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THE KENYAN STOCK MARKET: INEFFICIENCY, LONG MEMORY, PERSISTENCE AND ANOMALIES IN THE NSE-20

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Abstract

This paper examines the statistical properties of the NSE-20 index in the Kenyan stock market over the period 2001-2009. The analysis applies both unit root tests and long-range dependence techniques based on the concept of fractional integration. The results indicate that the order of integration of stock prices is significantly above 1, which implies the presence of long memory. This is also detected in the absolute and squared returns. The lowest degrees of integration (very close to zero) are found for Mondays and Fridays, and therefore a day-of-the-week-effect appears to be present.

Keywords: Market efficiency; Kenyan stock market; Long memory

JEL classification: C22, G14

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1. Introduction

The emergence and expansion of stock markets in African countries in recent decades has been an important step for them towards attracting more private investment and becoming more integrated into the global financial markets. In 1990 there were only five stock markets in Africa, but their number had risen to nineteen by 2007; in the period between 1992 to 2002 the total capitalisation of African stock markets increased from US$113,423m to US$244,672m. In 2004 six of the ten best performing markets in the world were in Africa: Ghana, Uganda, Kenya, Egypt, Mauritius and Nigeria, and in 2005 Egypt, Uganda and Zambia were in the top-5.

Excluding South Africa and Nigeria the stock market capitalisation in the Sub-Saharan Africa was only around 10% of GNP, as opposed to 159% in the case of South Africa. Further, these markets, with the exception of South Africa, have a high degree of illiquidity. The average price to earnings (P/E) ratio at the start of 1996 was 2.7 for Ghana, 6 for Kenya and 7.8 for Zimbabwe; for a comparison, the corresponding figure for the US was about 17. These low P/E ratios and the high growth potential make African stock markets an attractive option for reducing portfolio risk through diversification as long as returns remain acceptable and prospects for economic and political stability reasonable.

Kenya is one of the most financially developed African countries. Yet, it still only has 15 bank branches per million people. Other financial institutions, such as pension funds and insurance companies, are also very small. The present study focuses on the Kenyan stock market. In particular, it examines the statistical properties of the NSE-20 index over the period 2001-2009. The analysis applies both unit root tests and long-range dependence techniques based on the concept of fractional integration, and addresses issues such as market (in)efficiency and the possible presence of anomalies creating abnormal profit opportunities.

The layout of the paper is as follows. Section 2 provides some information about the NSE-20 index (the main stock market index in Kenya) and its components. Section 3 briefly reviews the relevant literature on the Kenyan and other African stock markets. Section 4 outlines the empirical methodology. Section 5 describes the data and presents the empirical results. Finally, Section 6 offers some concluding remarks.

2. The Kenyan Stock Market

Kenya attained independence from the United Kingdom in December 1963, and finally introduced a democratic system in 1991 after prolonged turbulence and increasing international pressure. At present it is one of the best performing economies in East Africa.

The NSE-20 index was created in 1964, when Kenya was under colonial rule, and it is the main index for the Kenyan stock market. This had an upsurge in activity after 1993 as a result of economic reforms and the relaxation of restrictions on foreign investment and exchange controls. However, political problems remain, leading to market volatility. The components of the NSE-20 index are presented in Table 1. It includes different types of companies: four of them are banks (*Barclays Bank (K) Ltd, Equity Bank, Kenya Commercial Bank, and Standard Chartered Bank (K) Ltd*), and there is also an investment company (*ICDC Investment Company*), therefore five out of the twenty companies in the NSE-20 belong to the financial sector.

[Insert Table 1 about here]

The industrial sector is represented by two electricity companies, namely "*Kenya Electricity Generating Company*" (generation) and "*Kenya Power & Lighting Company~* (distribution and regulation); it also includes "*East African Cables*", which produces electrical cables and accessories. Another important component is manufacturing, represented by "*Mumias Sugar Company*", producing sugar, water, ethanol and electricity; "*CMC holdings*", which is an automobile company; "*Bambury Cement Ltd*", which is the largest cement manufacturing company in the region; "*British American Tobacco Ltd*", which manufactures cigarettes under contract; "*East Africa Breweries Ltd*", producing alcoholic drinks and other non-alcoholic drinks for adults (ANDs), and "*Athi River Mining*", which is a leading mineral extraction and processing in Kenya.

There are also some companies from the service sector: "*Express Ltd*", which is a logistic company that has five divisions (sea freight, air freight, packing and removals, transport, and warehousing); "*Nation Media Group*", which is a media company; "*Kenya Airways*", which is the main company for commercial aviation in Kenya, and finally "*Safaricom Ltd*", a mobile phone company that is part of Vodafone.

The primary sector company in the index are "*Sasini Ltd*", which is one of the leading tea and coffee producers in Kenya and has other types of business such as dairy livestock, horticulture, tourism and export activities (the last two activities belong to the service sector), and "*Rea Vipingo Plantations Ltd*", which is by far the largest sisal fiber producer in Africa.

3. Literature Review

This section briefly reviews the literature on African stock markets. Jefferis and Smith (2005) tested the efficiency market hypothesis in Kenya for the period 1990-2001 using a GARCH approach with time-varying parameters; they concluded that weak-form efficiency does not hold, i.e., past movements in stock prices can be used to predict future movements. Magnusson and Wydick (2002) also investigated market efficiency in African stock markets, using data from eight African countries (Botswana, Côte d'Ivoire, Ghana, Kenya, Mauritius, Nigeria, South Africa, Zimbabwe), and found weak-form efficiency in six of them. In a related paper, Appiah-Kusi and Menyah (2002) used EGARCH-M models capturing the effects of conditional volatility on the pricing process without imposing undue restrictions on the parameters of the conditional variance equation; they considered eleven African stock markets and found evidence against weak-form efficiency in the majority of cases.

Mlambo and Biekpe (2005) tested the efficient market hypothesis in ten African stock markets using the runs test methodology for serial dependency; they could not reject weak-form efficiency in Kenya and Zimbabwe since a significant number of stocks were found to follow a random walk. Vitali and Mollah (2010) carried out unit root, autocorrelation, runs and variance ratio tests on daily price indices of Kenya and other six countries for the time period 1999 – 2009; their results imply a rejection of the random walk hypothesis for all countries except South Africa. Claessens et al. (1995) investigated return anomalies and predictability in nineteen emerging countries and stressed the importance of time variation in the price of risk in emerging markets. Another paper by Olowe (1999) found weak-form efficiency in the Nigerian stock market using correlation analysis.

All the above-mentioned studies investigate market efficiency in various sub-Saharan countries by applying unit root tests or related techniques to test the random walk hypothesis. However, the unit root case is a rather restrictive one to consider; by contrast, the present paper adopts a more general and flexible framework to examine the NSE-20 index: instead of limiting the analysis to the I(0)/I(1) dichotomy the possibility of fractional integration (allowing the degree of integration d to be fractional) is also entertained.

