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ON THE PERSISTENCE AND VOLATILITY IN EUROPEAN, AMERICAN AND ASIAN STOCKS BULL AND BEAR MARKETS

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ABSTRACT

In this paper we examine the statistical properties of several stock market indices in Europe, the US and Asia by means of determining the degree of dependence in both the level and the volatility of the processes. In the latter case, we use the squared returns as a proxy for the volatility. We also investigate the cyclical pattern observed in the data and in particular, if the degree of dependence changes depending on whether there is a bull or a bear period. We use fractional integration and GARCH specifications. The results indicate that the indices are all nonstationary I(1) processes with the squared returns displaying a degree of long memory behavior. With respect to the bull and bear periods, we do not observe a systematic pattern in terms of the degree of persistence though for some of the indices (FTSE, Dax, Hang Seng and STI) there is a higher degree of dependence in both the level and the volatility during the bull periods.

Keywords: Long memory; stock returns; volatility; bull and bear periods

JEL Classification: C22; G14; G15

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1. Introduction

This paper deals with the analysis of the persistence in the level and in the volatility of several stock market prices in different countries. In particular, we focus on the behavior of three US stock markets (Standard and Poor 500; Dow Jones and Nasdaq), three European markets (FTSE; CAC and DAX) and three Asian (Nikkei, Hang Seng and STI) indices. However, instead of focusing exclusively on their behavior across the whole sample period, we also examine the properties in the bull and bear periods, testing if the degree of persistence is different in these periods in our series. In the same line we also investigate the volatility of the series and the subseries according to the bull and bear periods.

Many empirical papers have studied stock market volatility during bull and bear periods. A number of authors have found that volatility is higher during bear markets than in bull periods, including Maheu and McCurdy (2000), Edwards et al. (2003), Gomez-Biscarri and Perez de Gracia (2004), Jones et al. (2004), Gonzalez et al. (2005), Guidolin and Timmermann (2005), Nishina et al. (2006), Tu (2006), etc. On the other hand, persistence is highly related with volatility. Various authors have found that periods of high volatility are also persistent and occur during periods of stock market declines. The analysis of persistence in the level and in the volatility of stock markets is important for several reasons: first, if stock market prices are persistent, either with mean reverting behavior or alternatively with long memory returns it means that there is margin for prediction in its behavior showing clear inefficiencies in the markets. Second, volatility is a proxy for investment risk. Thus, persistence in volatility implies that the risk and return trade-off changes may also be predicted over the business cycle. Moreover, persistence in volatility can be used to predict future economic variables (Campbell, Lettau, Malkiel and Xu, 2001). Thus, we examine in this paper the degree of dependence in the series not only in the level but also in the squared returns which are taken as proxies for the volatility series. For these purposes we will employ fractional integration or I(d) models, along with GARCH specifications.

The outline of the paper is as follows: Section 2 briefly describes the methodology employed in the paper. Section 3 presents the data and the empirical results, conducting the analysis first for the whole sample period, and then for each bull and bear sub-period in each series. Section 4 contains some concluding comments.

2. Methodology

We model persistence by means of long range dependence (LRD) techniques. This is more general than other approaches employed in the literature such as the sum of the AR coefficients (Andrews and Chen, 1994) or the largest AR root, as we will show below. There are two definitions of LRD, one in the time domain and the other in the frequency domain. The former states that given a covariance stationary process $\{x_t,\ t = 0, \pm 1, \dots \}$, with autocovariance function $E[(x_t - Ex_t)(x_{t-j} - Ex_t)] = \gamma_j$, x_t displays LRD if

$$\lim_{T \to \infty} \sum_{j=-T}^{T} \left| \gamma_j \right|$$

is infinite. A frequency domain definition may be as follows. Suppose that x_t has an absolutely continuous spectral distribution, and therefore a spectral density function, denoted by $f(\lambda)$, and defined as

$$f(\lambda) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j \cos \lambda j, \qquad -\pi < \lambda \le \pi.$$

Then, x_t displays LRD if the spectral density function has a pole at some frequency λ in the interval $[0, \pi]$, i.e.,

$$f(\lambda) \to \infty, \quad \text{as} \quad \lambda \to \lambda^*, \quad \lambda^* \in [0, \pi],$$

(see McLeod and Hipel, 1978). Most of the empirical literature has focused on the case when the singularity or pole in the spectrum occurs at the zero frequency ($\lambda^* = 0$). This is the case of the standard $I(d)$ models of the form:

$$(1 - L)^d x_t = u_t, \quad t = 0, \pm 1, ..., \tag{1}$$

where L is the lag-operator ($Lx_t = x_{t-1}$) and u_t is $I(0)$.[1] However, fractional integration may also occur at other frequencies away from 0, as in the case with the seasonal/cyclical models. Note that the polynomial on the left-hand-side of (1) can be expanded as

$$(1 - L)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - d\,L + \frac{d\,(d-1)}{2} L^2 - \ldots, \tag{2}$$

implying that

$$(1 - L)^d x_t = x_t - d\,x_{t-1} + \frac{d\,(d-1)}{2} x_{t-2} - \ldots . \tag{3}$$

Thus, if d is an integer value, x_t will be a function of a finite number of past observations, while if d is non-integer, x_t depends upon values of the time series far away in the past, and the higher the d is, the higher the level of dependence is between the observations.[2] Also, if u_t in (1) is ARMA(p, q), x_t is then said to be a fractional ARIMA, ARFIMA(p, d, q) process, and thus, it includes the AR(I)MA specifications (widely used to describe persistence) as particular cases of interest. The origin of these processes dates back to the 1960s, when Granger (1966) and Adelman (1965) pointed out that many aggregate series have a typical shape where the spectral density increases dramatically as the frequency approaches zero. However, differencing the data frequently leads to overdifferencing at the zero frequency. Fifteen years later, Robinson (1978) and Granger (1980) showed that aggregation could be a source of fractional integration. Since then, fractional processes have been widely employed

