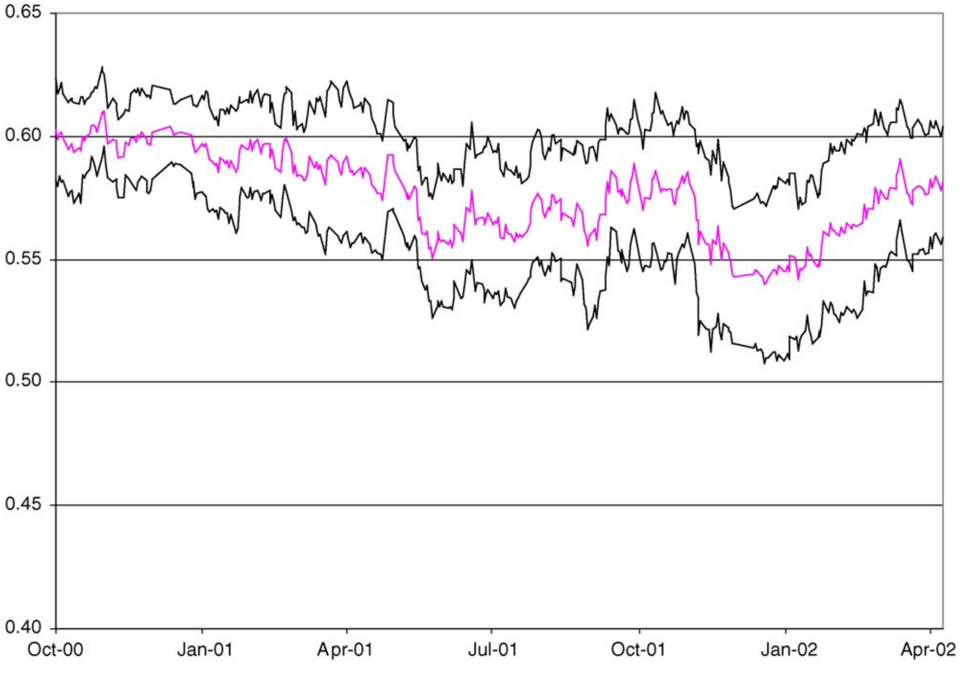

Fig. 1. Time-varying Hurst exponents with 95% confidence interval for the Bulgaria Stock Exchange Index – SOFIX.

(SOFIX) and the Ukrainian KAC-20 Liquid Index (UKASW), we can reject the null hypothesis.

A major problem with the use of VR statistics is that the finite sample distribution is generally not known, since returns do not follow a normal distribution.[18] Therefore, in order to assess for the robustness of the results, we use a bootstrap procedure to estimate the empirical distribution. Furthermore, in order to test for multiple VR, we build a Wald statistic.

[18] These indices do not follow a normal distribution. Results are available upon request. They are not reported here to conserve space.

