LONG MEMORY IN EASTERN EUROPEAN FINANCIAL MARKETS RETURNS

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ABSTRACT

The paper examines the long memory property of stock returns and its implications using daily index returns for eight CEE emerging markets: Romania, Hungary, Czech Republic, Poland, Slovenia, Bulgaria, Slovakia, and Croatia. Several nonparametric methods for testing for long memory are employed, as well as parametric long memory models. The ARFIMA-FIGARCH model seems the most appropriate specification since the nonlinearity tests can not reject the null of independent and identically distributed residuals, implying that this specification accounts for the nonlinearity in the data. The estimated fractional differencing parameter is statistically significant in seven of the eight emerging economies employed in the study, suggesting the presence of long memory in the returns in these financial markets.

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I. INTRODUCTION

The existence of long memory in financial asset returns has been an important subject of both theoretical and empirical research. If asset returns display long memory, the series realizations are not independent over time, and values from the remote past can help forecast future returns. According to Fama (1970), under the 'efficient market hypothesis' (EMH), stock market prices must always show a full reflection of all available and relevant information and should follow a random walk process. Market efficiency implies the absence of pure arbitrage opportunities and denies the profitability by the use of historical data. Successive returns should therefore be independently and identically distributed (*iid*). An efficient financial market can be described as one for which no deterministic pattern can be detected. Efficiency validation is sometimes reduced to test whether the returns data generating process of is deterministic or stochastic. Therefore, the presence of long memory in asset returns contradicts the weak form of the market efficiency hypothesis, which states that, conditioned on historical returns, future asset returns are unpredictable. Mandelbrot (1971) suggests that in the presence of long memory, pricing derivative securities with martingale methods may not be appropriate.

Based on the information set, there are three types of efficient markets: weak-form, semi-strong-form, and strong-form efficient if the set of information includes past prices and returns only, all public information, and any information public as well as private, respectively. A large body of literature accumulated over the past three decades has focused on the validity of the weak-form efficient market hypothesis (EMH) with respect to stock markets. Worthington and Higgs (2006) have studied the weak-form market efficiency of twenty-seven emerging markets in different regions concluding that most of them are weak-form inefficient. Kvedaras and Basdevant (2002) have tested the efficiency of financial markets in the Baltic States concluding that they are approaching the weak form of efficiency. Harrison and Paton (2004) examined the evolution of stock market efficiency in the Bucharest Stock Exchange using a GARCH model. They found strong evidence of inefficiency in the Bucharest Stock Exchange. Work on testing the weak form of market efficiency where nonlinearities are taken into account is limited and international evidence includes Brooks (2007), Lim et al. (2008), Panagiotidis (2005), and Alagidede and Panagiotidis (2009). Alagidede and Panagiotidis (2009) examines the efficiency of seven emerging African markets finding no evidence to reject weak form efficiency for these markets.

A number of studies have tested the long memory hypothesis for stock returns and the evidence is mixed. Using the classical rescaled-range method, Greene and Fielitz (1977) report evidence of persistence in daily U.S. stock returns. Lo and MacKinley (1988) and Poterba and Summers (1988) concluded that stock returns exhibit mean reversion. Fama and French (1988), who examined the autocorrelations of one-period returns, also found mean reversion. Lo (1991), using modified rescaled range statistic finds no evidence of long memory in a sample of U.S. stock returns. Mills (1993), using the modified statistic and the semi-parametric approach of Geweke and Porter-Hudak (1983) finds evidence of long memory in monthly U.K. stock returns. Cheung and Lai (1995), using the same methods, find no evidence of persistence in several international stock returns series. On the other hand, Henry (2002) finds long memory in the German, Japanese and Taiwanese markets. Lobato and Savin (1997) and Caporale and Gil-Alana (2001) find no evidence of long memory in daily Standard and Poor 500 returns. The vast majority of studies focused on developed financial markets, with less attention to emerging countries. CEE emerging markets are characterized by a lower liquidity and a higher volatility than developed financial markets. These features may induce different dynamics of the financial returns in these markets. Kasman et al. (2008) investigate the presence of long memory in eight CEE emerging stock markets and find strong evidence of long memory in both conditional mean and variance and that the ARFIMA-FIGARCH model outperforms ARFIMA-GARCH and ARFIMA-HYGARCH models in terms of out-of-sample forecast.