[1] An I(0) process is defined as a covariance stationary process with spectral density function that is positive and finite at all frequencies. It includes the standard white noise, stationary AR, MA and other models, and it is considered as a minimal requirement for statistical inference in time series analysis.
[2] Though not displayed, the I(d) model also admits an infinite MA representation.

to describe the dynamics of many economic time series (see, e.g. Diebold and Rudebusch, 1989; Sowell, 1992; Baillie, 1996; Gil-Alana and Robinson, 1997; etc.).[3]

The methodology employed in the paper to estimate the fractional differencing parameter is based on the Whittle function in the frequency domain (Dahlhaus, 1989) along with a testing procedure developed by Robinson (1994) that permits us to test any real value d, encompassing thus stationary ($d < 0.5$) and nonstationary ($d \geq 0.5$) hypotheses. Moreover, the limiting distribution in Robinson (1994) is standard normal, and this limit behaviour holds independently of the inclusion or exclusion of deterministic terms in the model and the modelling approach for the I(0) disturbances. Moreover, Gaussianity is not a requirement, a moment condition of only 2 being sufficient. This method, based on the Lagrange Multiplier (LM) principle, tests the null hypothesis:

$$H_o: \; d \; = \; d_o \qquad (4)$$

in (1) where x_t can be the errors in a regression model of the form:

$$y_t \; = \; \beta^T z_t \; + \; x_t, \qquad t \; = \; 1, 2, \ldots, \qquad (5)$$

where y_t is the observed time series; β is a (kx1) vector of unknown coefficients, and z_t is a set of deterministic terms that might include an intercept (i.e., $z_t = 1$), an intercept with a linear time trend ($z_t = (1,t)^T$), or any other type of deterministic processes.

In the following section we consider a model given by the equations (1) and (5) with z_t in (5) equal to $(1, t)^T$, $t \geq 1$, 0 otherwise, i.e.,

$$y_t \; = \; \beta_0 \; + \; \beta_1 t \; + \; x_t, \qquad (1 - L)^d x_t \; = \; u_t, \qquad t \; = 1, 2, \ldots, \qquad (6)$$

and I(0) u_t, and examine the three standard cases of no regressors ($\beta_0 = \beta_1 = 0$ a priori in (6)), an intercept (β_0 unknown and $\beta_1 = 0$ a priori) and an intercept with a linear trend (β_0 and β_1

[3] See also Gil-Alana and Hualde (2009) for an updated review of fractional integration and its applications in economic time series.

unknown). However, given the insignificancy of the time trend coefficients in the results obtained, we only report in the paper the results based on a model with an intercept.[4]

Another common framework for modelling volatility of stock returns is the AutoRegressive Conditionally Heteroscedastic (ARCH) model introduced by Engle (1982) and the GARCH (Generalized ARCH) of Bollerslev (1986). The basic idea of the ARCH model is that the shocks of an asset are serially uncorrelated but dependent and this can be described by a simple quadratic function of the lagged values. Let a_t be the shocks of an asset, then the GARCH(*p*,*q*) model assumes that

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \qquad (7)$$

where α_i and β_j are non-negative constants and ω is a strictly positive constant. The log return series is given by $\varepsilon_t = \log\left(x_t / x_{t-1}\right)$ while σ_t^2 is the time varying variance.

The conditional variance is expressed as a linear function of the squared past values of the series. This specification is able to capture and reproduce several important characteristics of financial time series (Francq and Zakoian, 2010). These include succession of quiet and turbulence periods; autocorrelation of the squares but absence of autocorrelation of returns, and leptokurticity of the marginal distributions.

In this paper, the persistence in volatility in the bull and bear periods is examined using the GARCH(1,1) model

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \qquad t = 1, 2, ..., \qquad (8)$$

where $\omega > 0$; $\alpha > 0$; $\beta \geq 0$; and $\alpha + \beta < 1$ for the full series and each of the subseries of the return for the nine indices. The unconditional variance is measured by $\omega / (1 - \alpha - \beta)$

[4] Note that under H_o (4), equation (6) can be rewritten as $y_t^* = \beta_0 1_t^* + \beta_1 t_t^* + u_t$, where $y_t^* = (1-L)^{d_o} y_t$; $1_t^* = (1-L)^{d_o} 1_t$; and $t_t^* = (1-L)^{d_o} t_t$; and given that u_t is supposed to be I(0), β_0 and β_1 can be estimated with OLS/GLS methods,t-values remaining valid in this context.

while the level of persistence is measured by ($\alpha + \beta$), the closer this is to unity the more persistent the volatility of return is. The half-life volatility, a measure of the average time it takes the persistence to reduce by one – half is obtained by $\ln(0.5)/\ln(\alpha + \beta)$. The closer $\alpha + \beta$ is to 1, the larger the half – life of the volatility is. The unconditional standard deviation of the return series is measured by $\bar{\sigma} = \sqrt{\omega/(1-\alpha-\beta)}$, (Shittu, Yaya and Oguntade, 2009).

3. Data and empirical results

3.1 The data

The data sets used in this work are monthly US, European and Asian open stock market indices. They are Standard & Poor (S&P), Nasdaq, Dow Jones for the US; FTSE, CAC 40 and DAX for the European market and Nikkei, Hang Seng and STI for the Asian markets. The data were retrieved from Yahoo Finance website:

http://finance.yahoo.com.