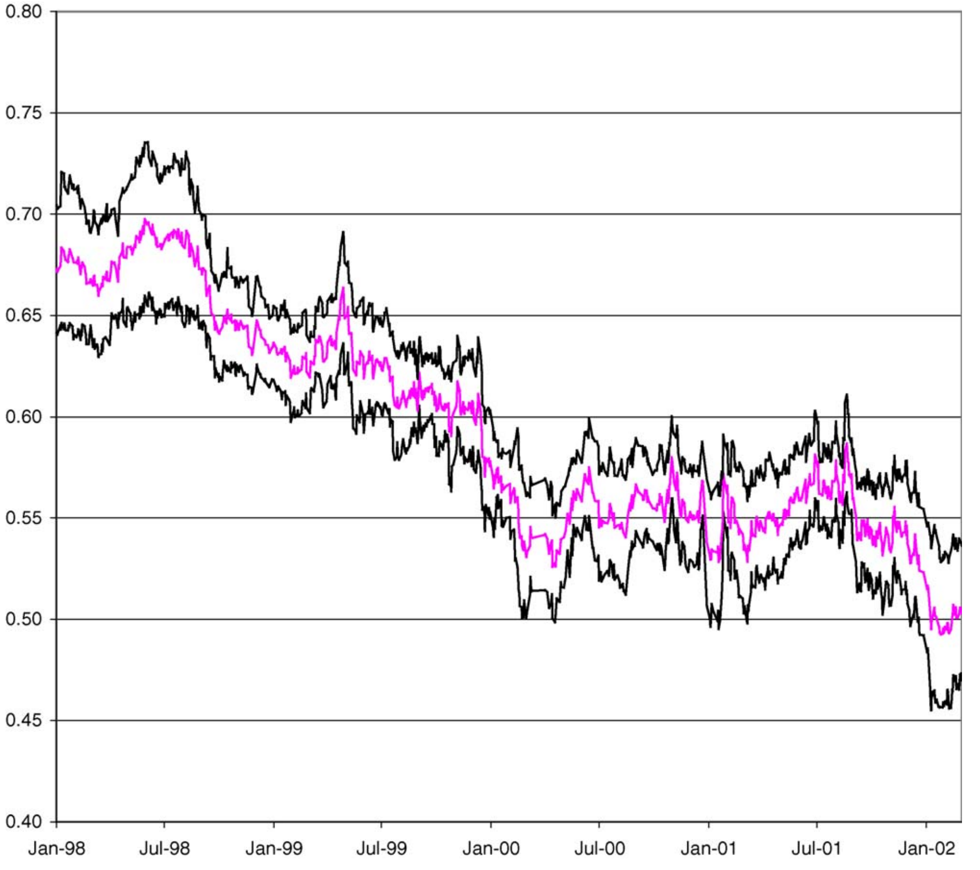

Fig. 2. Time-varying Hurst exponents with 95% confidence interval for the Croatia Zagreb Stock Index – ZSICI.

Table 3 presents the results for bootstrapped VR statistics. The first line of each country's index presents the VR and p-value (based on the empirical distribution built with a bootstrap procedure). Results are qualitatively similar to the ones obtained before.

Therefore, for most countries and indices, rejection of the random walk hypothesis is straightforward and suggests some degree of predictability in such equity returns.

An important source of bias in the empirical results found so far could be due to the infrequent trading problem discussed in Lo and Mackinlay (1988). The authors argue that artificial autocorrelation may appear due to infrequent trading, which would suggest spurious predictability. In order to check whether such an argument can be made in this case, we average annual market capitalization for all countries.[19] There does not seem to be any clear relationship between market capitalization and the size of the Wald statistics, which is our proxy for the rejection of the RWH in Table 3.

[19] We average market capitalization using available data in Emerging Stock Markets Factbook (1999) for the same period for which VR statistics were calculated.

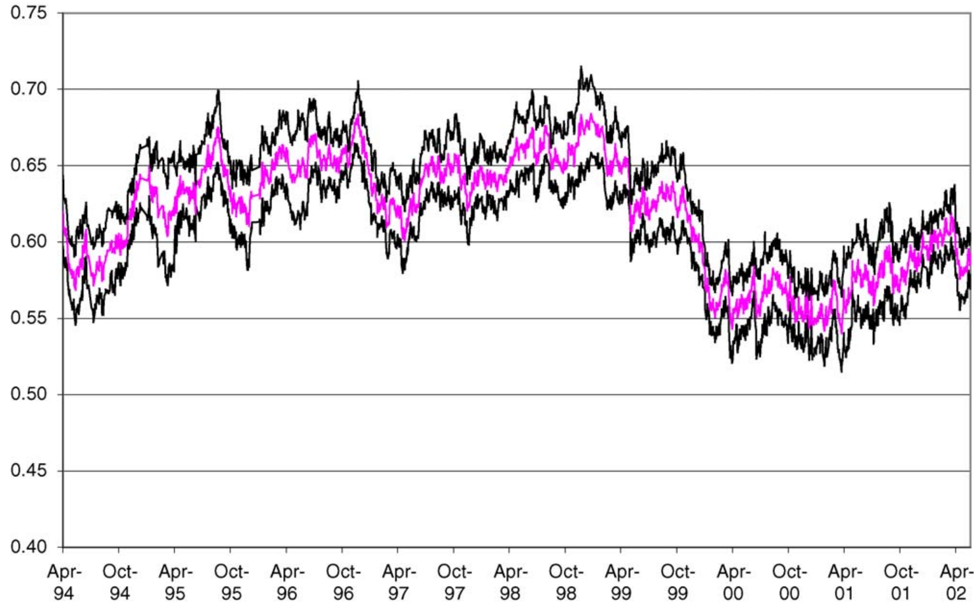

Fig. 3. Time-varying Hurst exponents with 95% cofidence interval for the Prague Stock Exchange Index – PX50.