This paper examines the long memory property of stock returns and its implications using daily index returns for several CEE emerging markets: Romania, Hungary, Czech Republic, Poland, Slovenia, Bulgaria, Slovakia, and Croatia. In this study, we use the basic Random Walk (RW) model, several nonparametric methods for testing for long memory, as well as parametric long memory models. The basic RW model is used directly to test for the random walk hypothesis (RWH). GARCH models are also employed to capture the main characteristics of financial time series such as fat tails, volatility clustering, and persistence in volatility. GARCH type models are a convenient modality to capture the stylized facts of financial returns. For example, the two-dimensional Copula-GARCH model developed in Necula (2010) can be employed to analyze the dependency structure between financial returns.

Our paper differs from similar studies in that the focus is on CEE emerging markets and in that the methodology permits a thorough investigation of the dynamics of financial returns. More specifically, we use nonlinear serial independence tests to confirm the adequacy of these models by employing a battery of tests used by Patterson and Ashley (2000). Patterson and Ashley (2000) point out that a standalone statistical test for nonlinearity can only detect (or fail to detect) nonlinearity. Therefore, the application of a battery of nonlinearity tests can provide valuable information about any nonlinear structure in the data generating process on a given time series. The five tests include the McLeod and Li (1983) for ARCH effects; the Engle (1982) LM test for GARCH effects; the BDS test proposed by Brock et al. (1996); the Tsay (1986) test for quadratic serial dependence; and the Hinich (1996) bicovariance test for third order serial dependence. All the tests are based on the same hypothesis that once any linear serial dependence is removed from the data, the remaining serial dependence must be due to a nonlinear data generating process.

The rest of the paper is structured in three sections. The second section presents the data and the econometric methodology, the third section points out the main finding of the study and the final section concludes.

II. DATA AND METHODOLOGY

The data consists of daily returns of BET (Romania), BUX (Hungary), PX50 (Czech Republic), WIG20 (Poland), SVSM (Slovenia), SOFIX (Bulgaria), SAX (Slovakia), and CROBEX (Croatia) for a period up to December 2010. Table 1 reports the summary statistics of the daily return series together with the sample period. These include the mean, the standard deviation (highest in Poland, lowest in Slovenia), skewness (negative for almost all countries) and kurtosis (highest in Bulgaria, lowest in Poland).

The Jarque–Bera statistic rejects normality, evidence similar to the findings in Necula (2009) that look at the distribution of emerging markets index returns and concludes that the Generalized Hyperbolic Distribution is more appropriate than the Gaussian distribution to model stock index returns. Non-normality could be induced in part by temporal dependencies in returns, especially second moment temporal dependence. The presence of such dependence is tested by the Ljung–Box statistic calculated for ten lags. The hypothesis that all autocorrelations up to the 10th lag are jointly zero is rejected for all the eight countries. It is well documented that infrequent non-synchronous trading generates spurious autocorrelation in index returns (Scholes and Williams, 1977; Muthuswamy, 1990). A number of studies have suggested ways to correct for infrequent trading. Miller et al. (1994) proposed to remove the effects of thin trading by using moving averages, which reflects the number of non-trading days, and then adjusting returns accordingly. However, after applying Miller procedure the autocorrelations were still present in the data entailing the usage of a long memory model.

The econometric methodology employed consists of the following steps:

1. the random walk model (RW) is estimated for the returns of each of the eight indexes and the residuals are tested for *iid* through a battery of five nonlinearity tests as described in Patterson and Ashley (2000): McLeod and Li (1983) for ARCH effects; the Engle (1982) LM test for GARCH effects; the BDS test proposed by Brock et al. (1996); the Tsay (1986) test for quadratic serial dependence; and the Hinich (1996) bicovariance test for third order serial dependence; see Patterson and Ashley (2000) for more details about each test;