[Insert Table 1 about here]

Table 1 displays for each series the starting and the ending month in the sample period along with the sample size. The longest series is the one corresponding to the Dow Jones, with data starting in October 1928. The shortest one is the German DAX, with data starting in January 2000. All series end in February 2012.

3.2 Persistence in the level and volatility of the indices

We first examine the behavior of the whole samples. Table 2 displays the estimates of d (and the 95% confidence bands for the non-rejection values of d using Robinson, 1994) for each series in a model with an intercept (i.e., $\beta_1 = 0$ in (6)) and supposing that the errors are white noise, Bloomfield (1973) and seasonal AR. The model of Bloomfield (1973) is a nonparametric approach to model I(0) processes that produces autocorrelations decaying exponentially as in the AR case. Thus, it approximates ARMA structures with a small number of parameters. It can be seen in this table that the estimated values of d are very similar across the three specifications for the I(0) disturbances. We observe that the estimates are very close to 1. In fact, the unit root null hypothesis (i.e., d = 1) cannot be rejected for any type of disturbances for the cases of the DAX, the FTSE, the Nasdaq and the three Asian indices (Nikkei, Hang Seng and STI). For the remaining three indices (the CAC 40, the Dow Jones and the S&P500), the unit root cannot be rejected if the disturbances are autocorrelated throughout the model of Bloomfield (1973) but this hypothesis is rejected in favour of orders of integration above 1 in the other cases.

[Insert Tables 2 and 3 about here]

Table 3 presents the same structure as Table 2 but now all series start at January 2000. In doing so we get better comparisons across the series. The results here support the unit root hypothesis in all cases except for the STI with white noise and seasonal AR disturbances. These results are completely in line with those obtained in other works that find evidence of I(1) behavior in the stock market indices of different countries and across different sample periods even in the context of long range dependence models. (Aydogan and Booth, 1988; Lo, 1991; Hiemstra and Jones, 1997; etc.)[5]

Next we examine the volatility of the series by means of using the squared returns. Alternatively, using the absolute returns the results were similar.[6] Table 4 displays the estimates of d and the 95% intervals in the nine volatility series. Here we obtain evidence of long memory volatility (i.e. d > 0) for the three types of disturbances (white noise, Bloomfield and AR) in the three series corresponding to the US market. The same evidence is reported for two of the Asian indices (Nikkei and STI) and also for the DAX. For the squared returns of the CAC we cannot reject the I(0) hypothesis if the disturbances are

[5] The same evidence of I(1) behavior is obtained in many other works using standard unit root methods.
[6] Squared returns have been employed by Lobato and Savin (1998), Gil-Alana (2003), Cavalcante and Assaf (2004), Cotter (2005) and Elder and Jin (2007), whereas absolute returns have been used by Granger and Ding (1996), Bollerslev and Wright (2000), Sibbertsen (2004), Gil-Alana (2005) and others.

seasonally AR, and for the remaining two indices (FTSE and Hang Seng) the I(0) is never rejected. Performing the same type of analysis on the series starting in January 2000, in Table 5 we obtain more evidence of long memory and the I(0) hypothesis cannot be rejected only for the series corresponding to the three Asian markets if the disturbances follow the model of Bloomfield (1973). Once more, this is consistent with the results reported in other papers, finding evidence of long memory or long range dependence in the squared (and absolute) return series (Ding et al., 1993; Lobato and Savin,1998; Dufrenot et al., 2005; etc.).

[Insert Tables 4 and 5 about here]

3.3 Detection of bull and bear periods

A framework to identify the bull and bear periods is given in Pagan and Sossounov (2003). We followed the procedures stated in the paper and this led to many cycles, where some of the peaks and troughs were not significant, that is, giving an increase or decrease less than 20% from two successive troughs and peaks. Due to the constraint of available sample size to estimate the persistence and GARCH model, we removed the insignificant cycles and the results of the separation are presented in Table 6.

[Insert Table 6 about here]

It is observed in this table that the cycles are very similar across all series, detecting two troughs and one peak throughout the sample in all cases and therefore two bear and two bull periods are obtained for each series. For the US market, the troughs take place at 2002m10 and 2009m3 and the peak occurs at 2007m11 in the three series. For the European market, the dates differ in some cases. Thus, the first trough occurs at 2003m2 in the case of the FTSE and at 2003m4 for CAC and DAX; the second trough is at 2009m3 in third series, however the peak takes place at 2007m11 for FTSE, at 2007m6 for CAC, and at 2008m1 for DAX. Slight differences also occur in the case of the Asian markets.

3.4 Persistence and volatility in the bull and bear periods

First, we focus on the level of each subseries. We present again the estimates of d and the 95% confidence bands for the three types of disturbances (white noise, Bloomfield and seasonal AR) in a model with an intercept. The results are displayed in Table 7. Starting with the US market (Table 7a) the first noticeable feature is that the confidence intervals are very wide, which is clearly a consequence of the small sample sizes used in most of the subseries. We also notice that most of the estimates are in the interval (0, 1) implying fractional integration and mean reverting behavior. However, we cannot systematically say that the degree of persistence is higher or lower in the bull or bear periods. Thus, we observe that the orders of integration are higher in the second subsamples (bull period) compared with the first (bear), but in the third period (which is bear) the values again increase, decreasing in the final subsample (bull). Table 7b displays the results for the European indices. As in the previous cases, we do not observe any systematic pattern in case of the CAC. However, for the other two indices (FTSE and DAX) we observe an increase in the order of integration when going from a bear period to a bull period and this happens in all cases with uncorrelated and correlated disturbances. The same evidence is reported for two of the three Asian indices (Hang Seng and STI) but not for the Nikkei (Table 7c).