A spearman rank correlation between Wald statistics and average market capitalization, provided in the Emerging Stock Markets Factbook (1999), is 0.36 (with a p-value of 0.33) and is clearly insignificant.

In order to check for robustness, we also use market capitalization for the indices that were used in this study. The main qualitative results do not change. Furthermore, the spearman correlation between market capitalization (provided in the Emerging Stock Markets Factbook) and market capitalization for the indices employed in our study, is 67% and is significant at the 5% level.

The main lesson we can take from this exercise is that perhaps other characteristics of such stock markets and indices must play a role in explaining our results, rather than market capitalization by itself.

Summarizing, we reject the RWH for all markets, with the exception of the SOFIX index, using a customized empirical distribution. Therefore, there is strong evidence of predictability for these stock markets, at least in the short run. It is important to notice that these findings are in line with other research such as that found in Harvey (1995), Malliaropulos and Priestley (1999), Chang et al. (2004) and Mateus (2004).

5.2. Long-range dependence parameter

In this section, we report the results of testing long-range dependence in emerging European transition equity returns. Table 4 presents the Hurst exponent (H) estimated using the R/S methodology and shuffling to eliminate short-term autocorrelation. The second column in the table presents the standard error associated to the estimated Hurst exponents, which allows the calculation of a Wald statistic to test the null of H equal to 0.5 (absence of long memory). This Wald statistic has a χ^2 distribution with one degree of freedom.

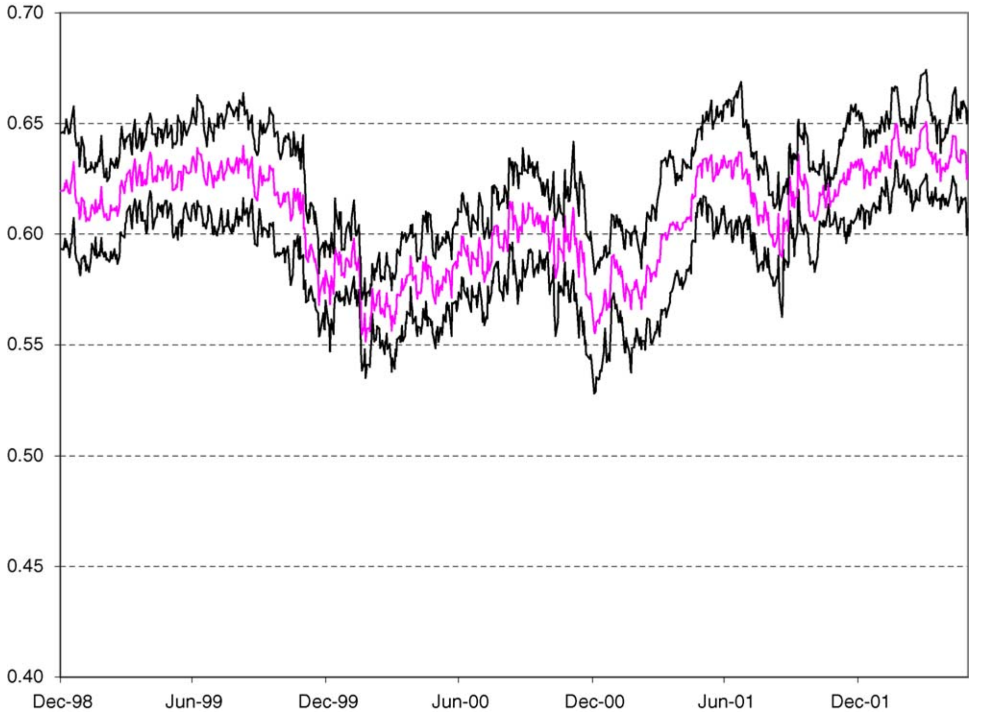

Fig. 4. Time-varying Hurst exponents with 95% confidence interval for the Tallin Stock Exchange Main Index – TALSE.