TABLE 1. Descriptive statistics of the daily returns

	Romania	Hungary	Czech Republic	Poland	Slovenia	Bulgaria	Slovakia	Croatia
period	1997 - 2010	1991 - 2010	1994 - 2010	1991 - 2010	1994 - 2010	2000 - 2010	1993 - 2010	2002 - 2010
no. obs.	3249	4997	4104	4464	4128	2523	4152	2074
mean	0.000514	0.000612	0.000049	0.000865	0.000284	0.000496	0.000201	0.000275
std. dev.	0.020287	0.017308	0.014622	0.020864	0.011998	0.018584	0.015846	0.015141
skewness	-0.203059	-0.553215	-0.422449	-0.004647	-0.389906	-0.461261	0.360834	0.30793
kurtosis	13.51945	14.04536	14.31309	9.390193	12.97703	27.96914	22.47978	18.45869
JB	15002.76***	25656.31***	22007.66***	7595.246***	17225.68***	65630.5***	255461.8***	20683.87***
LB	44.141***	88.684***	66.431***	274.01***	323.41***	62.622***	181.91***	63.290***

Source: authors calculations

*Notes: *** deotes statistical significance at 1% level; JB is the Jarque-Bera test statistic for normality; LB is the Ljung-Box statistic for autocorrelation up to 10 lags*

2. several non-parametric or semi-parametric methods are employed for testing for long memory: the generalized R/S statistic (Lo, 1991; Cavaliere, 2001) and the GPH method (Geweke and Porter-Hudak, 1983); R/S tests seem to be unaffected by the so-called 'converse Perron effect' that consists in rejection of the unit root hypothesis (in favor of trend-stationarity) when the true generating process is I(1) with a broken trend;
3. if the residuals of the RW model are not *iid* or the nonparametric tests detect long memory in the returns, an $ARFIMA(0,d,0)$ long memory (LM) model is estimated to account for autocorrelations in returns and the residuals are tested for *iid*;
4. if the residuals of the LM model are not *iid*, GARCH effects are taken into account and an $ARFIMA(0,d_1,0)-FIGARCH(0,d_2,0)$ model is estimated to account for volatility clustering and persistency in volatility.

To test the assumptions implied by the random walk model, the following equation is estimated by OLS:

$$r_t = \mu + \varepsilon_t \tag{1}$$

where r_t is the return in day t.

Under the RW model the estimate of the constant μ should be insignificantly different from zero and the residuals should be *iid*. If the null of *iid* cannot be accepted, the implication is that the residuals contain some hidden, possibly non-linear structure. The estimation procedure and the five nonlinearity tests have been implemented using Ox object-oriented matrix programming language (Doornik, 2007).

A popular parametric method of capturing long memory is the fractionally differenced time series model of Granger (1980), Granger & Joyeaux (1981), and Hosking (1981). To test for long memory an *ARFIMA(0,d,0)* is estimated using the arfima package in Ox (Doornik & Ooms, 2003):

$$(1-L)^d r_t = \varepsilon_t \tag{2}$$

where L is the lag operator, $(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)} L^k$, and $\Gamma(\cdot)$ is the Gamma function. The mean parameter, μ, is omitted since the theory suggests that it should be statistically insignificant.

Three different types of specifications for the variance equation are estimated in this study using the G@RCH Ox package (Laurent and Peters, 2006). The first is the plain GARCH(1,1) model. The lag order (1,1) seems to be sufficient to capture all of the volatility clustering that is present in financial returns data (Brooks and Burke, 2003). The second specification accounts for the leverage effect. The notion of asymmetry has its origins in the work of Black (1976). A model that captures asymmetry is the EGARCH model of Nelson (1991). Numerous studies (Ding et al., 1993; Briedt et al., 1998) conclude that the volatility of financial assets is persistent. To account for this persistence the *FIGARCH(0,d,0)* model of Baillie et al. (1996) is employed in this study. The most sophisticated specification, consisting of long memory in the mean equation (d_1), of long memory in the volatility (d_2), and leptokurtic distribution (*t*-Student) is given by:

$$\begin{gathered}(1-L)^{d_1} r_t = \varepsilon_t \\ \varepsilon_t = z_t \sigma_t \\ (1-L)^{d_2} \varepsilon_t^2 = \omega + \left(\varepsilon_t^2 - \sigma_t^2\right) \\ z_t \sim t(\nu)\end{gathered} \tag{3}$$

where ν is the degree of freedom of the t -Student distribution.