We can conclude from the results reported in Table 7 that higher degrees of dependence are detected in the bull periods compared with the bear ones only in the cases of FTSE, DAX, Hang Seng and STI. However, for the remaining indices (S&P500, Nasdaq, Dow Jones, CAC-40 and Nikkei) we do not observe any significant pattern.

[Insert Tables 7 and 8 about here]

The same analysis is conducted on the square returns series for the nine indices. Results are now displayed in Table 8. Similarly to Table 7 the intervals are very wide including the null of d = 0 in all cases. Starting again with the US market we observe an increase in the estimates of d in the bull periods in the cases of S&P500 and Dow Jones but not in the Nasdaq. This behavior is also observed in the DAX index and in some cases in the CAC-40 for the European market (Table 8b) and for the Hang Seng and STI indices as well in the Asian market (Table 8c).

As a general conclusion we find little evidence of any systematic pattern in the persistence in the level and in the volatility in bull and bear periods. If any, higher degrees of dependence are detected in both (level and volatility) in some indices during the bull periods.

3.5 GARCH approach on the bull and bear periods

The GARCH(1,1) model was estimated for all the subsamples and the full sample of stock returns for the nine indices in the three markets. The results are displayed in Table 9. Starting with the US market in Table 9a, and setting a benchmark of 9.0E-01 for the persistence, it can be observed from the Dow Jones stock that volatility in the bull periods are more persistent when compared with the bear period (this is indicated in the 2nd and 4th subsamples and the full sample). Also, the half-life indicated that it takes about 44 months and 7 months for the stock in the bull periods of Dow Jones to revert back to their mean levels. As expected the stronger the level of persistence, the longer it takes to revert back to the mean level. The same analysis is conducted on the squared return series of the nine indices. The results are also displayed in Table 9.

[Insert Table 9 about here]

In the US market, volatility in the bull periods and the full sample were found to be persistent in the Dow Jones and the S&P500. In the European market, only the 2nd subsample (bull period) and the full sample showed persistence in volatility, while these results cannot be confirmed for the CAC 40 and the DAX. Asian indices do not indicate any persistence except for the Hang Seng where the 1st and 2nd subseries were found to be highly persistent.

4. Concluding comments

In this article we have examined the degree of persistence in the level and volatility of several stock market indices in the US, Europe and Asia. For this purpose we have used methodologies based on fractional integration and GARCH approaches. The results indicate that the indices are nonstationary I(1) though fractional degrees of integration with values slightly below or above 1 are also plausible in some cases. We also obtain evidence of stationary long memory for the volatility measured in terms of the squared returns. In the paper we also detect the peaks and troughs in the sample for each series in order to detect bull and bear periods. The results are very consistent across the different indices, obtaining in all cases two troughs and one peak and thus, implying two bear and two bull periods. Then, we examine again persistence but this time for each subsample in each series. The results indicate that there is not a systematic pattern across all indices though in some of them we observe higher degrees of dependence in both the level and volatility in the bull periods. This is in fact the case of S&P500, Dow Jones, FTSE, Dax, Hang Seng and STI.

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Tables and Figures

Table 1: Data and sample sizes examined

Market	Index	Starting month	Ending month	Sample size
U.S.	Nasdaq	February 1971	February 2012	493
	S&P 500	January 1950	February 2012	746
	Dow Jones	October 1928	February 2012	1001
Europe	CAC-40	March 1990	February 2012	264
	FTSE	April 1984	February 2012	335
	DAX	January 2000	February 2012	146
Asia	Nikkei	January 1984	February 2012	338
	Hang Seng	December 1986	February 2012	303
	STI	December 1987	February 2012	291

Table 2: Estimates of d and 95% confidence intervals

Whole simple	White noise	Bloomfield	Seasonal AR
CAC	1.085 (1.014, 1.176)	**1.072 (0.951, 1.228)**	1.083 (1.011, 1.176)
DAX	**1.056 (0.958, 1.195)**	**0.958 (0.802, 1.179)**	**1.061 (0.959, 1.205)**
FTSE	**1.005 (0.940, 1.086)**	**0.973 (0.872, 1.104)**	**1.002 (0.937, 1.085)**
DOW JONES	**1.037 (0.998, 1.082)**	**0.989 (0.935, 1.073)**	1.042 (1.001, 1.090)
S&P 500	1.061 (1.016, 1.114)	**1.024 (0.952, 1.111)**	1.050 (1.014, 1.114)
NASDAQ	**1.039 (0.979, 1.109)**	**1.024 (0.922, 1.148)**	**1.039 (0.984, 1.108)**
NIKKEI	**1.029 (0.967, 1.109)**	**1.010 (0.909, 1.130)**	**1.029 (0.966, 1.111)**
HANG SENG	**1.039 (0.949, 1.150)**	**0.870 (0.742, 1.076)**	**1.016 (0.929, 1.126)**
STI	**1.064 (0.984, 1.161)**	**1.048 (0.879, 1.260)**	**1.068 (0.986, 1.170)**

In bold: Evidence of unit roots at the 5% level.