Considering Table 4, it is evident that emerging European transition economies have strong long-range dependence in equity returns. Hurst exponents range from 0.561 for the Bulgarian Stock Exchange Index (SOFIX Index) to 0.682 for the Latvia equity Index (RICI Index), which is considered to be high in the light of results found for developed and other emerging markets.[20]

These countries have been experiencing several major changes in the past decade[21] and also suffered the pressure of large crises, like the Asian and the Russian crises. Therefore, we employ a ''rolling sample'' approach to verify how the Hurst exponents vary over time. Evidence of time-varying Hurst exponents is in line with multifractality for equity returns.

In Fig. 1 we present Hurst exponents with a 95% confidence interval estimated using 504 observations (approximately 2 years of data). The first Hurst exponent is estimated using the sample June 1993–June 1995. We roll the sample by dropping the first observation and including a new one and then re-estimating the Hurst exponent. We do so until the end of the sample. A striking feature of the Budapest stock exchange index (BUX) is that Hurst exponents are very high in the beginning of the sample (in the 0.65–0.75 range) and remain high (in the 0.60–0.65 range) until the end of the sample, although they have decreased over time.

[20] See Cajueiro and Tabak (2004a,b).

[21] Some of these countries have been trying to access the EU. Therefore, they have been improving their insider laws and investor protection, their market regulation and banking supervision, developing their standards of disclosure and compliance of their banking systems and strengthening their enforcement capabilities. See, for instance, Claessens (1997), Chun (2000), Konings et al. (2003) and IMF (2000).

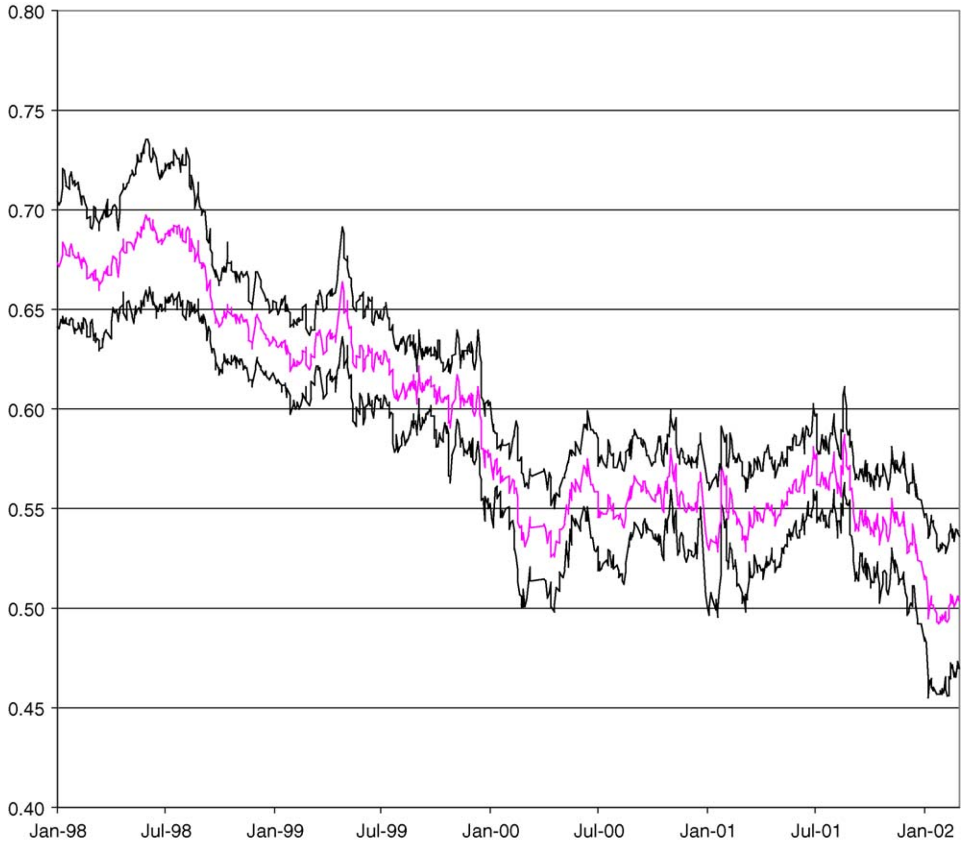

Fig. 5. Time-varying Hurst exponents with 95% confidence interval for the Latvia Stock Equity Index – RICI.