4. Methodology

We model the NSE-20 index, denoted by π_t, as follows:

$$\pi_t = \beta^T z_t + x_t, \quad t = 1, 2, \dots, \tag{1}$$

where z_t is a (kx1) vector of deterministic terms that may be an intercept ($z_t = 1$) or an intercept with a linear trend (i.e., $z_t = (1,t)^T$), and x_t is the error term, which follows an I(d) process of the form:

$$(1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots, \tag{2}$$

where d can be any real number, and u_t is assumed to be I(0), specifically a covariance stationary process with a spectral density function that is positive and bounded at the zero frequency and therefore allows for weak autocorrelation of the ARMA form:

$$\phi(L) u_t = \theta(L) \varepsilon_t, \quad t = 1, 2, \ldots, \tag{3}$$

where φ(L) and θ(L) are the AR and MA polynomials and ϵ_t is a white noise process.

This model is very general: d = 0 corresponds to the classical "trend stationary" I(0) representation; d = 1 is the classical "unit root" or I(1) model suggested by many other authors. This became very popular after the seminal work by Nelson and Plosser (1982), who examined fourteen US macroeconomic series and found that all except one could be characterised as unit roots as opposed to trend-stationary processes. Commonly used unit root tests include the ADF (Dickey and Fuller, 1979), Phillips and Perron (1988), Kwiatkowski et al. (KPSS, 1992), Elliot et al (ERS, 1996), Ng and Perron (2001) tests.

In this paper we also allow d in (2) to be a fractional number, and even to take values above 1. Note that the polynomial $(1–L)^d$ in (2) can be expressed in terms of its Binomial expansion, such that, for all real d:

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

and thus:

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

In this context, d plays a crucial role, since it is an indicator of the degree of dependence of the series: the higher the value of d, the higher the level of association between the observations will be. Processes with d > 0 in (2) display the property of "*long memory*", i.e. their autocorrelations decay hyperbolically and the spectral density function is unbounded at the origin. Such processes were first analysed in the 1960s, when Granger (1966) and Adelman (1965) pointed out that most aggregate economic time series have a typical shape with the spectral density increasing sharply as the frequency approaches zero. However, differencing the data frequently leads to over-differencing at the zero frequency. Subsequently, Robinson (1978) and Granger (1980) showed that aggregation could be a source of fractional integration through the aggregation of heterogeneous autoregressive (AR) processes.[1] Since then, fractional processes have been widely employed to describe the dynamics of economic and financial time series (see, e.g. Diebold and Rudebusch, 1989; Sowell, 1992a; Baillie, 1996; Gil-Alana and Robinson, 1997; etc.).[2]

In the current study first we apply standard unit root testing methods. Then, we estimate the fractional differencing parameter using the Whittle function in the frequency domain (Dahlhaus, 1989). We also employ a testing procedure developed by Robinson (1994) that allows for the testing of any real value of d in I(d) models. The latter is a Lagrange Multiplier (LM) procedure that has been shown to be the most efficient in the context of fractional integration. It tests the null hypothesis H_o: d = d_o for any real value d_o in (1) and (2) and different types of I(0) disturbances, and given the fact that the test statistic follows a standard (normal) limit distribution, it is possible to construct confidence bands for the non-rejection values.[3] Other parametric methods, like Sowell's (1992b) maximum likelihood estimation in the time domain, along with a semi-parametric Whittle method in the frequency domain (Robinson, 1995) where no functional form is imposed in u_t, are implemented as well.

We also estimate a more general ARFIMA(p, d, q) model of the form:

$$\phi(L)\,(1-L)^{d}\,(y_t - \alpha - \beta\, t) \;=\; \theta(L)\,\varepsilon_t, \qquad \varepsilon_t \sim i.i.d.(0,\sigma_\varepsilon^2), \tag{4}$$

[1] Cioczek-Georges and Mandelbrot (1995), Taqqu et al. (1997), and Chambers (1998) also use aggregation to motivate long-memory processes, while Parke (1999) uses a closely related discrete time error duration model.
[2] See also Gil-Alana and Hualde (2009) for a review of fractional integration and its applications to economic time series.
[3] The functional form of this method is specified in various empirical applications (Gil-Alana and Robinson, 1997; Gil-Alana, 2000; Gil-Alana and Henry, 2003; etc.).

where ϕ (L) and θ(L) are the AR and MA polynomials of order p and q respectively (assumed to be equal to or smaller than 2 in the empirical analysis).

If the (log of) NSE-20 is non-stationary, the regression has to be run in first differences. The parameters in (4) are estimated using MLE, assuming that the error term is white noise and follows a normal distribution. For model selection diagnostic tests are carried out, specifically the Breusch-Godfrey LM test for serial correlation and the Jarque-Bera test for normality, and likelihood criteria. [4]

4. Empirical Results

We use daily data on the NSE-20 taken from the Nairobi Securities Exchange (NSE) over the period from January 1st, 2001, to December 31st, 2009. For missing observations we calculate the arithmetic mean of the value of the previous and the following day.

4.1 NSE-20 Returns

Figure 1 displays the index under investigation and the corresponding returns obtained as the first differences of the logged series. Visual inspection suggests that the former is non-stationary, while the latter might be stationary.

[Figure 1 about here]

This is confirmed by a battery of unit root tests for both the levels and the first differences (see Table 2): DF and ADF (Dickey and Fuller, 1979); Phillips and Perron (PP, 1988), Kwiatkowski et al. (KPSS, 1992), and Elliot et al. (ERS, 1996).

Next we focus on the fractional integration results obtained from estimating a model as in (1) and (2) with $z_t = (1,t)^T$, $t \geq 1$, $(0, 0)^T$ otherwise, i.e.,

[4] We use AIC and BIC though these criteria may not necessarily be optimal for applications involving fractional differences, as they focus on the short-term forecasting ability of the fitted model and may not pay sufficient attention to the long-run properties of ARFIMA models (see, e.g. Hosking, 1981, 1984, and more recently Beran et al., 1998).

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

Table 3 displays the results based on the Whittle function in the frequency domain (Dahlhaus, 1989) under the assumption that the error term is in turn a white noise, an AR(1) and a more general AR process as in Bloomfield (1973). As in the case of the unit root tests we display the results for the three cases of no regressors, an intercept and a linear time trend, and we also report in Table 3 the 95% confidence band of the non-rejection values of d using Robinson's (1994) parametric approach.

