Physica A 392 (2013) 1631–1637

Contents lists available at SciVerse ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

How fast do stock prices adjust to market efficiency? Evidence from a detrended fluctuation analysis

Juan C. Reboredo [a], Miguel A. Rivera-Castro [a,*], José G.V. Miranda [b], Raquel García-Rubio [c]

[a] Department of Economics, University of Santiago de Compostela, Spain
[b] Institute of Physics, Federal University of Bahia, Brazil
[c] Department of Finance, University of Salamanca, Spain

ARTICLE INFO

Article history:
Received 25 May 2012
Received in revised form 3 September 2012
Available online 26 November 2012

Keywords:
Finance
Market efficiency
Speed of adjustment
Detrended fluctuation analysis

ABSTRACT

In this paper we analyse price fluctuations with the aim of measuring how long the market takes to adjust prices to weak-form efficiency, i.e., how long it takes for prices to adjust to a fractional Brownian motion with a Hurst exponent of 0.5. The Hurst exponent is estimated for different time horizons using detrended fluctuation analysis – a method suitable for non-stationary series with trends – in order to identify at which time scale the Hurst exponent is consistent with the efficient market hypothesis. Using high-frequency share price, exchange rate and stock data, we show how price dynamics exhibited important deviations from efficiency for time periods of up to 15 min; thereafter, price dynamics was consistent with a geometric Brownian motion. The intraday behaviour of the series also indicated that price dynamics at trade opening and close was hardly consistent with efficiency, which would enable investors to exploit price deviations from fundamental values. This result is consistent with intraday volume, volatility and transaction time duration patterns.

1. Introduction

The market efficiency hypothesis [1,2] states that asset prices adjust to fully reflect all available information and so show martingale behaviour. Although the formulation of this hypothesis refers to a rapid and unbiased price adjustment process, in practice, prices tend not to adjust to new information instantly but after a certain amount of time. During this time investors take actions to exploit temporary profit opportunities arising from new information, ultimately pushing prices towards efficiency. The time the market takes to adjust prices to market efficiency is an important dimension of the market efficiency hypothesis [3], with notable practical implications for trading and risk management.

The adjustment of asset prices to information has been widely studied at the theoretical and empirical level. Theoretical models have been developed by Grossman [4], Grossman and Stiglitz [5] and Cornell and Roll [6], in which the incorporation of stock price information depends on the cost of information production. For a rational expectation framework, Brown and Jennings [7] and Grundy and McNichols [8] show how prices adjust in a sequence of trades to fully reveal all relevant information. For a model populated by Bayesian traders, Chakrabarti and Roll [9] found, in a simulation study, that the market usually converged more rapidly to an equilibrium price when arbitrageurs reacted to one another. Behavioural finance models have been developed by Barberis et al. [10], Daniel et al. [11] and Hong and Lee [12] to provide explanations for empirically documented under- and over-reactions of stock prices to news.

* Corresponding author. Tel.: +34 55 71 32337518.
E-mail addresses: juancarlos.reboredo@usc.es (J.C. Reboredo), marc@ufba.br (M.A. Rivera-Castro), vivas@ufba.br (J.G.V. Miranda), rgr@usal.es (R. García-Rubio).

0378-4371/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
doi:10.1016/j.physa.2012.11.038

Empirically, several studies have examined market efficiency in terms of the speed with which prices react to new information arising from any specific event e.g., [13] or in a more general setting with no specific event identified e.g., [14]. Early tests of weak-form market efficiency employed the linear autocorrelation test and the Lo and Mackinlay variance ratio test [15] for daily, weekly and monthly stock returns. However, those tests assume linearity e.g., [16,17,12], so they only check for serial uncorrelatedness rather than for the martingale property of asset returns.

