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IS THERE LONG TERM MEMORY IN UROPEAN STOCK MARKETS?

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ABSTRACT

This paper investigates for predictable components in the return series of 12 European stock markets using the tests of Geweke and Porter-Hudak (1983), and Robinson (1995b), to analyze the degree of dependence in the intertemporal structure of stock returns. Evidence of high degree of predictability is documented in almost all market indices over the sample periods. Furthermore, by using full Whittle maximum likelihood with the Geweke and Porter-Hudak estimates of the fractionally differenced parameter as starting values, more supportive evidence in the series is found. It appears that most European stock markets are persistent dependent, resulting in improved long-horizon predictability and stock market inefficiencies.

JEL Classification: G12, G14, C53.

Keywords: Efficient market hypothesis, Stock returns, Fractional differencing, Full Whittle maximum likelihood.

1. INTRODUCTION

One of the most popular issues of recent research in empirical finance is whether or not there are predictable components in stock market returns over long horizons. Many empirical studies have examined the evidence for long horizon predictability in stock returns, such as, Greene and Fielitz (1977), Aydogan and Booth (1988), Poterba and Summers (1988), Lo (1991), Cheung, Lai, and Lai (1994), Mills (1993), Crato (1994), Cheung and Lai (1995), Barkoulas and Baum (1996), Lobato and Savin (1998), Barkoulas, Baum, and Travlos (2000), Wright (2001), Panas (2001), Sadique and Silvapulle (2001), Caporale and Gil-Alana (2002), Henry (2002), and Tolvi (2003). Unfortunately, the results of these studies have been mixed. The main purpose of most empirical research in this area has been the establishment of time series properties of stock returns in major stock markets.

The efficient market hypothesis requires that stock returns are totally unpredictable, that is, the arrival of new information is arbitraged away immediately. In an efficiently functioning market, the price of a share of stock should follow a martingale or random walk process in which each price change is totally unrelated to its history and there exist zero autocorrelations at all lags. If the stock return series are long-range dependent, there are significant positive autocorrelations between observations widely separated in time. Since the realized series are not independent over time, historical stock returns can be used for prediction purposes, disputing the validity of the efficient market hypothesis. Therefore, the question of whether or not stock markets are efficient is equivalent to whether or not long-range dependence is present in the stock returns.

This empirical study extends previous research on long-range dependence in two respects. First, European evidence concerning dependence in stock returns is explored. Since the evidence on long-range dependence is mixed, an analysis of the behavior of stock markets may be deemed appropriate. Second, the robustness of the fractionally differencing parameter is examined by applying two estimation techniques to daily index return data on 12 European countries.

This paper is divided into five sections. Section 2 briefly describes the model of longrange dependence in time series. Section 3 outlines the tests of Geweke and Porter-Hudak (1983) and Robinson (1995b) for *I(d)* statistical models which we apply to daily stock returns and the full Whittle maximum likelihood (1951, 1962). Section 4 describes the data and presents the empirical results. The final section provides the concluding remarks.

2. LONG RANGE DEPENDENCE AND FRACTIONAL STATISTICAL ANALYSIS

A series $\{x_t\}$ is a linear long memory time series if

$$x_t = \varepsilon_t + \sum_{j=1}^{\infty} b_j \ \varepsilon_{t-j} \tag{1}$$

where ε_t is *i.i.d.* $(0, \sigma^2)$ and the spectral density of the series satisfies

$$f_x(\lambda) \sim C\lambda^{-2d} \qquad \lambda \to 0 \text{ for } 0 < d < 0.5$$

In practical econometric research, it is often useful to analyze the long-range dependence of the time series of interest by employing the Autoregressive Fractionally Integrated Moving Average, or ARFIMA (p,d,q), approach. ARFIMA models have been introduced by Granger and Joyeux (1980) and Hosking (1981) and are defined as

$$\phi(L)\,(1-L)^d\,(x_t - \mu) = \theta\,(L)\,\varepsilon_t \tag{2}$$

where L is the lag operator $(L_j x_t = x_{t-j})$, $\phi\,(L) = 1 - \phi_1 L - \ldots - \phi_p L_p$ is the autoregressive polynomial, and $\theta(L) = 1 + \theta_1 L + \ldots + \theta_q L_q$ the moving average polynomial, and μ is the mean.