[Insert Table 3 about here]

The t-values of the deterministic terms (not reported) imply that the specification with an intercept is the most appropriate in all cases. When assuming white noise disturbances, the results are very similar for the raw and logged series: the estimated value of d is about 1.4 and the unit root null hypothesis (d = 1) is decisively rejected in favour of higher orders of integration. With an AR(1) specification the estimated values of d are much smaller and the unit root cannot be rejected. Finally, we use the exponential spectral model of Bloomfield (1973). This is a non-parametric approach not requiring the functional form for the *I(0)* error term u_t in (2) to be specified; it is implicitly determined by its spectral density function, which is given by

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi} \exp\left(2 \sum_{r=1}^{m} \tau_r \cos(\lambda r)\right), \tag{5}$$

where σ^2 is the variance of the error term, and m is the number of parameters required to describe the series. The main advantage of this model is that it mimics the behaviour of ARMA (AutoRegressive Moving Average) structures with a small number of parameters. Assume that u_t follows an ARMA process of the form:

$$\left(1 - \sum_{k=1}^{p} \phi_k L^k\right) u_t = \left(1 + \sum_{k=1}^{q} \theta_k L^k\right) \varepsilon_t, \qquad t = 1, 2, \ldots,$$

where ε_t is a white noise process and all zeros of $\varphi(L) = (1 - \varphi_1 L - \ldots - \varphi_p L^p)$ lying outside the unit circle and all zeros of $\theta(L) = (1 + \theta_1 L + \ldots + \theta_q L^q)$ lying outside or on the unit circle. The spectral density function of this process is then:

$$f(\lambda;\tau) = \frac{\sigma^2}{2\pi} \left| \frac{1 + \sum_{k=1}^{q} \theta_k e^{i\lambda k}}{1 - \sum_{k=1}^{p} \phi_k e^{i\lambda k}} \right|^2, \qquad (6)$$

where τ corresponds to all the AutoRegressive (AR) and Moving Average (MA) coefficients and σ^2 is the variance of ε_t. Bloomfield (1973) showed that the logarithm of an estimated spectral density function is often a fairly well-behaved function and thus can be approximated by a truncated Fourier series, and also that (5) approximates (6) extremely well with a smaller number of parameters. Moreover, this model is stationary for all values of τ, and fits extremely well in the context of Robinson's (1994) tests (see, e.g., Gil-Alana, 2004).

Since the results seem to be very sensitive to the specification of the error term we also apply a semi-parametric method due to Robinson (1995) which is based on a "local" Whittle estimator of d around the zero frequency. This is implicitly defined by:

$$\hat{d} = \arg\min_d \left(\log \overline{C(d)} - 2d \frac{1}{m} \sum_{s=1}^{m} \log \lambda_s \right), \qquad (7)$$

$$\overline{C(d)} = \frac{1}{m} \sum_{s=1}^{m} I(\lambda_s) \lambda_s^{2d}, \qquad \lambda_s = \frac{2\pi s}{T}, \qquad \frac{m}{T} \to 0,$$

where $I(\lambda_s)$ is the periodogram of the raw time series, x_t, given by:

$$I(\lambda_s) = \frac{1}{2\pi T} \left| \sum_{t=1}^{T} x_t e^{i\lambda_s t} \right|^2,$$

and $d \in (-0.5, 0.5)$. Under finiteness of the fourth moment and other mild conditions, Robinson (1995) proved that:

$$\sqrt{m}(\hat{d} - d_o) \to_d N(0, 1/4) \quad as\ T \to \infty,$$

where d_o is the true value of d.[5] This estimator is robust to a certain degree of conditional heteroscedasticity (Robinson and Henry, 1999) and is more efficient than other more recent semi-parametric competitors.

[Figure 2 about here]

Figure 2 displays the estimates of d for the whole range of bandwidth parameters, and also confidence bands for the I(1) case. It is clear that the results are very sensitive to the choice of the bandwidth parameter.[6] For the original series, there are some values which are within the I(1) interval; however, if m is large most of the values are above 1. For the logged data practically all values are significantly above 1, which implies long memory in the returns and therefore some degree of predictability of the return series (inconsistently with market efficiency).

4.2 Absolute and Squared Returns

In this section we use absolute and squared returns as proxies for volatility. The former have been employed among others by Ding et al. (1993), Granger and Ding (1996), Bollerslev and Wright (2000), Gil-Alana (2005), Cavalcante and Assaf (2004), Sibbertsen (2004) and Cotter (2005), whereas the latter have been used in Lobato and Savin (1998), Gil-Alana (2003), Cavalcante and Assaf (2004) and Cotter (2005).

Figure 3 shows both absolute and squared returns. Visual inspection suggests that they are both stationary, which is confirmed by various unit root tests (see Table 4).

[Insert Figure3 and Table 4 about here]

[5] This method has been further examined and refined by Velasco (1999), Velasco and Robinson (2000), Phillips and Shimotsu (2004, 2005), Abadir et al. (2007) and others.
[6] The choice of the bandwidth parameter is crucial for this method given the trade-off between bias and variance: the asymptotic variance of this estimator is decreasing with m while the bias is growing with m.

Table 5 displays the estimates of d for the absolute and squared returns using the parametric methods of Dahlhaus (1989) and Robinson (1994). The results strongly support the hypothesis of long memory for both series, with values of d above 0.3 in all cases.

[Insert Table 5 and Figure 4 here]

The same conclusion is reached by looking at Figure 4, which is based on the semi-parametric Whittle approach as in Robinson (1995). This is consistent with the results obtained in many other stock markets across the world (see, e.g. Ding et al., 1993; Granger and Hyung, 2004; etc.).

4.3 Day-of-the-Week Effects

Calendar effects (such as the weekend, day-of-the-week, and January effects) in financial series have been reported in many studies starting with Osborne (1962). Negative Monday returns were found by Cross (1973), French (1980), and Gibbons and Hess (1981), the former two analysing the S&P 500 index, the latter the Dow Jones Industrial Index. Similar findings were reported for other US financial markets, such as the futures, bond and Treasury bill markets (Cornell, 1985, Dyl and Maberly, 1986), foreign exchange markets (Hsieh,1988), and for Australian, Canadian, Japanese and UK financial markets (e.g., Jaffe and Westerfield, 1985, Jaffe, Westerfield and Ma, 1989, Agrawal and Tandon, 1994). Effects on stock market volatility have also been documented (Kiymaz and Berument, 2003).

Various explanations have been offered for the observed calendar effects. Some focus on delays between trading and settlement in stocks (Gibbons and Hess, 1981): buying on Fridays creates a two-day interest-free loan until settlement; hence, there are higher transaction volumes on Fridays, resulting in higher prices, which decline over the weekend as this incentive disappears. Others emphasise a shift in the broker-investor balance in buying-selling decisions which occurs at weekends, when investors have more time to study the market themselves (rather than rely on brokers); this typically results in net sales on Mondays, when liquidity is low in the absence of institutional trading (Miller, 1988). It has also been suggested that the Monday effect largely reflects the fact that, when daily returns are calculated, the clustering of dividend payments around Mondays is normally ignored; alternatively, it could be a consequence of positive news typically being released during the week, and negative ones over the weekend (Fortune, 1998). Additional factors which could be relevant are serial correlation, with Monday prices being affected by Friday ones, and a negative stock performance on Fridays being given more weight (Abraham and Ikenberry,1994); measurement errors (Keim and Stambaugh, 1984); size (Fama and French, 1992); volume (Lakonishok and Maberly, 1990).