III. RESULTS

A. The Random Walk Model

The Random Walk Model estimates (1) are presented in Table 2. The t-statistic of the estimated constant indicates that the expected daily return is not significantly different from zero. Also the Ljung–Box test indicates there is correlation up to 10 lags in the data.
The next step is to subject the residuals of the model to the battery of the five nonlinearity tests. All the test statistics reject the null of *iid* residuals of the RW model. This indicates that the data generating mechanism (DGP) is non-linear. We, therefore, reject the random walk as an adequate characterization of returns in our sample of Central and Eastern European countries. The presence of nonlinearities in the series could imply evidence of return predictability. The autocorrelation in returns entail the usage of a long memory model.

TABLE 2. Estimates of the Random Walk Model

	Romania	Hungary	Czech Republic	Poland	Slovenia	Bulgaria	Slovakia	Croatia
μ	0.000514212	0.00061236**	0.0000494	0.0008648**	0.000283748	0.000496225	0.000201002	0.000275431
	(0.0003559)	(0.0002448)	(0.0002282)	(0.0003123)	(0.0001867)	(0.0003700)	(0.0002459)	(0.0003325)
LB	13.7266	50.9805***	20.4634**	44.2906***	65.6439***	62.1747***	141.829***	55.4087***
ML	677.557***	1166.92***	1957.81***	2278.89***	1699.83***	200.053***	756.629***	651.357***
LM	124.13***	177.57***	240.43***	264.48***	241.28***	39.492***	145.06***	94.962***
TAR	27.3721***	6.43308***	20.6239***	9.93839***	13.4531***	0.444321	11.5445***	10.656***
HP	1880.36***	6523.84***	16852.4***	6474.48***	4847.66***	2350.68***	19253.4***	5229.48***
BDS	20.427***	20.290***	18.637***	20.193***	32.877***	19.804***	11.342***	12.465***

Source: authors calculations

*Notes: *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels respectively; μ is the estimated mean of eq. 1; standard errors are reported in paranthesis; LB is the Ljung-Box test statistic for autocorrelation up to 10 lags; ML is the McLeod-Li test statistic for ARCH effects up to 5 lags; LM is the Engle LM test statistic for GARCH effects up to 5 lags; TAR is the Tsay test statistic for quadratic serial dependence with k=2; HP is the Hinich-Patterson bicovariance test for third order serial dependence; BDS is the Brock et al. test statistic for serial independence with embedding dimension equal to 2.*

B. Non parametric tests for long memory

Table 3 presents the results concerning the nonparametric and the semi-parametric tests employed for testing the long memory property.

TABLE 3. Non parametric tests for long-memory

	GPH		R/S statistic	
	estimate	t-statistic	LR/S	CR/S
Romania	0.0763**	2.5310	1.9952**	1.7693**
Hungary	0.0414**	2.1082	1.6680*	1.4144
Czech Republic	0.0381**	2.1480	1.9135**	2.1382***
Poland	0.0452**	1.9567	2.0452***	2.1270***
Slovenia	0.0533**	2.1672	1.3055	1.3416
Bulgaria	0.0568**	1.9463	2.5151***	2.2921***
Slovakia	0.1576***	6.8561	2.2924***	2.0699***
Croatia	0.0819**	2.4357	2.0887***	2.1989***

SOURCE: authors calculations

*Notes: *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels respectively; GPH stands for the log-peridogram based estimation method of Geweke and Porter-Hudak (1983); LR/S and CR/S are Lo (1991) and Cavaliere (2000) modified R/S statistics computed using the Quadratic Spectral kernel*

The fractional differencing parameters estimated using the semi-parametric method of Geweke and Porter-Hudak (1983) are statistically significant. Also, the modified R/S statistics suggest the presence of the long memory property in the analyzed financial markets.

C. The ARFIMA long memory model

The *ARFIMA(0,d,0)* model estimates (2) are presented in Table 4. The fractional differencing parameter, d, is statistically different from zero for all the countries, implying the presence of long memory in the mean equation of stock index returns.

However, the nonlinearity test statistics reject the null of *iid* residuals of the *ARFIMA(0,d,0)* model (Table 4) for all the countries. The results of the McLeod and Li and Engle LM tests entail the usage of GARCH type stochastic processes to account for volatility clustering.