The roots of $\phi(L)$ and $\theta(L)$ are assumed to lie outside the unit circle and that they do not have common roots. The differencing parameter d can take on any real value and is not restricted to the integer domain.

The fractional differencing operator $(1\text{-}L)^d$ is defined for non-integer d by an infinite binomial expansion

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

The long-range dependence properties of such series depend on the value of d. For $d \in (0, 0.5)$ the ARFIMA process is covariance-stationary and it displays long-range dependence. This property characterizes the behavior of the series' long-lagged autocovariances. In this case, all autocorrelations are positive and they decay hyperbolically to zero as the lag length increases, compared to the usual exponential decay of a stationary ARMA model with $d = 0$. Thus, if a series is long-range dependent, there are significant autocorrelations even at very long intervals and the autocovariances decline very slowly (in the time domain). A shock to the series has a long-lasting impact, even though it eventually dies out. For all practical purposes, a long-range dependent process may be considered to have an infinite span of statistical interdependence. In the frequency domain, long-range dependence is indicated by the fact that the spectral density becomes unbounded as the frequency approaches zero.

Standard ARIMA processes cannot possess long-term dependence since they can only describe the short-run behavior of a time series. For $d \in (-0.5, 0)$ the process is covariance-stationary and displays short memory. Short memory describes the loworder correlation structure of a series and is shown by quickly declining autocovariances in the time domain and significant power at high frequencies in the frequency domain. In this case the autocorrelations are all negative. For a shortmemory process, events from the distant past have negligible effect on the present. For $d \geq 0.5$ the series are no longer covariance stationary, and have infinite variance (for a more detailed discussion see, for example, Baillie (1996)).

3. TESTING METHODS

There exist a large number of methods, proposed in the literature, to test for longrange dependence. These estimation techniques may be classified in different ways. They may be classified in *two-step* (Geweke and Porter-Hudak, 1983) and *one-step* procedures (Li and McLeod, 1986, and Fox and Taqqu, 1986) or *time-domain* (Li and McLeod (1986) and Sowell, 1992a) and *frequency-domain* procedures (Fox and Taqqu, 1986, and Geweke and Porter-Hudak, 1983) or *approximate maximum likelihood* (Li and Mcleod, 1986, and Fox and Taqqu, 1986) and *exact maximum likelihood* (Sowell, 1992a). Exact maximum likelihood techniques have been criticized as being too computationally demanding, while the other methods have been criticized as being inaccurate for finite samples (Sowell, 1992a, b). The semiparametric and nonparametric may seem advantageous since fully specified parametric models may be subject to misspecification. They help to avoid the modeling of short-run components. Another advantage is the computational simplicity of these techniques. The Whittle MLE has the same asymptotic properties as the exact MLE and has three advantages over the exact MLE: the asymptotic properties of the Whittle estimator hold even if the series is not Gaussian; the computation of the Whittle likelihood is computationally simple since the periodogram at Fourier frequencies can be computed quickly using the Fast Fourier Transform; the periodogram at non-zero Fourier frequencies is location invariant. Thus, one does not have to mean-correct the data, unlike in the case of the exact MLE. This can be beneficial in small samples (Cheung and Diebold, 1990).

In this empirical study two types of tests are used. The d parameter is estimated using the semiparametric methods proposed by Geweke and Porter-Hudak (GPH,1983) and the Robinson's Gaussian estimator (RGSE, 1995b). In addition, ARFIMA models are fitted to the return series using the full Whittle ML with GPH estimates as starting values (this approach does not use the approximation advocated by Fox and Taqqu, 1986).

3.1. The Geweke Porter-Hudak log Periodogram Regression Estimator

Geweke and Porter-Hudak (1983) proposed a semiparametric procedure to obtain an estimate of the memory parameter of a fractionally integrated process. The estimate is obtained from the application of ordinary least squares to

$$\log(I_x(\lambda_s)) = \hat{c} - \hat{d} \log|1 - e^{i\lambda_s}| + \eta_i \tag{3}$$

computed over the fundamental frequencies $\{\lambda_s = 2\pi/n,\ s = 1, \ldots, v,\ v<n\}$. We define $\omega(\lambda_s) = (1/\sqrt{2\pi}) \Sigma X_t e^{i\lambda s}$ as the discrete Fourier transform of the time series X_t $I(\lambda_s) = \omega_x(\lambda_s)\, \omega_x(\lambda_s)^*$ as the periodogram, and $X = |1 - e^{i\lambda s}|$. Ordinary least squares on (3) yields

$$\hat{d} = 0.5 \frac{\sum_{s=1}^{m} X_s \log I_x(\lambda_s)}{\sum_{s=1}^{m} X_s^2} \tag{4}$$