The observations ordered by day of the week also appear to be stationary on the basis of both visual inspection and unit root tests (see Figure 5 and Table 6).

[Insert Figures 5 and 6 and Tables 6 and 7 about here]

Table 7 displays the fractional integration results from the parametric method of Robinson (1994). They appear to be robust to the specification for the error term (whether white noise, AR(1) and Bloomfield-type). The lowest estimates of d are obtained for Mondays and Fridays in all cases. When u_t is assumed to be a white noise, the I(0) hypothesis is decisively rejected in favour of long memory on Tuesdays and Wednesdays but not on Mondays, Thursdays and Fridays. It u_t is modelled as an autocorrelated process (whether AR(1) or Bloomfield-type), the only cases when the I(0) hypothesis cannot be rejected are Mondays and Fridays, which is consistent with the presence of a day-of-the-week effect. This is corroborated by the plots in Figure 6 based on the semi-parametric method, where evidence of I(0) behaviour is only found on Mondays and Fridays (in some cases also on Thursdays).

5. Conclusions

In this paper we have examined the statistical properties of the NSE-20, which is the main index for the Kenyan stock market. We have used both unit roots and fractional integration techniques to investigate several issues such as market efficiency, long memory, mean reversion and persistence. The day-of-the-week effect has also been analysed.

The results of the unit root tests suggest that first-differencing is required to make the series stationary. The fractional integration analysis implies that the order of integration is significantly above 1 and therefore returns (constructed as the first differences of the logged prices) display long-memory behaviour. Long memory is also detected in the absolute and squared returns that are used as proxies for the volatility processes. This is consistent with what is observed in other stock markets around the world. As for the day-of-the-week effect, the lowest degrees of integration (very close to 0) are found on Mondays and Fridays, whilst the remaining days are characterised by long memory (with values of d significantly above 0). This anomaly points to possible non-linearities in the Kenyan stock market that will be investigated in future papers.

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Table1. Components of NSE-20

NAME OF THE COMPANY	ACTIVITY OF THE COMPANY
ICDC Investment Company	Investment
Kenya Electricity Generating Company	Generate Electricity
Mumias Sugar Company	Manufacturates
Rea Vipingo Plantations Ltd.	Sisal fiber production
CMC Holdings	Automovile
Express Ltd.	Logistic
Nation Media Group	Means ofcommunication
Sasini Ltd.	Coffe producer
Kenya Airways	Commercial aviation
Safaricom Ltd.	Mobile phone
Barclays Bank (K) Ltd.	Commercial bank
Equity Bank	Commercial bank
Kenya Commercial Bank	Commercial bank
Standard Chartered Bank (K) Ltd.	Commercial bank
Bamburi Cement Ltd.	Manufacturates
British American Tobacco Ltd.	Manufacturates
East African Breweries Ltd.	Drinks production
East African Cables	Cables production
Kenya Power & Lighting Company	Electrical distribution and regulation
Athi River Mining	Mineral extraction and processing

Source: “securities.com” but also I obtain information from: “kengen.co.ke”, “nationmedia.com”, “kenya-airways.com” and “lafarge.co.ke”.