In Figs. 1–9 we present time-varying Hurst exponents for European transition stock indices. For most indices it is clear that there is strong long-range dependence in equity returns. There is a clear tendency towards rejection of long-range dependence only for the Ukrainian KAC-20 Liquid Index (UKASW) and for the Croatian Zagreb Stock index (ZSICI), as Hurst exponents gravitate around 0.5 after 2002.

The empirical evidence suggests that Hurst exponents are time-varying and therefore, the degree of long-term predictability is changing over time. Only in a few cases a tendency towards efficiency was observed. The results suggest that these series seem to have multifractality.

Table 5 presents the data summary for these time-varying Hurst exponents. As we can see, maximum Hurst exponents are quite high, ranging from 0.61 (for the SOFIX Index, Bulgaria) to 0.75 (for the UKASW Index, Ukraine). For all indices, we reject the null hypothesis that time-varying Hurst exponents are normally distributed.[22]

Our findings are important for both academics and practitioners, since many implications stem from our results for financial modeling. First, option-pricing models should incorporate long-range dependence in pricing equations. Secondly, for portfolio managers there seem to be

[22] See the Jarque–Bera statistic.

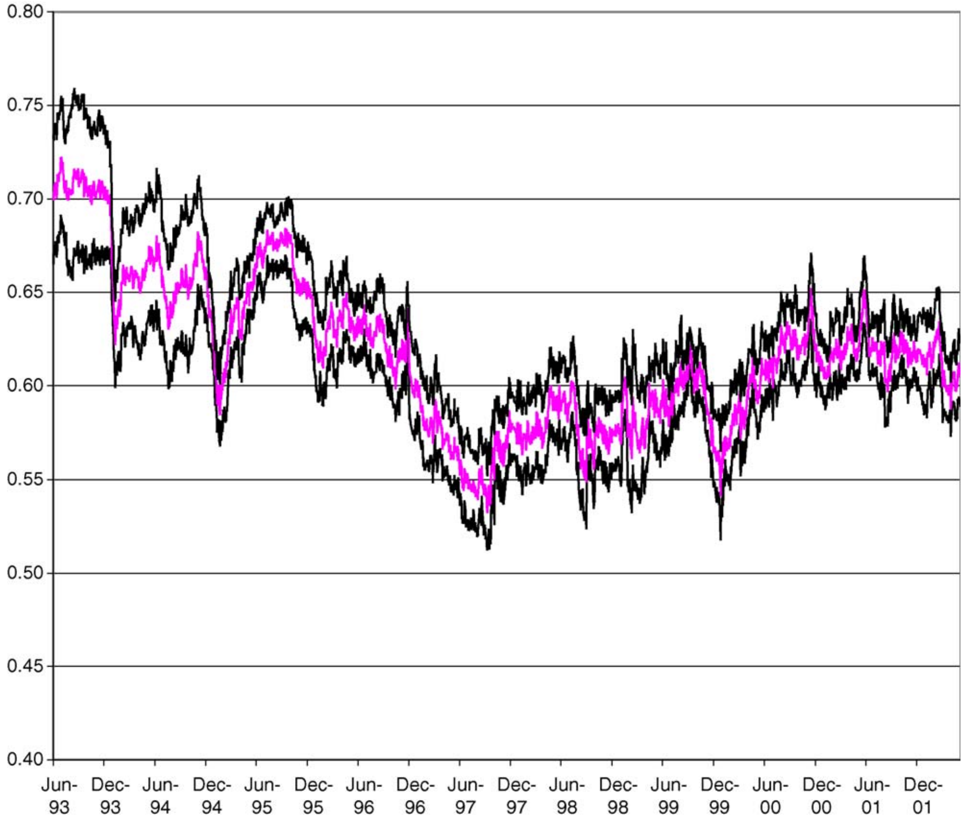

Fig. 6. Time-varying Hurst exponents with 95% confidence interval for the Budapest Stock Exchange Index – BUX.

interesting investment opportunities in European transition economies, due to their predictability patterns. As these economies are becoming more integrated and increasing their participation in global portfolios, liquidity should also rise, and a virtuous circle may be observed in these stock markets.