Various authors have proposed methods for the choice of v, the number of Fourier frequencies included in the regression. The regression slope estimate is an estimate of the slope of the series spectrum in the vicinity of the zero frequency; if too few ordinates are included, the slope is calculated from a small sample. If too many are included, medium and high-frequency components of the spectrum will contaminate the estimate. A choice of $\sqrt{T}$, or power = 0.5 is often employed. To evaluate the robustness of the GPH estimate, a range of power values (from 0.40 - 0.75) is commonly calculated as well. Two estimates of the d coefficient's standard error are commonly employed: the regression standard error, giving rise to a standard t-test, and an asymptotic standard error, based upon the theoretical variance of the log periodogram of ($\pi^2/6$). The statistic based upon that standard error has a standard normal distribution under the null.

There is evidence of long-range dependence if the least squares estimate of d is significantly larger than 0. With the proper choice of v, the asymptotic distribution of d depends on neither the order of the ARMA component nor the distribution of the error term of the ARFIMA process.

3.2. Robinson's log Periodogram Regression Estimator

Robinson (1995a) suggested an alternative log-periodogram regression estimator. Let X_t denote a G-dimensional vector with g-th element X_{gt}, g = 1, …,G. Assume that X_t has a spectral density matrix $\int_{\pi}^{-\pi} e^{ij\lambda} f(\lambda) f\lambda$ with (g, h) element denoted as $f_{gh}(\lambda)$. The g-th diagonal element, $f_{gg}(\lambda)$, is the power spectral density of X_{gt}. For $0 < C_g < \infty$ and $-½ < d_g < ½$ assume that $f_{gg}(\lambda) \sim C_s \lambda^{-2d}$ as $\lambda \to 0+$ for $g = 1, \ldots, G$. The periodogram of X_{gt} is then denoted as

$$I_g(\lambda) = (2\pi\eta)^{-1} \left| \sum_{t=1}^{n} X_{gt} e^{i\lambda} \right|^2, g = 1, \ldots., G \tag{5}$$

Without averaging the periodogram over adjacent frequencies or omitting initial frequencies from the spectral regression, we may define $Y_{gk} = \log I_g(\lambda_k)$. The least squares estimates of $c = (c_1, \ldots, c_G)'$ and $d = (d_1, \ldots, d_{c_G})'$ are given by

$$\begin{bmatrix} \tilde{c} \\ \tilde{d} \end{bmatrix} = vec\left\{ Y' Z(Z'Z)^{-1} \right\}, \tag{6}$$

where $Z = (Z_1, \ldots, Z_m)'$, $Z_k = (Z_1, -2\log \lambda_k)'$, $Y = (Y_1, \ldots, Y_G)'$ and $Y = (Y_{g,1}, \ldots, Y_{g,m})'$ for v periodogram ordinates.

Standard errors for $g\ \tilde{d}_g$ and for a test of the restriction that two or more of the d_g are equal may be derived from the estimated covariance matrix of the least squares coefficients. The standard errors for the estimated parameters are derived from a pooled estimate of the variance in the multivariate case, so that their interval estimates differ from those of their univariate counterparts.

3.3. Full Whittle Maximum Likelihood

The Whittle likelihood requires the computation of the periodogram of the series defined as

$$I_x(\lambda_j) = \frac{1}{2\pi n} \left| \sum_{t=1}^{n} x_t \exp(-i\lambda_j t) \right|^2$$

where $I(\lambda_j)$ denotes the periodogram at the j-th Fourier frequency, λ_j ($\lambda_j = 2\pi j/n$, $j = 1, \ldots, m$).

It can be shown that for j = 1, 2, … $I_x(\lambda_j)/f_x(\lambda_j)$ behave approximately like *i.i.d.* standard exponential random variables for almost all Fourier frequencies. The Whittle likelihood is thus obtained by writing the likelihood of standard exponential variables using the normalized periodogram ordinates as the observations.