Figure 1: NSE-20 index and its corresponding returns

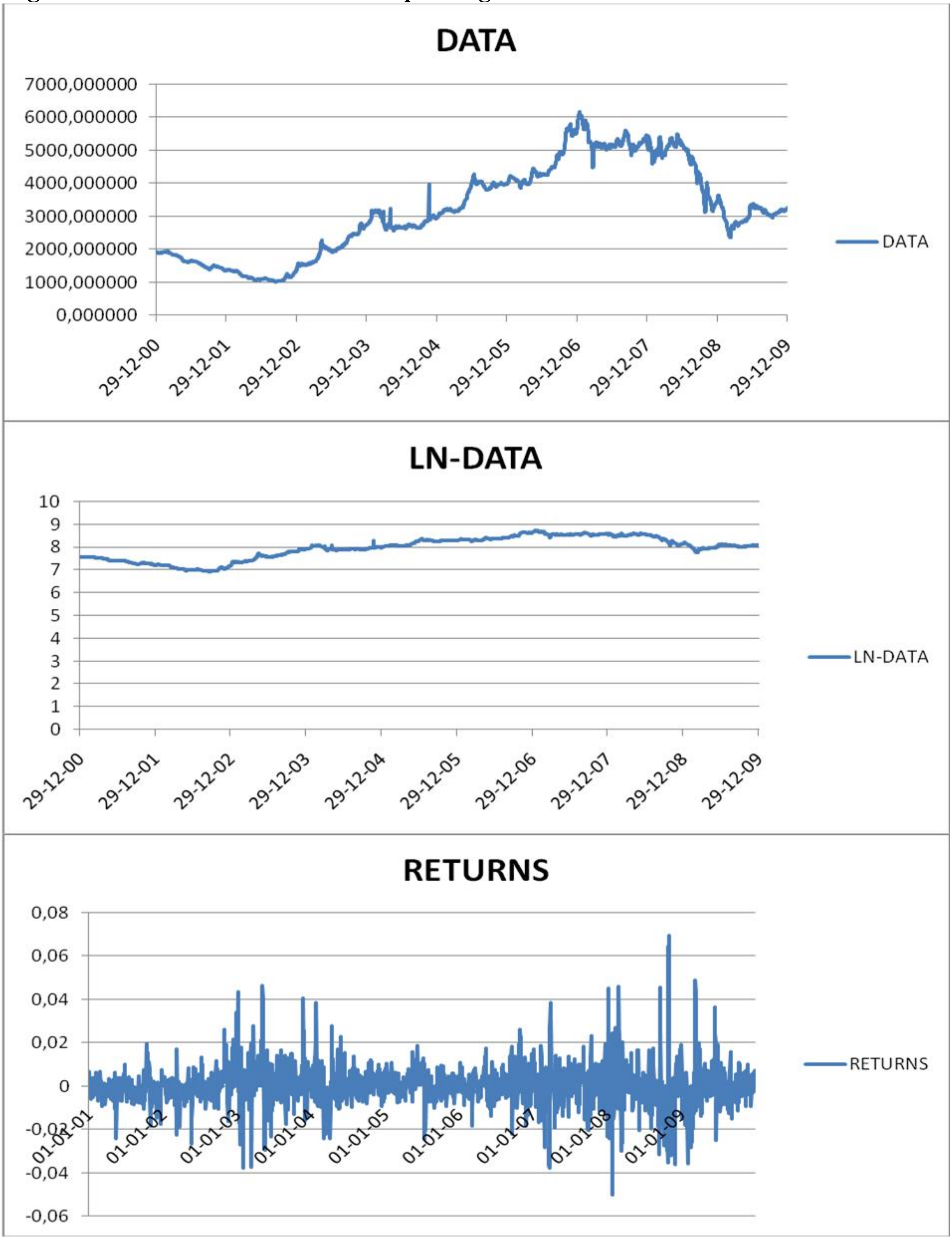


Table 2: Unit root test results

i) DF tests (Fuller, 1976)			
	No regressors	An intercept	A linear time trend
Data	xxx	-0.460735	-1.123148
Log-data	xxx	-0.373849	-0.986390
Returns	xxx	-22.69812***	-22.64716***
i) ADF tests (Dickey and Fuller, 1979)			
	No regressors	An intercept	A linear time trend
Data	0.060601	-1.108386	-0.689085
Log-data	0.604559	-0.992274	-0.860785
Returns	-22.69635***	-22.70349***	-22.70762***
iii) PP tests (Phillips and Perron, 1988)			
	No regressors	An intercept	A linear time trend
Data	0.047311	-1.112565	-0.711718
Log-data	0.688395	-0.908159	-0.638040
Returns	-29.06451***	-29.05583***	-29.10858***
iv) KPSS tests (Kwiatkowski et al., 1992)			
	No regressors	An intercept	A linear time trend
Data	xxx	4.084636***	0.845815***
Log-data	xxx	4.303477***	0.906712***
Returns	xxx	0.343198	0.270594***
v) ERS tests (Elliot et al., 1996)			
	No regressors	An intercept	A linear time trend
Data	xxx	31.30013	33.66141
Log-data	xxx	32.94623	35.53811
Returns	xxx	0.033250***	0.121229***

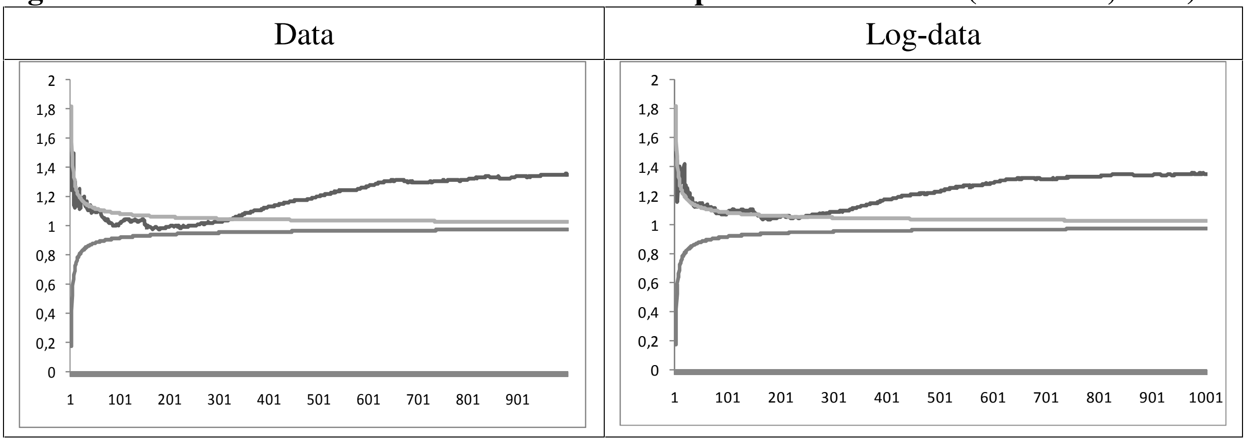
***: Significance at the 5% level.

Table 3: I(d) test results

i) white noise disturbances			
	No regressors	An intercept	A linear time trend
Data	1.16 (1.12, 1.20)	**1.40 (1.36, 1.45)**	1.40 (1.36, 1.45)
Log-data	1.00 (0.97, 1.03)	**1.39 (1.35, 1.44)**	1.39 (1.35, 1.44)
ii) AR(1) disturbances			
	No regressors	An intercept	A linear time trend
Data	xxx	**0.94 (0.88, 1.01)**	0.94 (0.88, 1.01)
Log-data	1.38 (1.33, 1.43)	**1.03 (0.97, 1.12)**	1.03 (0.97, 1.12)
iii) Bloomfield (m = 1) disturbances			
	No regressors	An intercept	A linear time trend
Data	1.08 (1.03, 1.14)	**1.13 (1.08, 1.20)**	1.13 (1.08, 1.20)
Log-data	0.99 (0.95, 1.05)	**1.20 (1.14, 1.26)**	1.20 (1.14, 1.26)

In bold the selected models according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d.

Figure 2: Estimates of d based on the Whittle semiparametric method (Robinson, 1995)



The horizontal axis concerns the bandwidth parameter while the vertical one refers to the estimated value of d.