There is no reason to suppose that stock prices are intrinsically linear. Human error in reasoning or information processing (e.g., information bias or overconfidence) may explain information imperfections in financial markets [18] that may give rise to price nonlinearity. Nonlinearity may also arise from price fads, rational speculative bubbles [17] or the assumption that prices are the result of complex interactions between informed and uninformed traders in the market place. Nonlinearity in stock returns is crucial for forecasting see, e.g., [19,20] and for determining the speed of convergence to market efficiency since zero autocorrelation does not imply the martingale property of asset returns. Statistical tests developed by Hurst [21], Brock et al. [22] and Peng et al. [23] are considered superior to the linear autocorrelation tests as they are able to detect the presence of short- and long-term dependence. Based on those tests, we propose a different approach to the problem of measuring the adjustment time of security prices towards weak-form market efficiency. This approach is based on employing detrended fluctuation analysis (DFA) [23] for different intraday time scales in order to identify the time horizon necessary for prices to adjust to a fractional Brownian motion (fBm) with a Hurst exponent of 0.5. The chief advantages of the DFA methodology compared with traditional methods (e.g., Hurst analysis, rescaled range statistic, root mean square, time-varying long-range dependence) are that (a) it allows self-similarity to be detected in nonstationary time series and so allows, in turn, log price to be analysed, and (b) it avoids the spurious detection of apparent long-range correlation by excluding the intrinsic trend of the financial time series.

DFA has been used for dynamic analysis, among others, of heart rate variability [24], human electroencephalographic fluctuations [25] and economic and financial series [26–32]. In particular, DFA has been recently employed to study market efficiency [33–37], even though all the existing empirical studies using DFA have analysed the efficiency at specific time scales without analysing the time the market takes to achieve weak-form efficiency. This is the focus of our study.

The remainder of the article is organized as follows. Section 2 provides a brief theoretical review and describes the DFA methodology for estimating the Hurst parameter to quantify the speed of adjustment of prices to a random walk; Section 3 describes our data; Section 4 reports our empirical results; and, finally, Section 5 concludes the article.

2. Methodology

The time dependence structure of a stochastic process can be captured by the autocorrelation function. Long memory, characterized by autocorrelations at very high lags, creates persistence (anti-persistence) in the series over long time horizons. In such cases, autocorrelation declines at a hyperbolic rate that is slower than the exponential rate in standard autoregressive moving average (ARMA) processes. Mills [38] suggested that many empirically observed time series, even though they may appear to satisfy the assumption of stationarity with or without differentiation, seem to exhibit dependence between distant observations that, even if small, is by no means negligible. The many approaches to estimating the long memory parameter (fractional differencing) include, in financial time series, the autoregressive fractionally integrated moving average model, ARFIMA (p, d, q), which has the desired ability to match the slow decay of the autocorrelation functions. The difference between the ARFIMA (p, d, q) model and the autoregressive integrated moving average model, ARIMA (p, d, q), is that the former does not restrict the parameter d to being an integer value but allows it to take a fractional value. For noninteger values of d, the autocorrelation declines hyperbolically. When $0 < d < 0.5$ the ARFIMA process is said to exhibit long memory with positive dependence. For $d = 1$ the ARFIMA process is therefore identical to an ARIMA in that the autocorrelations decay exponentially. For $d = 0$, the ARFIMA process is reduced to an ARMA process and exhibits only short memory and for $-0.5 < d < 0$ the ARFIMA process exhibits long memory with negative dependence.

2.1. Hurst exponent

To quantify financial fluctuations it is necessary to calculate and graph the autocorrelation function for price changes in a log–log plot. Obtained is a power law equation where the slope is the scaling exponent H, invariant under appropriate changes. Different techniques based on fractal analysis suggest that market data exhibit temporal correlations and fat-tailed probability distributions. Temporal correlation means that volatile fluctuations tend to occur with a particular trend, while fat-tailed probability distribution means that a more extreme event might be more frequent than a normally distributed event. The fractal concept, which is linked to time scale invariance, is used to identify the order in characteristic nonlinear problems.

DFA is a method developed by Peng et al. [23], Moreira et al. [39], Peng et al. [40] and used to determine the quantitative Hurst exponent H, which represents the correlation properties of a signal. Based on analysing fluctuations in a time series for different time scales, DFA focuses on removing the trend of a signal, which should not be related to the correlation properties of the signal. A trend may be produced by joint price movements in other markets. Under these circumstances it is very important to be aware if the trend can be filtered, as an intrinsic trend may be related to the local signal fluctuation properties. In general, DFA-q is the variable used to eliminate the first-order trend $q = 1$; in other words, the function is adjusted by a first-order polynomial equation. Therefore, in order to determine the DFA-q order it is crucial to consider external factors that could constitute the cause of a trend. The DFA method thus enables a quantitative parameter H to be identified that represents the correlation properties of a signal. We propose using this method to quantify the period of time during which a market behaves like an fBm, measured through the timing behaviour of the parameter H. Many other methods based on DFA have been developed recently, e.g., the detrended cross-correlation analysis (DCCA), which is a generalization of detrended fluctuation analysis and is based on detrended covariance [41,42].