Table 3: Estimates of d and 95% confidence bands with all series starting at 2000m1

146 observations	White noise	Bloomfield	Seasonal AR
CAC	**1.067 (0.975, 1.195)**	**1.022 (0.868, 1.226)**	**1.078 (0.971, 1.213)**
DAX	**1.056 (0.958, 1.195)**	**0.958 (0.802, 1.179)**	**1.061 (0.959, 1.205)**
FTSE	**1.022 (0.934, 1.144)**	**1.009 (0.867, 1.211)**	**1.027 (0.935, 1.154)**
DOW JONES	**1.037 (0.933, 1.180)**	**0.889 (0.699, 1.149)**	**1.051 (0.943, 1.195)**
S&P 500	**1.071 (0.969, 1.210)**	**0.946 (0.771, 1.172)**	**1.071 (0.969, 1.212)**
NASDAQ	**0.996 (0.907, 1.121)**	**0.947 (0.809, 1.122)**	**1.003 (0.919, 1.118)**
NIKKEI	**1.091 (0.998, 1.221)**	**1.071 (0.909, 1.291)**	**1.093 (0.997, 1.224)**
HANG SENG	**1.095 (0.974, 1.263)**	**0.871 (0.708, 1.108)**	**1.078 (0.964, 1.242)**
STI	1.110 (1.009, 1.245)	**1.081 (0.881, 1.351)**	1.111 (1.009, 1.249)

In bold: Evidence of unit roots at the 5% level.

Table 4: Estimates of d and 95% confidence intervals

Whole simple	White noise	Bloomfield	Seasonal AR
CAC	**0.161 (0.091, 0.251)**	**0.182 (0.061, 0.339)**	0.056 (-0.022, 0.159)
DAX	**0.106 (0.029, 0.223)**	**0.258 (0.091, 0.520)**	**0.104 (0.021, 0.212)**
FTSE	0.044 (-0.017, 0.123)	0.038 (-0.057, 0.177)	0.046 (-0.017, 0.122)
DOW JONES	**0.184 (0.161, 0.211)**	**0.319 (0.281, 0.387)**	**0.169 (0.142, 0.191)**
S&P 500	**0.134 (0.091, 0.184)**	**0.136 (0.073, 0.235)**	**0.194 (0.138, 0.263)**
NASDAQ	**0.187 (0.145, 0.239)**	**0.282 (0.196, 0.369)**	**0.179 (0.135, 0.233)**
NIKKEI	**0.167 (0.098, 0.254)**	**0.133 (0.009, 0.283)**	**0.167 (0.099, 0.253)**
HANG SENG	0.008 (-0.055, 0.091)	0.021 (-0.093, 0.164)	0.004 (-0.066, 0.087)
STI	**0.193 (0.137, 0.265)**	**0.263 (0.164, 0.386)**	**0.135 (0.092, 0.186)**

In bold: Evidence of long memory (d > 0) at the 5% level.

Table 5: Estimates of d and 95% confidence bands with all series starting at 2000m1

146 observations	White noise	Bloomfield	Seasonal AR
CAC	**0.166 (0.086, 0.283)**	**0.236 (0.072, 0.455)**	**0.171 (0.084, 0.293)**
DAX	**0.106 (0.027, 0.212)**	**0.258 (0.091, 0.520)**	**0.104 (0.021, 0.212)**
FTSE	**0.175 (0.089, 0.291)**	**0.206 (0.042, 0.441)**	**0.175 (0.091, 0.290)**
DOW JONES	**0.174 (0.087, 0.295)**	**0.155 (0.012, 0.364)**	**0.172 (0.084, 0.293)**
S&P 500	**0.241 (0.149, 0.363)**	**0.173 (0.026, 0.368)**	**0.241 (0.151, 0.368)**
NASDAQ	**0.268 (0.195, 0.371)**	**0.285 (0.163, 0.463)**	**0.282 (0.198, 0.404)**
NIKKEI	**0.095 (0.003, 0.224)**	0.044 (-0.091, 0.264)	**0.096 (0.005, 0.224)**
HANG SENG	**0.212 (0.114, 0.356)**	0.072 (-0.056, 0.250)	**0.205 (0.104, 0.350)**
STI	**0.114 (0.023, 0.243)**	0.052 (-0.077, 0.237)	**0.115 (0.025, 0.243)**

In bold: Evidence of long memory (d > 0) at the 5% level.

Table 6a: US Bull and bear markets phases

S&P	1st (bear)	2000m1 – 2002m10
S&P	2nd (bull)	2002m11 – 2007m11
S&P	3rd (bear)	2007m12 – 2009m3
S&P	4th (bull)	2009m4 – 2012m2
Nasdaq	1st (bear)	2000m1 – 2002m10
Nasdaq	2nd (bull)	2002m11 – 2007m11
Nasdaq	3rd (bear)	2007m12 – 2009m3
Nasdaq	4th (bull)	2009m4 – 2012m2
Dow Jones	1st (bear)	2000m1 – 2002m10
Dow Jones	2nd (bull)	2002m11 – 2007m11
Dow Jones	3rd (bear)	2007m12 – 2009m3
Dow Jones	4th (bull)	2009m4 – 2012m2

Table 6b: European Bull and Bear Markets phases

FTSE	1st (bear)	2000m1 – 2003m2
FTSE	2nd (bull)	2003m3 – 2007m11
FTSE	3rd (bear)	2007m12 – 2009m3
FTSE	4th (bull)	2009m4 – 2012m2
CAC	1st (bear)	2000m1 – 2003m4
CAC	2nd (bull)	2003m5 – 2007m6
CAC	3rd (bear)	2007m7 – 2009m3
CAC	4th (bull)	2009m4 – 2012m2
DAX	1st (bear)	2000m1 – 2003m4
DAX	2nd (bull)	2003m5 – 2008m1
DAX	3rd (bear)	2008m2 – 2009m3
DAX	4th (bull)	2009m4 – 2012m2