Figure 3: Absolute and squared returns

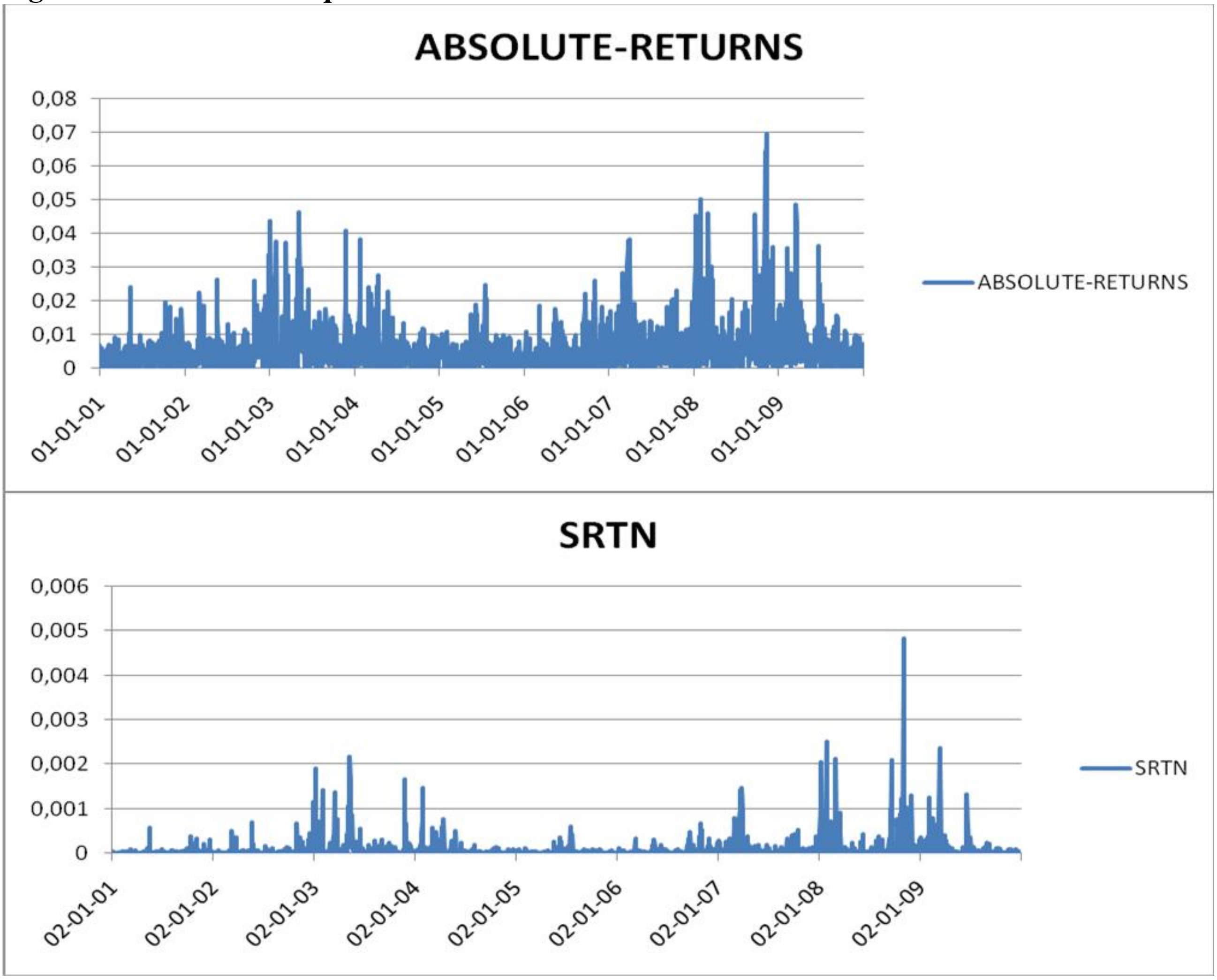


Table 4: Unit root test results on the absolute and square returns

i) DF tests (Fuller, 1976)			
	No regressors	An intercept	A linear time trend
Absolute returns	xxx	-7.004727***	-11.48365***
Squared returns	xxx	-13.09610***	-14.61125***
i) ADF tests (Dickey and Fuller, 1979)			
	No regressors	An intercept	A linear time trend
Absolute returns	-6.903141***	-13.50076***	-17.30106***
Squared returns	-11.87663***	-14.49458***	-14.71432***
iii) PP tests (Phillips and Perron, 1988)			
	No regressors	An intercept	A linear time trend
Absolute returns	-36.62615***	-41.37812***	-41.02276***
Squared returns	-36.57225***	-35.12007***	-34.91227***
iv) KPSS tests (Kwiatkowski et al., 1992)			
	No regressors	An intercept	A linear time trend
Absolute returns	xxx	0.992079***	0.173177**
Squared returns	xxx	0.708727**	0.143348*
v) ERS tests (Elliot et al., 1996)			
	No regressors	An intercept	A linear time trend
Absolute returns	xxx	0.141189***	0.216153***
Squared returns	xxx	0.068917***	0.227254***

***: Significance at the 5% level.

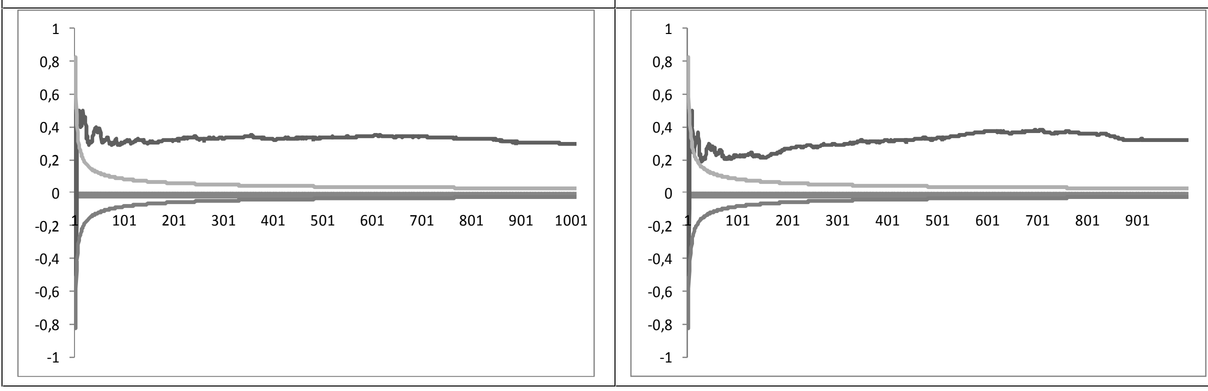
Table 5: I(d) test results on the absolute and squared returns

i) white noise disturbances			
	No regressors	An intercept	A linear time trend
Absolute returns	0.31 (0.28, 0.34)	**0.31 (0.29, 0.34)**	0.31 (0.28, 0.34)
Squared returns	0.36 (0.33, 0.39)	**0.36 (0.33, 0.39)**	0.36 (0.33, 0.39)
ii) AR(1) disturbances			
	No regressors	An intercept	A linear time trend
Data	0.36 (0.31, 0.41)	**0.36 (0.31, 0.41)**	0.36 (0.31, 0.41)
Log-data	0.33 (0.26, 0.39)	**0.33 (0.27, 0.39)**	0.33 (0.27, 0.39)
iii) Bloomfield (m = 1) disturbances			
	No regressors	An intercept	A linear time trend
Data	0.35 (0.31, 0.41)	**0.36 (0.31, 0.41)**	0.35 (0.31, 0.41)
Log-data	0.34 (0.27, 0.39)	**0.33 (0.27, 0.39)**	0.34 (0.27, 0.39)

In bold the selected models according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d.

Figure 4: Estimates of d based on the Whittle semiparametric method (Robinson, 1995)

Absolute returns	Squared returns



The horizontal axis concerns the bandwidth parameter while the vertical one refers to the estimated value of d.