The Whittle log likelihood is given by

$$\log L_w\left(\theta,\sigma_u^2\right) = -\sum_{j=1}^{m}\log f\left(\lambda_j \mid \theta,\sigma_u^2\right) - \sum_{j=1}^{m}\frac{I\left(\lambda_j\right)}{f\left(\lambda_j \mid \theta,\sigma_u^2\right)} \tag{7}$$

where m is the largest integer contained in $(n-1)/2$.

The reduced form of L_w with respect to the error variance σ_u^2 is

$$\log L_w^* = m\log(2\pi) - m\log\left[\frac{1}{m}\sum_{j=1}^{m}\frac{1(\lambda_j)}{g(\lambda_j)}\right] - \sum_{j=1}^{m}\log g(\lambda_j) - m$$

with $\sigma_u^2 = \sigma_u^{2*}$ and where $\sigma_u^2 = \sigma_u^{2*} = \frac{1}{m}\Sigma I(\lambda_j)/g(\lambda_j)$

4. DATA AND EMPIRICAL RESULTS

The data used in this study consist of stock index observations of daily frequency for Austria, Denmark, Finland, France, Germany, Greece, Holland, Italy, Norway, Spain, Turkey, and UK and they were obtained from the Bloomberg database. When daily observations are not available, next day index values are used. The data description is depicted in Table A in the appendix.

The data were transformed into continuously compounded returns by taking the first logarithmic difference of the index series. The main motivation to work with log returns is that they are usually (covariance) stationary. A second advantage of working with log returns, instead of levels, is that log returns present the behavior of the conditional volatility of the series in a more intuitive manner.

In selecting which stock indices to include in the analysis, the main criterion was the length of the available series. The decision was to include series with more than 2500 observations. Therefore the shortest series has 2,744 observations, and the longest one has 6,057. Using the Granger and Ding (1995a) approach, outliers have been transformed in a way that they do not heavily influence the d estimates towards zero. Based on their technique, any stock return larger than three standard deviations is set equal to three standard deviations and any return smaller than minus three standard deviations is set equal to minus three standard deviations.

Table 1 lists all the return series and presents summary statistics for the data. All of the series mean returns are positive. The mean of the mean series is 0.0005, that is, over the sample periods European stock markets have produced a return of 0.05%. The return series appear extremely non-normal. In 11 out of 12 series, return distributions are negatively skewed. The data also display a high degree of excess kurtosis (leptokurtic), since the kurtosis coefficients are all larger than three. Such skewness and kurtosis are common features in stock return distributions.

Table 1
Summary Statistics

Country	*Index Name*	*T*	*Mean*	*SD*	*Skewness*	*Kurtosis*
Austria	ATX	4482	0.0002	0.0118	-0.3206	9.6197
Denmark	KFX	3556	0.0003	0.0108	-0.2599	5.6874
Finland	HEX	3234	0.0006	0.0198	-0.2603	8.5602
France	CAC	4167	0.0002	0.0140	-0.2664	7.1219
Germany	DAX	6057	0.0003	0.0136	-0.4412	9.2484
Greece	ASE	4265	0.0008	0.0194	0.3420	14.9327
Holland	AEX	5358	0.0004	0.0134	-0.3022	10.7834
Italy	MIB30	2810	0.0004	0.0152	-0.0742	4.7589
Norway	OBX	4297	0.0003	0.0143	-1.4018	27.7436
Spain	MADX	2744	0.0004	0.0143	-3.1322	65.4415
Turkey	XUSIN	2954	0.0020	0.0324	-0.1001	20.5465
UK	UKX	5092	0.0003	0.0107	-0.7351	12.9105

Note: T is the sample size.

4.1. Fractional Difference

In this section we analyze the degree of dependence in the intertemporal structure of daily stock returns using the tests of Geweke and Porter-Hudak (1983) and Robinson (1995b). Table 2 reports the empirical estimates for the fractional differencing parameter, d, as well as the results regarding the statistical significance based on the GPH and RGSE tests, for all 12 stock indices. A concern in the application of the GPH estimator is the choice of v, the number of spectral ordinates from the periodogram of returns or the number of harmonic frequencies, to include in the estimation of d. Usually it is function of the sample size, T. Traditionally, the choice most widely used in this kind of research, is to set, $v = T^{0.50}$. However, this may not be the best possible choice in every situation, since it may bias the results. Some theoretical work has been done on this topic, but unfortunately there is no easily applicable rule for the appropriate choice of v.