Table 6c: Asian Bull and Bear Markets phases

Nikkei	1st (bear)	2000m1 – 2003m5
Nikkei	2nd (bull)	2003m6 – 2007m7
Nikkei	3rd (bear)	2007m8 – 2009m3
Nikkei	4th (bull)	2009m4 – 2012m2
Hang Seng	1st (bear)	2000m1 – 2003m4
Hang Seng	2nd (bull)	2003m5 – 2007m11
Hang Seng	3rd (bear)	2007m12 – 2009m3
Hang Seng	4th (bull)	2009m4 – 2012m2
STI	1st (bear)	2000m1 – 2003m4
STI	2nd (bull)	2003m5 – 2007m11
STI	3rd (bear)	2007m12 – 2009m3
STI	4th (bull)	2009m4 – 2012m2

Table 7a: Estimates of d and 95% confidence intervals in the bull and bear periods US market

	White noise	Bloomfield	Seasonal AR
S&P 1st (bear)	0.682 (0.539,	0.579 (0.252, 0.874)	0.673 (0.544,
S&P 2nd (bull)	0.831 (0.695,	0.644 (0.521, 0.817)	0.819 (0.674,
S&P 3rd (bear)	0.909 (0.462,	xxx	1.251 (0.503,
S&P 4th (bull)	0.692 (0.468,	0.448 (0.084, 1.693)	0.693 (0.471,
Nasdaq 1st (bear)	0.737 (0.601,	0.597 (0.344, 0.847)	0.672 (0.514,
Nasdaq 2nd (bull)	0.763 (0.566,	0.558 (0.376, 1.209)	0.827 (0.543,
Nasdaq 3rd (bear)	0.861 (0.398,	xxx	0.774 (0.341,
Nasdaq 4th (bull)	0.605 (0.455,	0.493 (0.174, 1.883)	0.615 (0.464,
Dow Jones 1st (bear)	0.487 (0.229,	0.091 (-0.522,	0.554 (0.324,
Dow Jones 2nd (bull)	0.873 (0.732,	0.744 (0.517, 1.033)	0.881 (0.723,
Dow Jones 3rd	0.794 (0.377,	xxx	1.092 (0.584,
Dow Jones 4th (bull)	0.641 (0.471,	0.416 (0.072, 1.544)	0.643 (0.481,

In bold: Evidence of unit roots at the 5% level.

Table 7b: Estimates of d and 95% confidence intervals in the bull and bear periods European market

	White noise	Bloomfield	Seasonal AR
CAC 1st (bear)	0.868 (0.742, 1.083)	0.822 (0.621, 1.144)	0.894 (0.776, 1.104)
CAC 2nd (bull)	0.782 (0.675, 1.045)	0.645 (0.433, 0.907)	0.784 (0.662, 1.004)
CAC 3rd (bear)	0.768 (0.533, 1.319)	xxx	0.754 (0.563, 1.288)
CAC 4th (bull)	0.961 (0.664, 1.386)	0.541 (-0.171, 1.293)	0.937 (0.632, 1.364)
FTSE 1st (bear)	0.676 (0.562, 0.997)	0.723 (0.491, 0.992)	0.703 (0.594, 1.017)
FTSE 2nd (bull)	0.718 (0.649, 0.909)	0.645 (0.501, 0.764)	0.711 (0.644, 0.907)
FTSE 3rd (bear)	0.654 (0.329, 1.056)	xxx	0.733 (0.401, 1.394)
FTSE 4th (bull)	0.828 (0.504, 1.263)	0.420 (0.012, 1.263)	0.866 (0.499, 1.332)
DAX 1st (bear)	0.833 (0.706, 1.089)	0.674 (0.469, 0.931)	0.849 (0.721, 1.093)
DAX 2nd (bull)	0.913 (0.797, 1.170)	0.783 (0.651, 0.973)	0.921 (0.806, 1.204)
DAX 3rd (bear)	0.832 (0.411, 1.317)	xxx	xxx
DAX 4th (bull)	0.845 (0.521, 1.396)	0.582 (0.254, 1.197)	0.873 (0.481, 1.422)

In bold: Evidence of unit roots at the 5% level.

Table 7c: Estimates of d and 95% confidence intervals in the bull and bear periods Asian market

	White noise	Bloomfield	Seasonal AR
Nikkei 1st (bear)	0.773 (0.636,	0.537 (0.233, 0.951)	0.774 (0.633,
Nikkei 2nd (bull)	0.968 (0.770,	0.827 (0.541, 1.644)	0.966 (0.772,
Nikkei 3rd (bear)	0.856 (0.542,	xxx	0.881 (0.585,
Nikkei 4th (bull)	0.764 (0.464, 1.144	0.342 (-0.277,	0.767 (0.452,
Hang Seng 1st (bear)	0.668 (0.557,	0.513 (0.351, 0.644)	0.633 (0.522,
Hang Seng 2nd (bull)	1.505 (1.211,	1.587 (0.217, 2.610)	1.914 (1.561,
Hang Seng 3rd	0.715 (0.352,	xxx	0.548 (0.224,
Hang Seng 4th (bull)	0.997 (0.566,	0.897 (0.031, 2.177)	0.934 (0.553,
STI 1st (bear)	0.529 (0.404,	0.394 (0.066, 1.173)	0.484 (0.381,
STI 2nd (bull)	1.005 (0.824,	0.858 (0.382, 1.374)	1.034 (0.892,
STI 3rd (bear)	0.951 (0.514,	xxx	0.692 (0.342,
STI 4th (bull)	0.975 (0.474,	1.093 (0.171, 2.389)	0.831 (0.434,

In bold: Evidence of unit roots at the 5% level.