Figure 5: NSE-20 index by day of the week

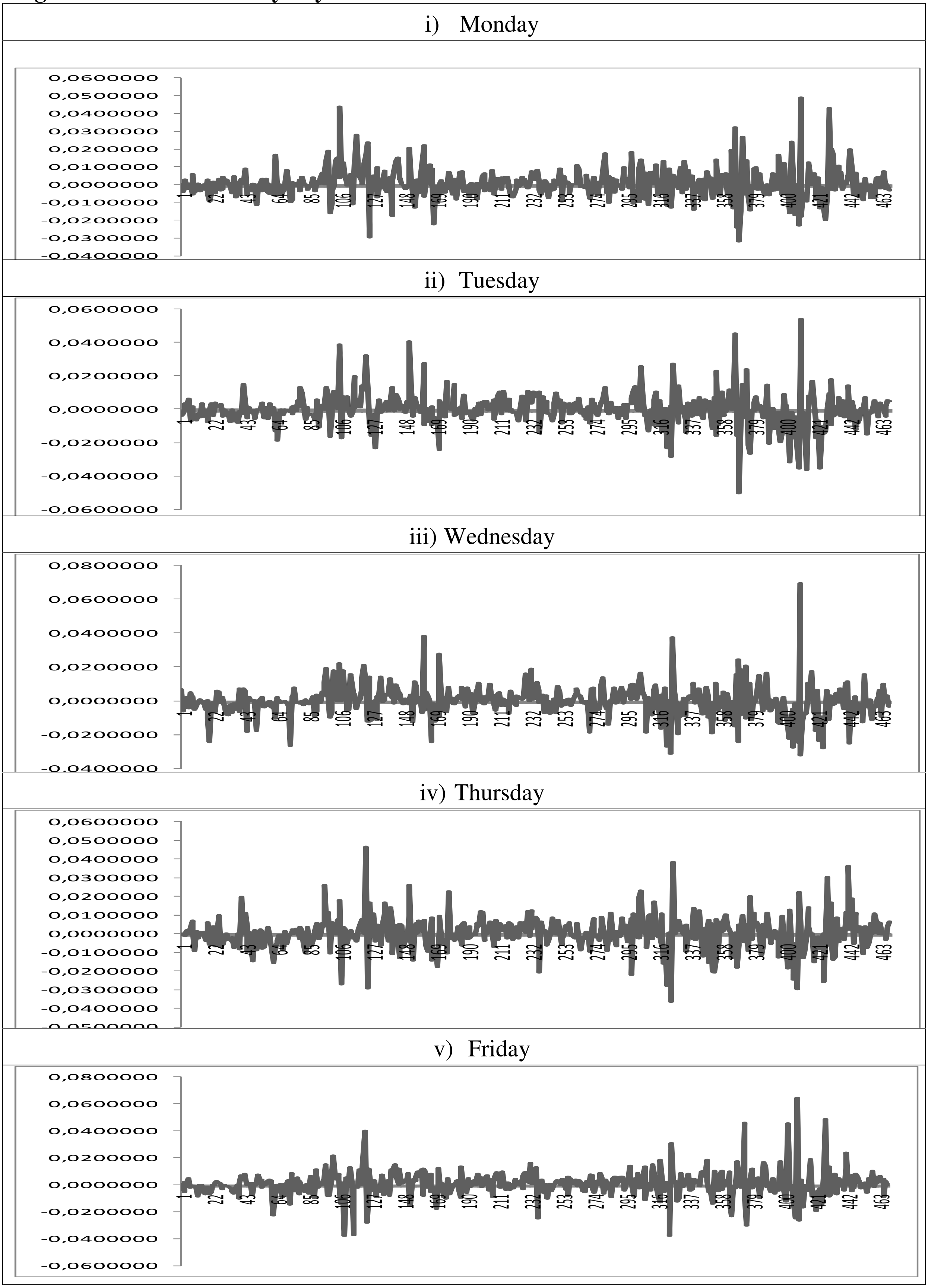


Table 6: Unit root test results on the absolute and square returns

i) DF tests (Fuller, 1976)			
	No regressors	An intercept	A linear time trend
Monday	xxx	-22.65899***	-22.67434***
Tuesday	xxx	-9.075883***	-12.68740***
Wednesday	xxx	-3.303200***	-12.39346***
Thursday	xxx	-21.85909***	-21.84855***
Friday	xxx	-4.964294***	-22.81587***
ii) ADF tests (Dickey and Fuller, 1979)			
	No regressors	An intercept	A linear time trend
Monday	-22.65643***	-22.72762***	-22.70325***
Tuesday	-20.20361***	-20.18417***	-20.39409***
Wednesday	-13.74730***	-13.73984***	-13.84647***
Thursday	-21.98668***	-21.97088***	-21.94883***
Friday	-23.30941***	-23.42323***	-17.84304***
iii) PP tests (Phillips and Perron, 1988)			
	No regressors	An intercept	A linear time trend
Monday	-22.66196***	-22.76841***	-22.74334***
Tuesday	-20.34698***	-20.32847***	-20.47802***
Wednesday	-23.09557***	-23.08063***	-23.14058***
Thursday	-22.10440***	-22.08896***	-22.06916***
Friday	-23.47783***	-23.76934***	-24.05078***
iv) KPSS tests (Kwiatkowski et al., 1992)			
	No regressors	An intercept	A linear time trend
Monday	xxx	0.100909	0.102093
Tuesday	xxx	0.690074**	0.222651***
Wednesday	xxx	0.523291**	0.282920***
Thursday	xxx	0.115804	0.119474*
Friday	xxx	0.344971	0.074121
v) ERS tests (Elliot et al., 1996)			
	No regressors	An intercept	A linear time trend
Monday	xxx	0.107126***	0.394650***
Tuesday	xxx	0.130302***	0.424117***
Wednesday	xxx	0.230281***	0.549022***
Thursday	xxx	0.114196***	0.398645***
Friday	xxx	0.129999***	0.320357***

***: Significance at the 5% level.

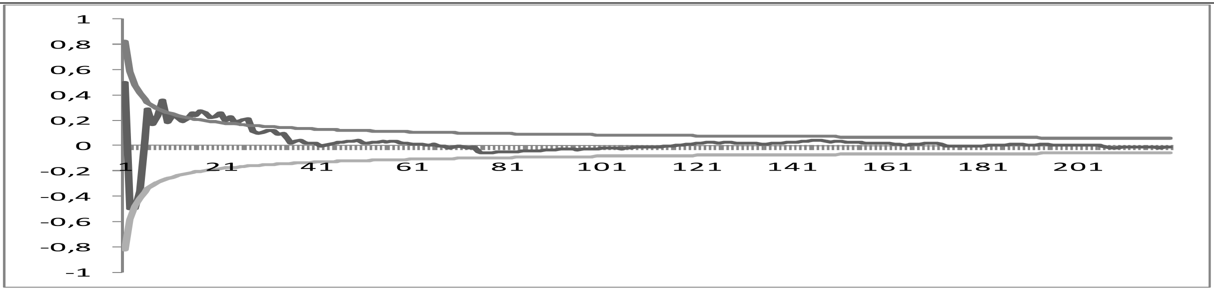
Table 7: I(d) test results for the day of the week returns