As suggested by Taqqu and Teverovsky (1996), one possibility for an empirically driven choice of v is to compute the estimate of d with different values of v, plot them, and search for a relatively horizontal range in the plot. In such a range, both the variance and the bias of the estimate should be small. To find the appropriate values for the data set used in this empirical study, GPH and RGSE estimates were computed for all series examined, using values of v ranging from 10 to $T/2$, which is the maximum usable value. Values around $v = T^{0.50}$ produce very random and unreliable results. However, based on our computations, a value of $v = T^{0.65}$ is a better choice and will be used in what follows. In order to check the sensitivity of the fractionally differencing parameter estimates to the choice of v, we also report results for $v = T^{0.60}$, and $v = T^{0.70}$. To test the statistical significance of the d estimates, one-sided ($d = 0$ vs. $d > 0$) test is performed.

Table 2
Results of Fractional Integration Analysis

			Estimates of fractional differencing parameter (d)				
			GPH			*RGSE*	
Country	*Index Name*	*0.60*	*0.65*	*0.70*	*0.60*	*0.65*	*0.70*
Austria	ATX	0.0147	0.0787**	0.0889	0.0177	0.0787**	0.0894*
		(0.794)	(0.069)	(0.011)	(0.754)	(0.069)	(0.011)
Denmark	KFX	0.0547	0.0707	0.0135	0.0487	0.0757	0.0111
		(0.389)	(0.166)	(0.725)	(0.445)	(0.138)	(0.772)
Finland	HEX	0.1030	0.0737	0.0425	0.1104**	0.0708	0.0422
		(0.107)	(0.144)	(0.337)	(0.085)	(0.162)	(0.340)
France	CAC	0.0599	0.0740	0.0125	0.0598	0.0666	0.0158
		(0.282)	(0.112)	(0.741)	(0.282)	(0.149)	(0.675)
Germany	DAX	0.0659	0.0543	0.0510**	0.0530	0.0541	0.0509**
		(0.190)	(0.150)	(0.099)	(0.278)	(0.153)	(0.099)
Greece	ASE	0.0788**	0.1194*	0.1235*	0.0788**	0.1193*	0.1247*
		(0.075)	(0.003)	(0.000)	(0.075)	(0.003)	(0.000)
Holland	AEX	0.0464	0.0471	0.0414	0.0463	0.0471	0.0414
		(0.451)	(0.303)	(0.246)	(0.451)	(0.304)	(0.247)
Italy	MIB30	-0.0005	0.0439	0.0210	0.0026	0.0439	0.0168
		(0.993)	(0.368)	(0.597)	(0.966)	(0.368)	(0.670)
Norway	OBX	0.0406	0.0552	0.0397	0.0323	0.0550	0.0421
		(0.477)	(0.201)	(0.254)	(0.570)	(0.204)	(0.226)
Spain	MADX	0.0506	0.0846	0.0352	0.0556	0.0883	0.0364
		(0.413)	(0.121)	(0.424)	(0.371)	(0.106)	(0.408)
Turkey	XUSIN	0.0514	0.0808**	0.0803*	0.0514	0.0808	0.0801*
		(0.307)	(0.070)	(0.025)	(0.306)	(0.070)	(0.025)
UK	UKX	0.0135	0.0319	0.0628**	0.0131	0.0319	0.0641**
	(0.779)	(0.417)	(0.066)	(0.788)	(0.417)	(0.060)	

p-values are given in parentheses. The superscript *, ** indicates statistical significance for the null hypothesis $d = 0$ against the alternative $d > 0$ at the 5%, 10% percent level or less, respectively.

The results reveal supportive evidence of long-range dependence in the return series, since most d estimates are significantly positive for the stock markets at hand, except the markets for Holland, Italy, and UK. The d parameter for Holland (0.0471), Italy (0.0439), and UK (0.0319) is quite small; however it is different from zero and suggests a weaker long memory in its mean process. The fractionally differenced estimates are generally similar in value across the two tests used for each of the return series. In all of the return series there is long-range dependence with positive values of *d*, varying from 0.0319 to 0.1194 for the GPH test and 0.0319 to 0.1193 for the RGSE test. This result can be considered as an indication of the existence of long-range dependence in these series. Both tests indicate that the evidence for the ASE (Greece) market index is far stronger and statistically significant at the 1% level, with *d* suggesting that there is a high degree of predictability in that index. There is marginal evidence of predictability in the stock return series of Holland, Italy, and UK since the estimates of *d* are very close to zero. The findings for these three countries support, to some degree, the weak form of capital market efficiency, which implies that future returns cannot be predicted based on past returns.