D. The ARFIMA - FIGARCH Model

As seen from the ARFIMA model, the lagged returns are significant in all countries implying that past information is useful in predicting the future path of prices evidence inconsistent with the EMH. However, this argument neglects the joint hypothesis of volatility clustering, a problem arising in all empirical efficiency studies. Schwaiger (1995) showed that GARCH in stock returns may be the result of rational and hence efficient equilibrium pricing. Time varying volatility models would be informative about weak form efficiency to the extent that conditional variances help in predicting future returns (Millionis and Moschos, 2000).

TABLE 4. Estimates of the Long Memory Model

	Romania	Hungary	Czech Republic	Poland	Slovenia	Bulgaria	Slovakia	Croatia
d	0.0753067***	0.0581023***	0.0698543***	0.154052***	0.170140***	0.0470623***	0.0782052***	0.0617062***
	(0.01384)	(0.01130)	(0.01264)	(0.01318)	(0.01407)	(0.01376)	(0.01121)	(0.01644)
LB	14.8867	64.5306***	40.9763***	130.842***	173.612***	56.9144***	78.3906***	51.8928***
ML	661.429***	1092.42***	2022.86***	2392.48***	1738.54***	186.779***	649.204***	655.182***
LM	116.28***	166.02***	249.85***	277.90***	244.72***	37.803***	120.74***	96.504***
TAR	33.3086***	10.6095***	26.6977***	8.02292***	24.4163***	0.547683	3.68119**	16.5295***
HP	2006.37***	6499.66***	17939.2***	4783.57***	5023.51***	2340.07***	14898.6***	5409.64***
BDS	19.147***	20.644***	17.860***	18.857***	27.349***	19.475***	12.211***	12.471***

Source: authors calculations

*Notes: *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels respectively; d is the estimatee long memory parameter in eq. 2; standard errors are reported in paranthesis; LB is the Ljung-Box test statistic for autocorrelation up to 10 lags; ML is the McLeod-Li test statistic for ARCH effects up to 5 lags; LM is the Engle LM test statistic for GARCH effects up to 5 lags; TAR is the Tsay test statistic for quadratic serial dependence with k=2; HP is the Hinich-Patterson bicovariance test for third order serial dependence; BDS is the Brock et al. test statistic for serial independence with embedding dimension equal to 2.*

TABLE 5. Estimates of the ARFIMA - FIGARCH Model

	Romania	Hungary	Czech Republic	Poland	Slovenia	Bulgaria	Slovakia	Croatia
d_1	0.093461***	0.071033***	0.115510***	0.092436***	0.197357***	0.102626***	0.010609	0.076643***
	(0.016603)	(0.012205)	(0.014990)	(0.014136)	(0.020196)	(0.017096)	(0.0087552)	(0.018189)
w	0.354802***	0.184077***	0.137056***	0.318888***	0.040880***	0.131333***	0.391105***	0.219080***
	(0.088204)	(0.039887)	(0.031359)	(0.043367)	(0.012089)	(0.049096)	(0.11085)	(0.065315)
d_2	0.403758***	0.288759***	0.293134***	0.252107***	0.377627***	0.444604***	0.273389***	0.333085***
	(0.030913)	(0.016667)	(0.015941)	(0.017570)	(0.020734)	(0.030083)	(0.020442)	(0.039606)
v	4.547361***	5.842363***	6.796420***	7.471646***	5.474219***	3.698250***	2.707462***	4.052594***
	(0.32813)	(0.42115)	(0.59654)	(0.78351)	(0.37126)	(0.20191)	(0.084258)	(0.35005)
LB	14.3539	17.5453*	21.8344*	21.9083*	137.198***	10.4994	5.98207	15.9654
ML	5.44697	1.32241	14.5040*	6.65317*	2.55969	2.11005	3.86460	2.70792
LM	0.64144	0.26579	3.0049*	3.8412*	0.50380	0.42529	0.77946	0.24977
TAR	1.36973	3.70768**	1.5819	2.03592	1.672	1.90269	0.856455	0.46682
HP	358.479*	491.596	448.354**	461.293*	401.815	282.752*	410.456	187.775
BDS	0.47994	-1.1179	-3.0573***	-3.7285***	-0.0966	0.41802	0.10924	-1.4000