i) white noise disturbances			
	No regressors	An intercept	A linear time trend
Monday	-0.03 (-0.08, 0.04)	**-0.03 (-0.08, 0.04)**	-0.03 (-0.08, 0.04)
Tuesday	0.08 (0.04, 0.14)	**0.08 (0.04, 0.14)**	0.07 (0.02, 0.13)
Wednesday	0.04 (0.00, 0.08)	**0.04 (0.00, 0.08)**	0.03 (-0.01, 0.08)
Thursday	0.03 (-0.02, 0.09)	**0.03 (-0.02, 0.09)**	0.03 (-0.02, 0.09)
Friday	-0.09 (-0.14, -0.03)	**-0.10 (-0.15, -0.03)**	-0.12 (-0.18, -0.05)
ii) AR(1) disturbances			
	No regressors	An intercept	A linear time trend
Monday	0.01 (-0.07, 0.12)	**0.01 (-0.08, 0.12)**	0.01 (-0.08, 0.12)
Tuesday	0.13 (0.06, 0.22)	**0.13 (0.06, 0.22)**	0.10 (0.02, 0.20)
Wednesday	0.17 (0.10, 0.26)	**0.17 (0.10, 0.26)**	0.16 (0.08, 0.25)
Thursday	0.11 (0.02, 0.22)	**0.11 (0.02, 0.22)**	0.11 (0.02, 0.22)
Friday	-0.10 (-0.16, -0.02)	**-0.11 (-0.18, -0.02)**	-0.16 (-0.25, -0.06)
iii) Bloomfield (m = 1) disturbances			
	No regressors	An intercept	A linear time trend
Monday	0.01 (-0.07, 0.12)	**0.01 (-0.07, 0.12)**	0.01 (-0.07, 0.12)
Tuesday	0.13 (0.06, 0.23)	**0.13 (0.06, 0.23)**	0.10 (0.02, 0.22)
Wednesday	0.18 (0.11, 0.29)	**0.18 (0.11, 0.29)**	0.17 (0.09, 0.28)
Thursday	0.12 (0.03, 0.24)	**0.12 (0.03, 0.24)**	0.12 (0.03, 0.24)
Friday	-0.10 (-0.16, -0.01)	**-0.09 (-0.19, -0.02)**	-0.17 (-0.24, -0.05)

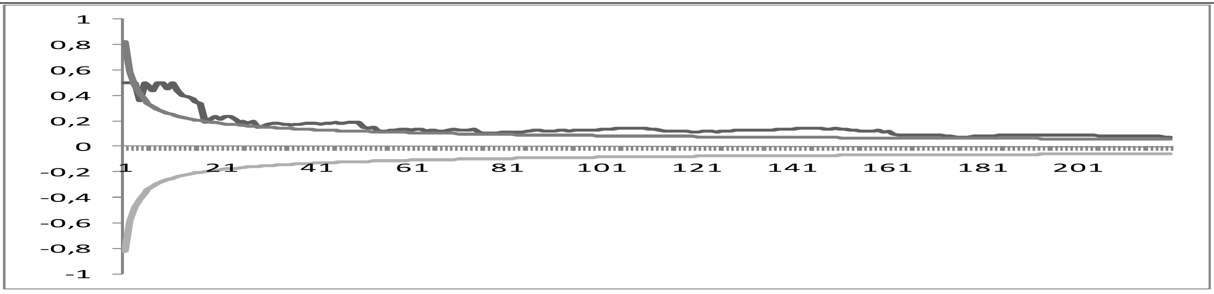
In bold the selected models according to the deterministic terms. In parenthesis, the 95% confidence intervals of the non-rejection values of d.

Figure 6: Whittle semi-parametric estimates of d for each day of the week

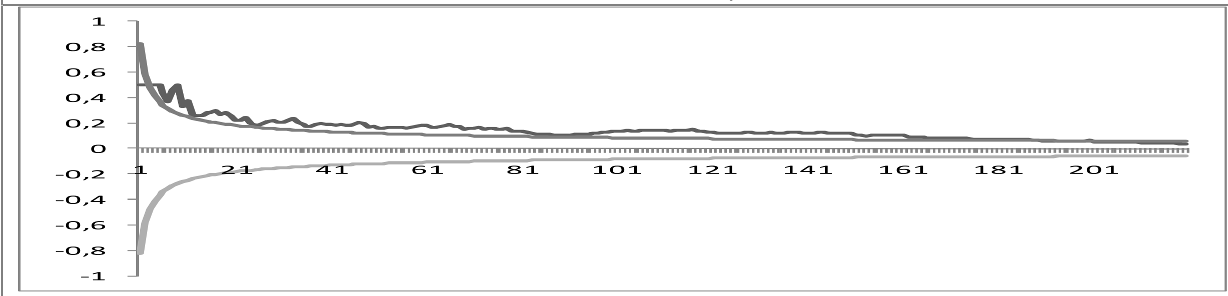
i) Monday



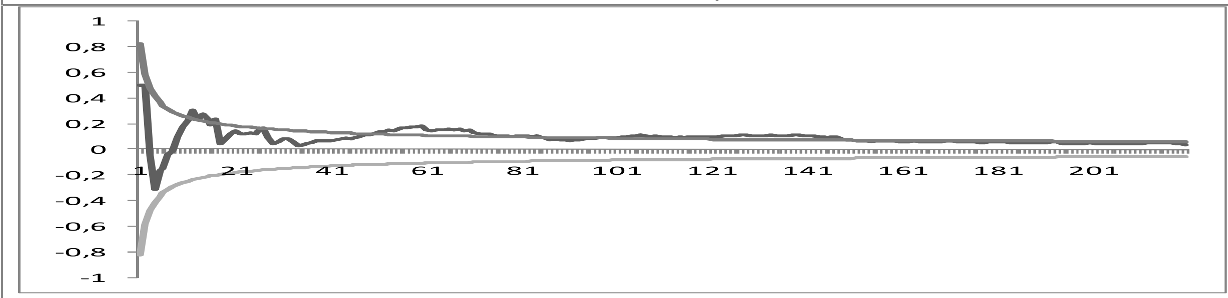
ii) Tuesday



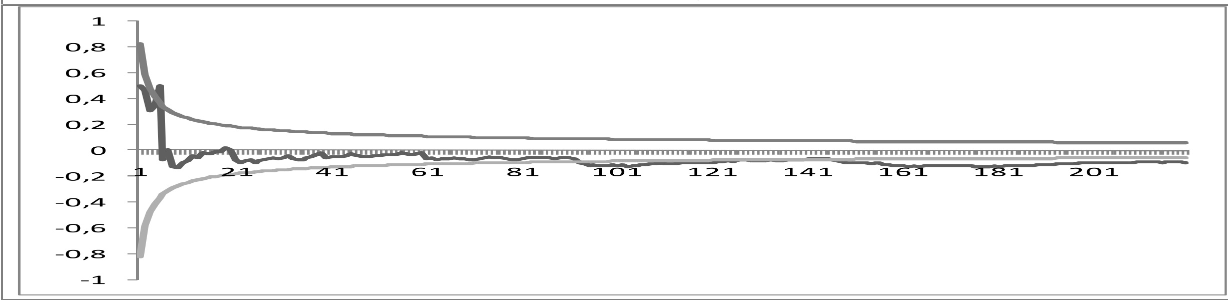
iii) Wednesday



iv) Thursday



v) Friday



The horizontal axis concerns the bandwidth parameter while the vertical one refers to the estimated value of d.