More evidence for return long-range dependence can be found in this data set than what has earlier been found in other empirical studies. In the majority of the series analyzed here, there is convincing evidence that the return series are strongly autocorrelated, since the series for most market indices appear to be long-range dependent processes, and that this property is robust to unit-root alternatives, providing strong support for persistent (not martingale) behavior of stock prices. These results suggest that stock markets experience long periods of generally upward-trending stock indices as well as long periods of generally downward-trending stock indices. Based on these findings, we can possibly conclude that most of the European stock markets are inefficient and the presence of long-range dependence could give rise to improved predictability, that is, systematically project returns make profits over the future course of stock returns.

4.2. Full Whittle MLE

The existence of long-range dependence as evident by the discovery of a fractional integration order suggests possibilities for constructing nonlinear models for improved forecasting performance of the return series. The ARFIMA process represents a flexible and parsimonious way to model both the short and long term dynamic properties of the series. The parameters of the ARFIMA (*p*,*d*,*q*) model can be jointly estimated by the frequency-domain full Whittle ML method using as starting values the GPH *d* estimates.

Table 3 displays the parameter estimates of the selected ARFIMA models. Whittle ML estimates of the parameters are obtained using the Broyden-Fletcher-Goldfarb-Shanno algorithm and based on the model specifications selected initially by the Akaike information criterion and finally by the Schwartz information criterion, with both *p* and *q* being permitted to be less than or equal to four. The number of lags is considered adequate in capturing the dynamics of fractionally integrated economic time series.

From the results reported in Table 3, it can be observed that except Germany, Italy, and UK with the weak evidence, the evidence for all the other nine countries significantly exhibits the long memory property. The estimated results of *d* parameter in the mean equation for all those 12 countries are lying between 0.0315 and 0.1201

Table 3
Parameter Estimates of the Selected ARFIMA Models

Country	*Index Name*	*d*	ϕ_1	ϕ_2	ϕ_3	θ_1	θ_2	θ_3
Austria	ATX	0.0966	0.0246	0.0095	0.0098	-	-	-
		(1.83)	(0.28)	(2.46)	(0.87)	-		
Denmark	KFX	0.0699	0.0016	0.0040	-	0.0016	0.0039	-
		(2.66)	(0.86)	(2.84)	(0.83)	(1.56)		
Finland	HEX	0.1147	0.6113	-	-	0.6683	0.0383	-
		(2.02)	(5.23)	(4.47)	(1.39)			
France	CAC	0.0747	-	-	-	-	-	-
		(8.62)						
Germany	DAX	0.0423	-	-	-	0.0397	0.0513	0.0267
		(1.96)	(1.63)	(3.39)	(2.06)			
Greece	ASE	0.1201	-	-	-	-	-	-
		(13.85)						
Holland	AEX	0.0690	-	-	-	0.0644	0.0437	0.0616
		(2.78)	(2.40)	(2.77)	(4.57)			
Italy	MIB30	0.0451	-	-	-	-	-	-
		(1.76)						
Norway	OBX	0.0560	-	-	-	-	-	-
		(6.46)						
Spain	MADX	0.0859	-	-	-	-	-	-
		(6.98)						
Turkey	XUSIN	0.0819	-	-	-	-	-	-
		(1.86)						
UK	UKX	0.0315	0.0004	0.0016	-	0.0004	0.0016	-
		(3.64)	(0.85)	(2.94)	(0.84)	(1.29)		

t-values are given in parentheses.

smaller than 0.5 implying a stationary process. In particular, the *d* parameter for Germany (0.0423), Italy (0.0451), and UK (0.0315) is quite small, however it is different from zero and suggests a weaker long memory in its mean process.

From the results of Table 3, we can obtain several interesting findings. In all 12 stock markets, the estimates for long memory parameter *d* in mean equation are below 0.5, which indicates that all series are stationary. The estimated long memory parameter is in the range $0.0315 < d < 0.1201$. The results indicate that all return series have an integration order of less than one ($d < 1$). The data uniformly reject the null of $d = 0$ in favor of fractional alternatives of $d > 0$ and most coefficient estimates are statistically significant at the 10 per cent level or better. The long memory parameters for all those countries are quite close to each. These results provide supporting evidence of mean reverting fractional dynamics in all series. In short, we find that the long memory effects are present in all 12 return series and can be better described by the ARFIMA process.