Table 5
Data summary for time-varying Hurst exponents

	Mean	Median	Maximum	Minimum	S.D.	Skewness	Kurtosis	Jarque–Bera	p-Value
SOFIX Index	0.58	0.58	0.61	0.54	0.02	−0.18	2.08	14.91	0
ZSICI Index	0.59	0.57	0.7	0.49	0.05	0.29	1.92	54	0
PX50 Index	0.62	0.63	0.68	0.54	0.04	−0.38	1.92	140.71	0
TALSE Index	0.61	0.61	0.65	0.55	0.02	−0.43	2.08	56.94	0
RICI Index	0.58	0.57	0.69	0.5	0.05	0.44	2.05	72.94	0
BUX Index	0.62	0.62	0.72	0.53	0.04	0.45	2.69	83.02	0
WIG Index	0.62	0.62	0.68	0.57	0.02	0.03	2.2	55.36	0
RTSI$ Index	0.64	0.64	0.71	0.57	0.03	−0.11	2.45	24.69	0
UKSAW Index	0.55	0.55	0.75	0.45	0.07	1.1	3.82	288.61	0

Hurst exponents were estimated using a shuffling procedure (blocks of size 20). The Jarque–Bera statistic tests the null hypothesis that Hurst exponents are normally distributed.

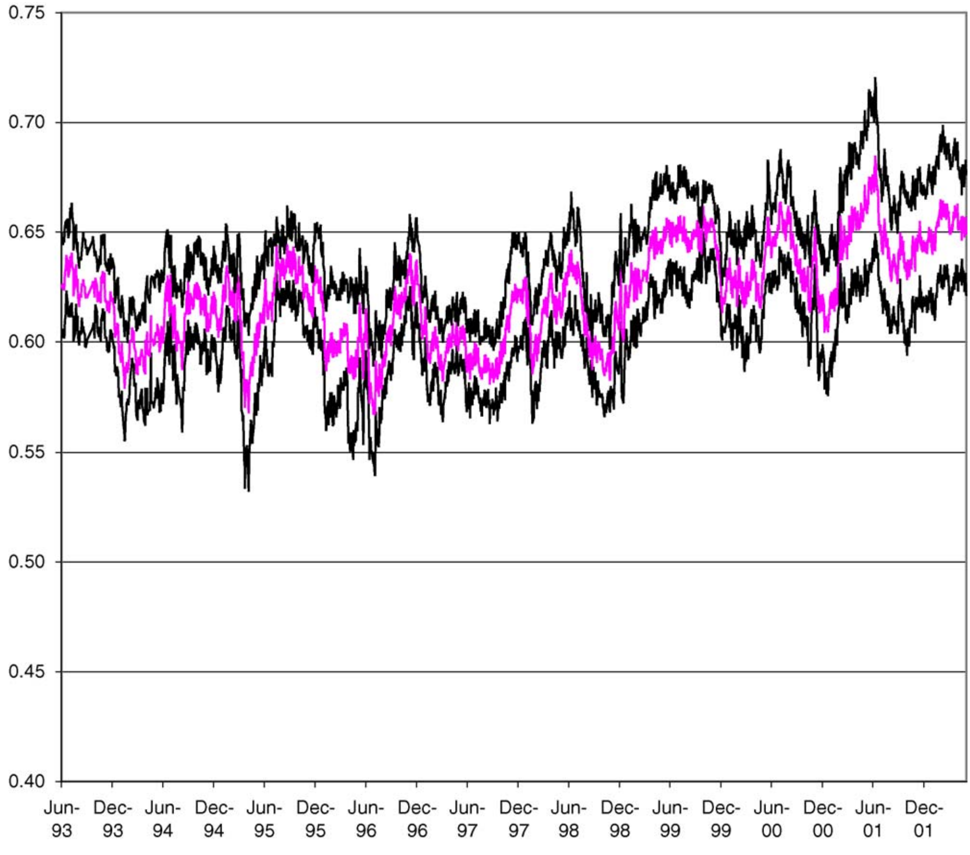

Fig. 7. Time-varying Hurst exponents with 95% confidence interval for the Polish Equity Index – WIG.