The DFA algorithm has six basic steps.

1. If we start with a series of equidistant time increments $\{x(t)\},\ t = 1, \ldots, N$, we can obtain the path (or the profile)

$$y(t) = \sum_{j=1}^{t} x(j). \tag{1}$$

2. The entire interval $[1, N]$ can be divided into a series of M_ν boxes of length ν, not necessarily self-excluding. Each box receives a label $(m, \nu),\ m = 1, \ldots, M_\nu$. In our calculations, we considered a certain level of overlap between the boxes for the purpose of increasing the number of boxes where the method is applied and, hence, to improve the statistics. To evaluate the magnitude of fluctuations in the box (m, ν) and, concomitantly, eliminate the trend of order q, we consider the difference

$$y_s(t) = y(t) - p_q(t; (m, \nu)), \tag{2}$$

3. where $p_q(t; (m, \nu))$ represents the polynomial of order q that minimizes the sum of $y_s(t)^2$ when t spans all points of the considered box. To be more precise, we consider the residue

$$f(m, \nu) = \frac{1}{\nu} \sum_{j=I_{min}(m,\nu)}^{I_{max}(m,\nu)} y_s^2(j), \tag{3}$$

4. where $I_{min}(m, \nu)$ and $I_{max}(m, \nu)$ are the lower and upper limits of the (m, ν) box. When $q = 0, f(m, \nu)$ corresponds to the roughness function $W(m, \nu)$ of the (m, ν) box. Subsequently, we consider the average

$$F(\nu) = \left[\frac{1}{M_\nu} \sum_{m=1}^{M_\nu} f(m, \nu)\right]^{1/2}, \tag{4}$$

5. which expresses the average detrended roughness at length scale ν of the entire profile. If the original series presents long-range correlations, it is expected that the values of $F(\nu)$ follow a power law

$$F(\nu) \sim \nu^H, \tag{5}$$

6. where the roughness exponent $H = 1 - \gamma/2$ is related to the exponent describing the decay of the correlation function $C(j) = E[y(t)y(t+j)] \sim j^{-\gamma}$ [38].

In practice, this means the exponent can be calculated with a linear adjustment to the logarithmic scale of ν in function of $F(\nu)$. The fluctuation exponent can be classified according to a dynamic band of values:

- $H < 0.5$: anti-correlated, anti-persistent signal.
- $H = 0.5$: non-correlated signal, white noise, no memory.
- $H > 0.5$: long-range correlated signal.

The temporal correlation properties of a series are given by the correlation persistence, which can be characterized by the Hurst exponent. An exponent $H > 0.5$ for a series indicates persistent behaviour: positive (negative) increments are more likely to be followed by positive (negative) increments in the future. If market fluctuations are persistent, price changes would be much more frequent in the long run, which is very attractive to speculators interested in earning extra returns. An exponent $H < 0.5$ for a series indicates anti-persistent behaviour: positive (negative) increments are more likely to be followed by negative (positive) increments in the future. If market fluctuations are anti-persistent, they would be smaller than the persistent fluctuations since anti-persistent fluctuations have smaller variance. Brownian fluctuations are a balance between persistent and anti-persistent behaviours because price changes are independent of each other. In fact, if $H = 0.5$ the time series is uncorrelated and its movements cannot be predicted, which is consistent with the market efficiency hypothesis. Therefore, a Hurst exponent can identify the characteristics of a system's self-regulatory mechanism. This is useful in quantifying the adjustment speed of prices to a random walk; its value at different time frequencies is considered in order to determine the time horizon in which the Hurst exponent becomes permanently equal to 0.5.