5. SUMMARY

This paper examines for long horizon predictability in the stock market returns of 12 European countries. Two semiparametric methods of estimating long-range dependence were employed, the Geweke and Porter-Hudak (GPH) and the Robinson's Gaussian estimator (RGSE). The study used stock index observations of daily frequency that were transformed into continuously compounded returns by taking the first logarithmic differences of the index series in order to make them (covariance) stationary. In the selection of the data, we decided to use series with more than 2500 observations. Outliers were transformed in a way that they do not heavily influence the *d* estimates towards zero.

The results reveal supportive evidence of long-horizon predictability in most return series and that it cannot be attributed to random variation. In fact, more evidence for return long-range dependence can be found in our data set than in other empirical studies. The existence of long-range dependence suggests ARFIMA model construction to model both the short- and long- term dynamical properties of the series, for improved forecasting performance, especially over longer forecasting horizons.

The implications of the study are that European stock markets are not efficient and they exhibit long-range dependence. The weak form of efficiency is rejected and past information can be used to predict the direction of future prices. That is, systematic profits can be made in most of the markets examined.

Questions also arise as to the source of long-range dependence in the European stock indices. The presence of long-range dependence in these series may reflect the statistical property of fundamental factors underlying their behavior. One possible mechanism that might generate long memory in the stock return series is structural change. It is well known that inference about the differencing parameter in presence of structural break in a series entails considerable difficulties. Therefore, given the financial crisis of 2000-2001 in Europe, further tests for unraveling of the memory property and presence of structural break in the stock return series are required. The exclusion of such tests from the present study can be considered as its limitation.

REFERENCES

AYDOGAN, K., G. G. BOOTH (1988), "Are there Long Cycles in Common Stock Returns?," *Southern Economic Journal*, 55, pp. 141-149.

BAILLIE, R.T. (1996), "Long Memory Processes and Fractional Integration in Econometrics," *Journal of Econometrics*, 73, pp. 5-59.

BARKOULAS, J. T. , C. F. BAUM (1996), "Long Term Dependence in Stock Returns," *Economics Letters*, 53, pp. 253-259

BARKOULAS, J. T., C. F. BAUM & N. TRAVLOS (2000), "Long Memory in the Greek Stock Market," *Applied Financial Economics*, 10, pp. 177-184.

CAPORALE, G.M., L.A. GIL-ALANA (2002), "Fractional Integration and Mean reversion in Stock Prices," *Quarterly Review of Economics and Finance*, 42, pp. 599-609.

CHEUNG, Y.W. - F.X. DIEBOLD (1994), "On Maximum Likelihood Estimation of the Differencing Parameter of Fractionally-Integrated Noise with Unknown Mean," *Journal of Econometrics*, 62, pp. 301-316.

CHEUNG, Y., K.S. LAI & M. LAI (1993), "Are There Long Cycles in Foreign Stock Returns?," *Journal of international Financial Markets, Institutions & Money*, 3, pp. 33-47.

CHEUNG, Y. & K. LAI (1995), "A Search for Long Memory in International Stock Market Returns," *Journal of international Money and Finance*, 14, pp. 597-615.

CRATO, N. (1994), "Some International Evidence Regarding the Stochastic Behavior of Stock Returns," *Applied Financial Economics*, 4, pp. 33-39.

FOX, R. & M.S. TAQQU (1986), "Large-sample Properties of Parameter Estimates for Strongly Dependent Stationary Gaussian Time Series," *Annals of Statistics*, 14, pp. 517-532.

GEWEKE, J. & S. PORTER-HUDAK (1983), "The Estimation and Application of Long Memory Time Series Models," *Journal of Time Series Analysis*, 4, pp. 15-39.

GRANGER, C.W.J. & Z. DING (1995a), "Some Properties of Absolute Returns. An Alternative Measure of Risk." *Annales d'economie et de statistique*, 40, pp. 67-91.

GRANGER, C.W.J. & Z. DING (1995b), "Stylized Facts on the Temporal and Distributional Properties of Daily Data from Speculative Markets," UCSD Working Paper.

GRANGER, C.W.J. & R. JOYEUX (1980), "An Introduction to Long Memory Time Series Models and Fractional Differencing, " *Journal of Time Series Analysis,* 1, pp. 15-30.