Table 8a: Estimates of d and 95% confidence intervals in the squared returns for the bull and bear periods. US market

	White noise	Bloomfield	Seasonal AR
S&P 1st (bear)	-0.437 (-0.814,	xxx	-0.463 (-0.851,
S&P 2nd (bull)	0.077 (-0.036,	0.004 (-0.177, 0.224)	0.084 (-0.034,
S&P 3rd (bear)	-0.043 (-0.457,	xxx	-0.084 (-0.387,
S&P 4th (bull)	-0.028 (-0.337,	-0.521 (-0.741,	0.055 (-0.336,
Nasdaq 1st (bear)	0.044 (-0.138,	-0.052 (-0.893,	0.146 (-0.077,
Nasdaq 2nd (bull)	0.119 (-0.044,	-0.166 (-0.417,	0.122 (-0.034,
Nasdaq 3rd (bear)	0.374 (-0.177,	xxx	0.426 (-0.244,
Nasdaq 4th (bull)	-0.048 (-0.376,	-0.387 (-0.817,	-0.054 (-0.297,
Dow Jones 1st	-0.287 (-0.651,	-0.512 (-0.817,	-0.107 (-0.466,
Dow Jones 2nd	0.076 (-0.044,	0.053 (-0.134,	0.062 (-0.053,
Dow Jones 3rd	-0.337 (-0.717,	xxx	-0.268 (-0.621,
Dow Jones 4th	-0.133 (-0.472,	-0.554 (-1.007,	-0.133 (-0.488,

In bold: Evidence of unit roots at the 5% level.

Table 8b: Estimates of d and 95% confidence intervals in the squared returns for bull and bear periods. European market

	White noise	Bloomfield	Seasonal AR
CAC 1st (bear)	0.072 (-0.094, 0.337)	0.074 (-0.381, 0.811)	0.217 (0.044, 0.453)
CAC 2nd (bull)	0.086 (-0.081, 0.332)	0.066 (-0.422, 0.717)	-0.007 (-0.247, 0.286)
CAC 3rd (bear)	-0.115 (-0.609, 0.174)	xxx	-0.207 (-0.555, 0.197)
CAC 4th (bull)	0.094 (-0.199, 0.974)	-0.511 (-0.907, 0.033)	0.081 (-0.206, 1.073)
FTSE 1st (bear)	0.166 (-0.014, 0.432)	0.097 (-0.533, 0.544)	0.236 (0.051, 0.535)
FTSE 2nd (bull)	-0.074 (-0.026, 0.141)	-0.038 (-0.351, 0.474)	-0.064 (-0.226, 0.176)
FTSE 3rd (bear)	-0.219 (-0.664, 0.513)	xxx	-0.211 (-0.634, 0.741)
FTSE 4th (bull)	-0.088 (-0.297, 0.222)	-0.217 (-0.661, 0.244)	-0.088 (-0.297, 0.206)
DAX 1st (bear)	0.047 (-0.116, 0.293)	0.098 (-0.334, 0.783)	0.126 (-0.024, 0.327)
DAX 2nd (bull)	0.064 (-0.071, 0.266)	0.104 (-0.381, 0.455)	0.262 (-0.074, 0.464)
DAX 3rd (bear)	-0.221 (-0.814, 0.314)	xxx	xxx
DAX 4th (bull)	-0.008 (-0.194, 0.283)	-0.108 (-0.552, 0.402)	-0.036 (-0.254, 0.275)

In bold: Evidence of unit roots at the 5% level.

Table 8c: Estimates of d and 95% confidence intervals in the squared returns for the bull and bear periods. Asian market

	White noise	Bloomfield	Seasonal AR
Nikkei 1st (bear)	0.122 (-0.144,	-0.453 (-0.808,	0.094 (-0.186,
Nikkei 2nd (bull)	0.005 (-0.164,	-0.054 (-0.662,	-0.017 (-0.417,
Nikkei 3rd (bear)	-0.128 (-0.442,	xxx	-0.184 (-0.704,
Nikkei 4th (bull)	-0.216 (-0.409,	-0.417 (-1.184,	-0.165 (-0.406,
Hang Seng 1st	-0.072 (-0.234,	-0.197 (-0.633,	-0.088 (-0.246,
Hang Seng 2nd	0.681 (0.398, 1.014)	-0.515 (-0.707,	0.681 (0.394, 1.043)
Hang Seng 3rd	-0.284 (-0.711,	xxx	-0.117 (-0.841,
Hang Seng 4th	0.224 (-0.014,	-0.222 (-0.602,	0.294 (0.022,
STI 1st (bear)	-0.233 (-0.481,	xxx	-0.253 (-0.544,
STI 2nd (bull)	0.074 (-0.057,	0.153 (-0.118,	0.074 (-0.054,
STI 3rd (bear)	-0.148 (-0.629,	xxx	-0.108 (-0.444,
STI 4th (bull)	0.185 (-0.004,	0.317 (-0.142,	0.233 (0.046, 0.465)

In bold: Evidence of unit roots at the 5% level.

Table 9a: Estimates of persistence and volatility in the return series of US indices