3. Data

We studied intraday tick-by-tick data for different stocks: two market indexes (the DJIA for the USA and IBEX-35 for Spain); the EUR–USD exchange rate; and Telefónica España stock (TEF). The data for 74 trading days covering 1 February 2011

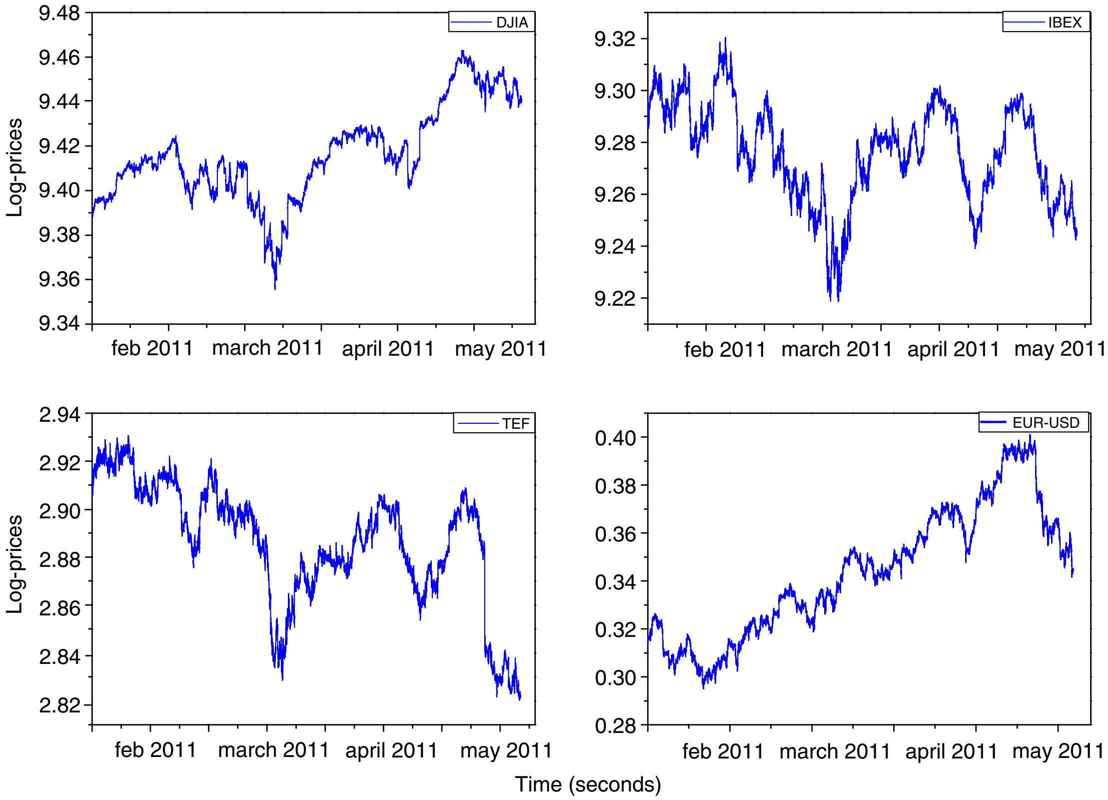

Fig. 1. Log prices for DJIA, IBEX-35, Telefónica España stock (TEF) and EUR–USD exchange rate indexes.

to 13 May 2011 were obtained from Bloomberg through Infomercados. The graphical representation of log price dynamics for all series is illustrated in Fig. 1 for time intervals of 1 min (the representative price was taken as the price closest to the end of the time interval, taking temporal intervals for each trading day from opening to closing times). As usual, intraday continuous stock returns for the different indexes were computed as the first difference for the logarithmic stock price index and filtered through an autoregressive process of order 1; Fig. 2.

Intraday data were subjected to two types of treatment depending on the type of response obtained from the DFA methodology. The first possibility provided by the DFA analysis was to observe the overall behaviour of a time series (overall time scale analysis). In this response format, the intraday time series was sampled at different time intervals. Specifically, we obtained 30 series of periods of 1 to 30 min for each of the 4 series analysed. For each of these series, we calculated the Hurst exponent for time scales between 5 and 120 min. We could thus determine the specific time scale (minute) from which prices adjusted to fBm with a Hurst exponent of 0.5.