Source: authors calculations

*Notes: *, **, and *** denotes statistical significance at 10%, 5%, and 1% levels respectively; d1, w, d2, and v are the estimated parameters in eq. 3; standard errors are reported in paranthesis; w and its std. error have been multiplied by 10^4; LB is the Ljung-Box test statistic for autocorrelation up to 10 lags; ML is the McLeod-Li test statistic for ARCH effects up to 5 lags; LM is the Engle LM test statistic for GARCH effects up to 5 lags; TAR is the Tsay test statistic for quadratic serial dependence with k=2; HP is the Hinich-Patterson bicovariance test for third order serial dependence; BDS is the Brock et al. test statistic for serial independence with embedding dimension equal to 2.*

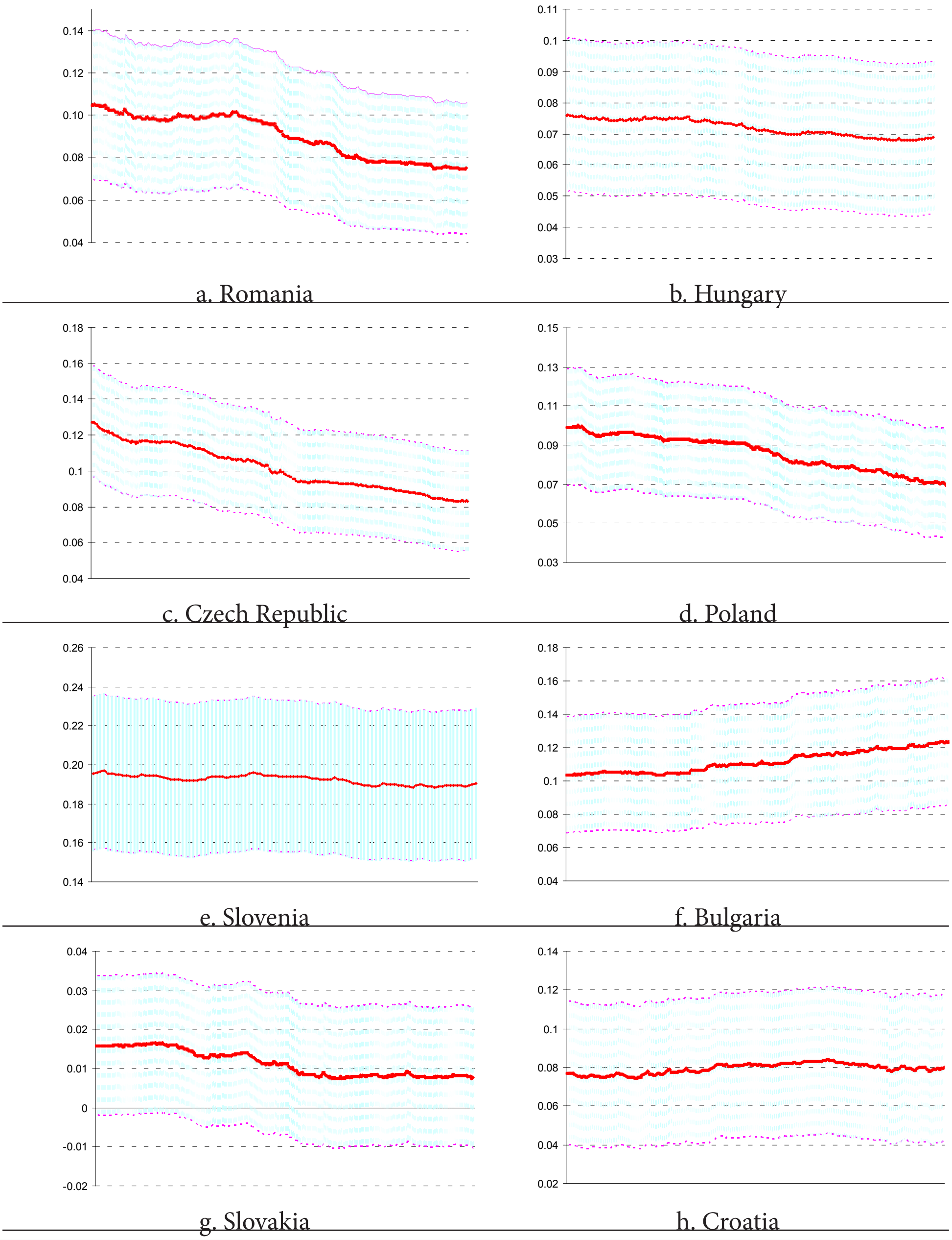
Our methodology consists in estimating different specifications for the variance equation (the basic GARCH specification, an EGARCH specification, and an FIGARCH specification). The Student *t*-distribution was employed for the all the GARCH estimates to allow for heavy tails (given the evidence from Table 1). For all the analyzed emerging economies an $ARFIMA(0,d_1,0)-FIGARCH(0,d_2,0)$ was the best specification, according to the information criteria. The best model specification estimates (3) are presented in Table 5.