Summarizing, multifractality is a pervasive characteristic of European emerging markets. Hurst exponents are quite high in average, suggesting that there is long-term predictability, which could be exploited by portfolio managers. Only two indices present convergence towards efficiency, the Croatian Zagreb Stock Index (ZSICI) and the Ukrainian KAC-20 Index (UKASW). Other indices do not present a clear trend towards efficiency (Hurst exponents evolving around 0.5).

6. Conclusions

This paper studies short and long-term predictability in emerging European transition equity markets. Strong evidence of short-term predictability from VR statistics (robust to heteroskedasticity), using a bootstrap procedure, was found in all indices, with the exception of the Bulgarian stock exchange index (SOFIX) and the Ukrainian KAC-20 Liquid Index (UKASW). These findings do not seem to be correlated with market capitalization, and short-term autocorrelation may be due to other factors. These results are in accordance with previous findings.[23]

[23] See Chang et al. (2004) and Patro and Wu (2004).

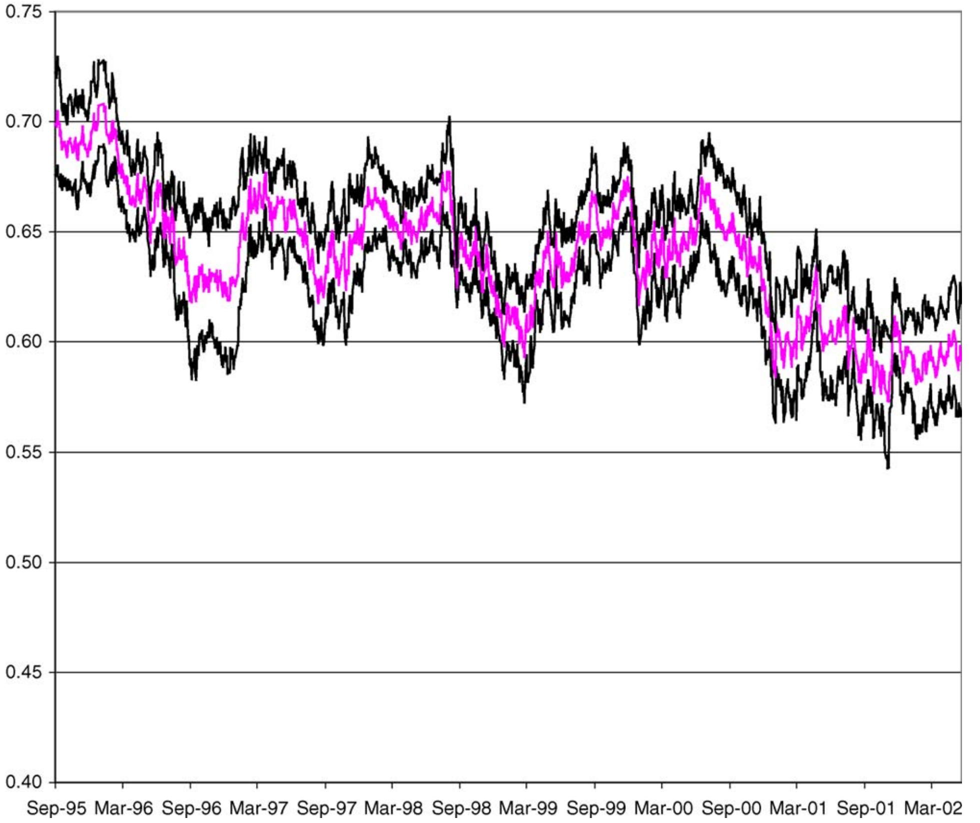

Fig. 8. Time-varying Hurst exponents with 95% confidence interval for the Russian Equity Index – RTSI$.