GREENE, M.T. & B.D. FIELITZ (1977), "Long Term Dependence in Common Stock Returns," *Journal of Financial Economics*, 4, pp. 339-349

HENRY, O. T. (2002), "Long Memory in Stock Returns: Some International Evidence," *Applied Financial Economics*, 12, pp. 725-729.

HOSKING, J. (1981), "Fractional Differencing," *Biometrica,* 68, pp. 165-76.

LI, W.K. & A. MCLEOD (1986), "Fractional Time Series Modeling," *Biometrika*, 73 (1), pp. 217-221.

LO, A.W. (1991), "Long-term Memory in Stock Prices," *Econometrica*, 59, pp. 1279-1313.

LOBATO, I.N. & N.E. SAVIN (1998), "Real and Spurious Long-memory Properties of Stock Market Data," *Journal of Business and Economic Statistics*, 16, pp. 261-268.

MILLS, T. C. (1993), "Is there Long Term Memory in U.K. Stock Returns?," *Applied Financial Economics*, 3, pp. 303-306.

PANAS, E. (2001), "Estimating Fractal Dimension Using Stable Distributions and Exploring Long Memory through ARFIMA Models in Athens Stock Exchange," *Applied Financial Economics*, 11, pp. 395-402.

POTERBA, J.M. & L.H. SUMMERS (1988), "Mean Reversion in Stock Prices: Evidence and Implications," *Journal of Financial Economics*, 22, pp. 59.

ROBINSON, P.M. (1995a), "Log-periodogram Regression of Time Series with Long Range Dependence," *Annals of Statistics*, 23, pp. 1048-1072.

ROBINSON, P.M. (1995b), "Gaussian Semiparametric Estimation of Long-range Dependence," *Annals of Statistics*, 23, pp. 1630-1661.

SADIQUE, S. & P. SILVAPULLE (2001), "Long-term Memory in Stock Market Returns: International Evidence," *International Journal of Finance and Economics*, 6, pp. 59-67.

SIOKIS, F. & C. CHRISTODOULOU (2004), "Long Memory and Persistence in Dollarbased Real Exchange Rates," *International Journal of Theoretical and Applied Finance*, 7 (1), pp. 31-44.

SOWELL, F. (1992a), "Maximum Likelihood Estimation of Stationary Univariate Fractionally Integrated Time Series Models," *Journal of Econometrics*, 53, pp. 185-188.

SOWELL, F. (1992b), "Modeling Long-run Behavior with the Fractional ARIMA Model," *Journal of Monetary Economics*, 29, pp. 277-302

TAQQU, M.S. & V. TEVEROVSKY (1996), "Semi-parametric Graphical Estimation of Long Memory Data," Vol. II: Time Series Analysis in Memory of E.J. Hannan by P.M. Robinson and M. Rosenblatt, Eds., Springer: New York

TOLVI, J. (2003), "Long Memory in a Small Stock Market," *Economics Bulletin*, 7, pp. 1-13.

WHITTLE, P. (1951), "Hypothesis Testing in Time Series Analysis," Almquist and Wiksell, Upssala.

WHITTLE, P. (1962), "Gaussian Estimation in Stationary Time Series," *Bulletin of the International Institute of Statistics*, 39, pp. 105-129.

WRIGHT, J. H. (2001), "Long Memory in Emerging Market Stock Returns," *Emerging Markets Quarterly*, 5, pp. 50-55.

APPENDIX

Table A
Data Description

Country	*Index Name*	*Data Period*		*No. of Obs*
		From	*To*	
Austria	ATX	8/1/1986	18/2/2004	4482
Denmark	KFX	4/12/1989	18/2/2004	3556
Finland	HEX	11/3/1991	18/2/2004	3234
France	CAC	9/7/1987	18/2/2004	4167
Germany	DAX	2/1/1980	18/2/2004	6057
Greece	ASE	2/1/1987	18/2/2004	4265
Holland	AEX	3/1/1983	18/2/2004	5358
Italy	MIB30	31/12/1992	18/2/2004	2810
Norway	OBX	2/1/1987	18/2/2004	4297
Spain	MADX	30/12/1988	18/2/2004	2744
Turkey	XUSIN	25/2/1992	18/2/2004	2954
UK	UKX	3/1/1984	18/2/2004	5092

Data Source: Bloomberg