For all the countries, the battery of nonlinearity test can not reject the null of *iid* residuals of the best specification (Table 5), implying that this model accounts for all the nonlinearities in the data.

Figure 1 depicts the dynamics of the long memory parameter in the returns in the eight emerging economies, as well as the 95% confidence bands. A rolling window estimation procedure was employed. The rolling window length is 90% of the whole sample size. To obtain the dynamics of the long memory parameter in the returns (*i.e* in the mean equation), the ARFIMA-FIGARCH model was employed with the parameters of the variance equation fixed to the values estimated for the whole sample.

THE DYNAMICS OF THE LONG MEMORY PARAMETER

FIGURE 1



SOURCE: Author

The parameter is consistently greater than zero for the period analyzed, except for Slovakia, implying the presence of long memory in the stock index returns for the seven remaining countries. The long memory parameter is decreasing in Romania, Czech Republic, and Poland and increasing in Bulgaria. For the rest of the countries it is relatively stable over the analyzed period.

IV. CONCLUDING REMARKS

This paper has examined the long memory property of stock returns and its implications using daily index returns for eight Central and Eastern European emerging economies (Romania, Hungary, Czech Republic, Poland, Slovenia, Bulgaria, Slovakia, and Croatia). Random Walk, ARFIMA, semi-parametric and different GARCH models were estimated and a battery of nonlinearity tests for the null of *iid* residuals was employed in all cases.

The random walk model was rejected for all the countries. Since volatility clustering is present in the analyzed index returns, one has to consider the hypothesis of heteroskedasticity. A series of different GARCH models specifications were estimated, the most appropriate one being a long memory specification, $ARFIMA(0,d_1,0)-FIGARCH(0,d_2,0)$. The estimated fractional differencing parameter in the mean equation is statistically significant in seven of the eight emerging economies employed in the study, implying the presence of long memory in the returns in these financial markets.

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DUGOROČNO PAMĆENJE U PRINOSU ISTOČNOEUROPSKIH FINANCIJSKIH TRŽIŠTA

SAŽETAK

Ovaj rad istražuje svojstvo dugoročnog pamćenja prinosa dionica i njegove implikacije koristeći dnevni indeks prinosa za osam CEE tržišta u nastajanju: Rumunjsku, Mađarsku, Češku, Poljsku, Sloveniju, Bugarsku, Slovačku i Hrvatsku. Testiranje dugoročnog pamćenja je izvedeno korištenjem više neparametarskih metoda kao i nekoliko parametarskih modela dugoročnog pamćenja. ARFIMA-FIGARCH model se pokazao kao najprikladnija specifikacija s obzirom da testovi nelinearnosti ne mogu odbaciti nul-hipotezu neovisnih i identično distribuiranih rezidua, implicirajući činjenicu da je ova specifikacija odgovorna za nelinearnost podataka. Procijenjeni frakcijski parametar diferenciranja je statistički značajan u sedam od osam ekonomija u nastajanju koje su istražene u radu, sugerirajući prisutnost dugoročnog pamćenja prinosa na ovim financijskim tržištima.

Ključne riječi: *dugoročno pamćenje, ARFIMA, FIGARCH, nelinearnost, tržišta u nastajanju*