Evidence of long-range dependence was found for all indices. Time-varying Hurst exponents were estimated using a ‘‘rolling sample’’ approach and evidence of time-varying Hurst exponents were found in line with previous research such as Cajueiro and Tabak (2004a,b). For most indices there is no clear trend in Hurst exponents, with the exception of the Ukrainian KAC-20 Liquid Index (UKASW) and the Croatian Zagreb Stock Exchange Index (ZSICI), as their Hurst exponents tend to 0.5 after 2002, and gravitate around it afterwards.

These results are comparable to previous research on developed and more mature emerging markets. Basically, evidence of short and long-term predictability seems to be stronger for emerging European transition economies. The degree of predictability seems to be higher than for other asset classes, which suggests that such equity indices are interesting for diversification purposes, specially due to their low international exposure. Furthermore, multifractal models such as the one presented in Calvet and Fisher (2001) may fit in well with this data and may be used for forecasting purposes, since these series exhibit multifractal properties.

Our findings are important for both academics and practitioners. European transition economies have been substantially enhancing their stock markets in the past years and can be considered as interesting diversifying opportunities for global investors. Predictability patterns in these countries suggest that they still have predictability that can be exploited. Furthermore, option pricing for these stock markets has to take into account long-range dependence, which is pervasive in our sample.

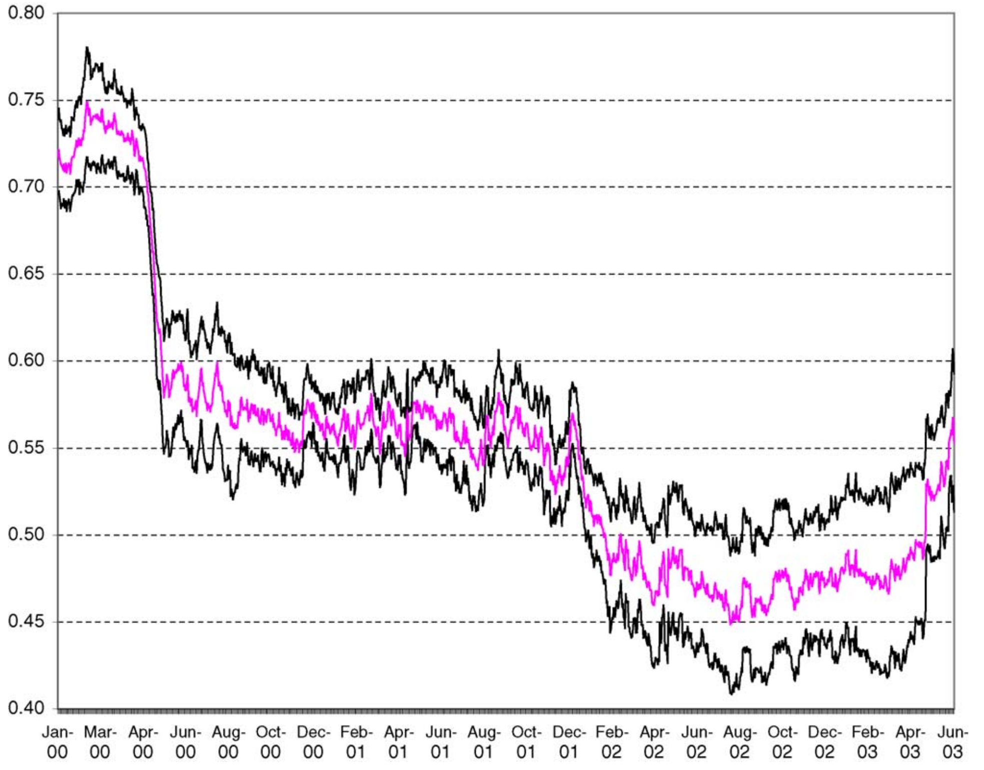

Fig. 9. Time-varying Hurst exponents with 95% confidence interval for the Ukraine KAC-20 Liquid Index – UKASW.

This paper has improved our understanding of the dynamics of European transition stock markets. Since these countries have important commonalities, due to geographical location, we have to be cautious as to generalizations to other transition economies such as the Chinese stock market. Nonetheless, our results suggest that developing models that exploit multifractal properties of returns in portfolio and risk management is extremely important. To the best of our knowledge, this has not been done yet. Nonetheless, this is certainly an important research question and should be in our research agenda in the future.

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