	sub-samples	GARCH estimates (ω,α,β)	Persistence $\alpha+\beta$	unconditional. Std. dev.	Half-life
Dow Jones	1st (bear)	(1.44E-04, 1.59E-03, 7.20E-01)	7.22E-01	5.17E-04	2.12
	2nd (bull)	(4.81E-07, 2.03E-02, 9.64E-01)	**9.84E-01**	3.06E-05	**43.8**
	3rd (bear)	(9.00E-04, 2.76E-02, 4.11E-02)	6.87E-02	9.66E-04	0.259
	4th (bull)	(2.16E-05, 5.00E-05, 9.00E-01)	**9.00E-01**	2.16E-04	**6.58**
	full sample	(1.49E-05, 1.81E-01, 7.94E-01)	**9.75E-01**	2.44E-02	**27.4**
S & P 500	1st (bear)	(1.45E-04, 8.24E-04, 7.34E-01)	7.35E-01	5.47E-04	**2.25**
	2nd (bull)	(2.20E-08, 3.24E-02, 9.51E-01)	**9.83E-01**	1.33E-06	**41.4**
	3rd (bear)	(1.09E-03, 1.13E-01, 2.09E-02)	1.34E-01	1.26E-03	0.345
	4th (bull)	(4.96E-04, 2.12E-03, 5.30E-02)	5.51E-02	5.25E-04	0.239
	full sample	(1.22E-05, 2.29E-01, 7.63E-01)	**9.92E-01**	3.91E-02	**86.3**
Nasdaq	1st (bear)	(3.89E-04, 9.99E-02, 7.49E-01)	8.49E-01	2.57E-03	**4.23**
	2nd (bull)	(4.83E-04, 9.84E-02, 2.64E-03)	1.01E-01	5.37E-04	0.302
	3rd (bear)	(1.49E-03, 1.07E-02, 7.10E-03)	1.78E-02	1.52E-03	0.172
	4th (bull)	(2.22E-04, 4.94E-04, 7.08E-01)	7.08E-01	7.62E-04	**2.01**
	full sample	(5.47E-05, 2.18E-01, 7.23E-01)	**9.41E-01**	3.04E-02	**11.4**

Table 9b: Estimates of persistence and volatility in the returns of European indices

	sub-samples	GARCH estimates (ω, α, β)	Persistence $\alpha + \beta$	unconditional. Std. dev.	Half-life
FTSE	1st (bear)	(1.40E-04, 1.78E-01, 5.29E-01)	7.07E-01	4.78E-04	**2**
	2nd (bull)	(4.25E-06, 2.70E-04, 9.62E-01)	**9.62E-01**	1.13E-04	**18**
	3rd (bear)	(8.04E-04, 1.38E-02, 5.43E-02)	6.81E-02	8.63E-04	0.258
	4th (bull)	(1.23E-04, 9.24E-03, 7.44E-01)	7.53E-01	4.98E-04	**2.45**
	full sample	(2.94E-05, 1.97E-01, 7.21E-01)	**9.18E-01**	1.89E-02	**8.10**
CAC 40	1st (bear)	(3.24E-04, 1.87E-01, 4.49E-01)	6.36E-01	8.90E-04	**1.53**
	2nd (bull)	(3.70E-05, 4.00E-01, 4.37E-01)	8.37E-01	2.27E-04	**3.90**
	3rd (bear)	(7.66E-04, 3.28E-03, 2.57E-01)	2.60E-01	1.04E-03	0.515
	4th (bull)	(1.70E-05, 7.05E-03, 9.66E-01)	**9.73E-01**	6.31E-04	**25.4**
	full sample	(5.88E-05, 2.40E-01, 6.82E-01)	**9.22E-01**	2.75E-02	**8.54**
DAX	1st (bear)	(3.49E-04, 3.93E-01, 4.43E-01)	8.36E-01	2.13E-03	**3.87**
	2nd (bull)	(7.41E-05, 1.73E-01, 5.99E-01)	7.72E-01	3.25E-04	**2.68**
	3rd (bear)	(1.26E-03, 3.50E-02, 2.04E-02)	5.54E-02	1.33E-03	0.240
	4th (bull)	(2.98E-05, 1.87E-03, 9.57E-01)	**9.59E-01**	7.25E-04	**16.5**
	full sample	(1.54E-04, 2.30E-01, 6.08E-01)	8.38E-01	3.08E-02	**3.92**

Table 9c: Estimates of persistence and volatility in the returns of Asian indices

	sub-samples	GARCH estimates (ω, α, β)	Persistence $\alpha + \beta$	unconditional. Std. dev.	Half-life
Nikkei	1st (bear)	(6.65E-04, 6.39E-02, 4.19E-02)	1.06E-01	2.73E-02	0.309
	2nd (bull)	**(4.60E-05, 4.40E-04, 8.81E-01)**	**8.81E-01**	**1.97E-02**	**5.48**
	3rd (bear)	(1.40E-03, 7.77E-04, 1.73E-02)	1.81E-02	3.78E-02	0.173
	4th (bull)	(4.38E-04, 2.06E-03, 4.27E-01)	4.29E-01	2.77E-02	0.819
	full sample	(2.44E-04, 2.26E-01, 4.23E-01)	**6.49E-01**	2.64E-02	**1.60**
Hang Seng	1st (bear)	(5.90E-07, 3.75E-02, 9.57E-01)	**9.94E-01**	1.01E-02	**120**
	2nd (bull)	(2.99E-07, 2.50E-02, 9.65E-01)	**9.90E-01**	5.34E-03	**65.8**
	3rd (bear)	(1.59E-03, 4.54E-04, 1.67E-01)	1.68E-01	4.37E-02	0.388
	4th (bull)	(1.61E-04, 1.63E-01, 4.88E-01)	**6.51E-01**	2.15E-02	**1.61**
	full sample	(1.78E-04, 2.97E-01, 5.79E-01)	**8.76E-01**	3.79E-02	**5.25**
STI	1st (bear)	(9.77E-04, 3.61E-04, 1.00E-01)	1.01E-01	3.30E-02	0.302
	2nd (bull)	(4.49E-05, 9.44E-02, 6.88E-01)	**7.83E-01**	1.44E-02	**2.83**
	3rd (bear)	(1.73E-03, 1.74E-02, 4.59E-02)	**6.33E-02**	4.29E-02	**0.251**
	4th (bull)	(1.96E-04, 4.06E-01, 3.15E-01)	**7.20E-01**	2.65E-02	**2.11**
	full sample	(3.11E-05, 1.56E-01, 8.11E-01)	**9.67E-01**	3.09E-02	**20.9**