The second possibility was to observe the behaviour of the Hurst exponent in a series for a pre-determined temporal level. This was done by time-varying Hurst through different days for the same time points (e.g., at 9:45:30 or 13:20:30, etc.) in order to locally obtain the Hurst exponent for each time (intraday second analysis). Taking intraday time series every 30 s after opening, we calculated the Hurst exponent for all moments of the trading day. Observing the average behaviour of the Hurst exponent for 74 trading days provided insights into the times of the day when prices tended to converge to an fBm.

4. Results

The Hurst exponent was calculated for the temporal intraday series for 1 to 30 min according to the methodology described in Section 2. The overall time scale analysis results are depicted in Fig. 3, whereas Fig. 4 displays results for the temporal intraday series for 30 s in a moving window of 400 observations (intraday second analysis).

The results for the overall time scale analysis depicted in Fig. 3 indicate that, for large time scales, all series show Brownian motion with an average roughness exponent of $H = 0.5$; this is evidence of uncorrelated behaviour, suggesting that price differences cannot be predicted. However, for small time scales, the results show two different tendencies: (a) price difference dynamics was persistent for the two share indexes and Telefónica stock; and (b) dynamics for the EUR–USD exchange rate was anti-persistent, suggesting a mean-reverting behaviour for small time scales. The time scale was different for each of the markets considered. In particular, persistent behaviour for the DJIA, IBEX-35 and Telefónica stock lasted for periods of less than 14 min, 17 min and 16 min, respectively, whereas the anti-persistence period for the

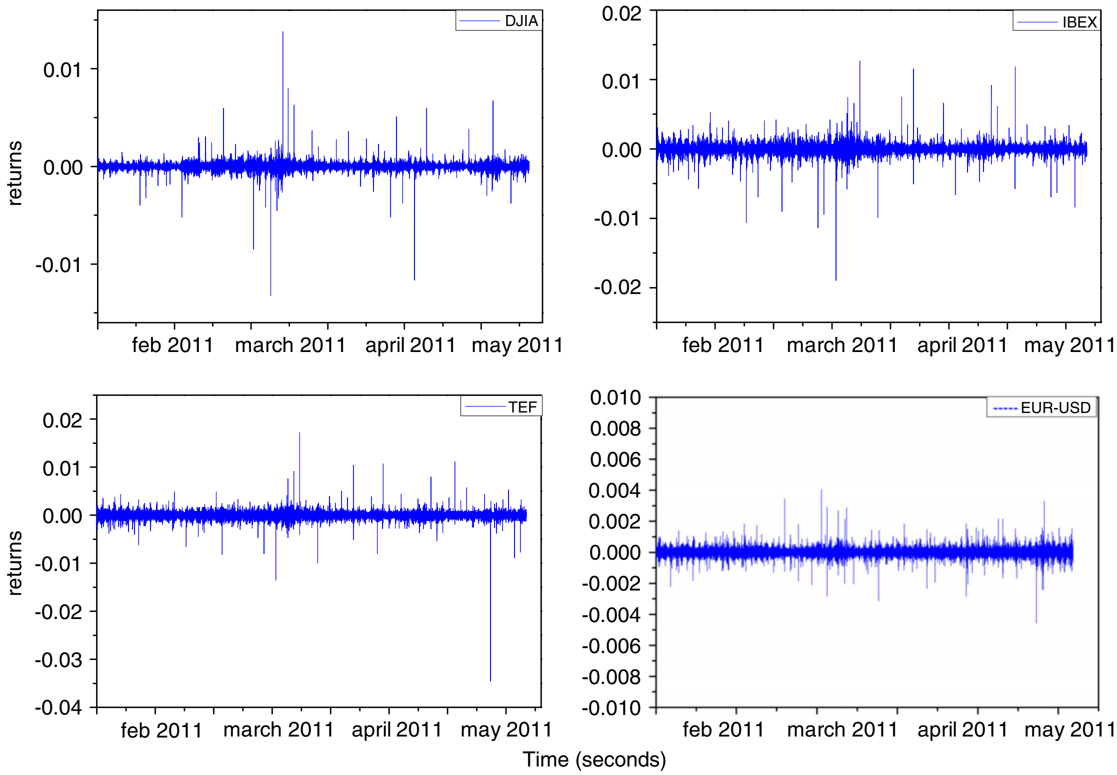

Fig. 2. Returns for DJIA, IBEX-35, Telefónica España stock (TEF) and EUR–USD exchange rate indexes.

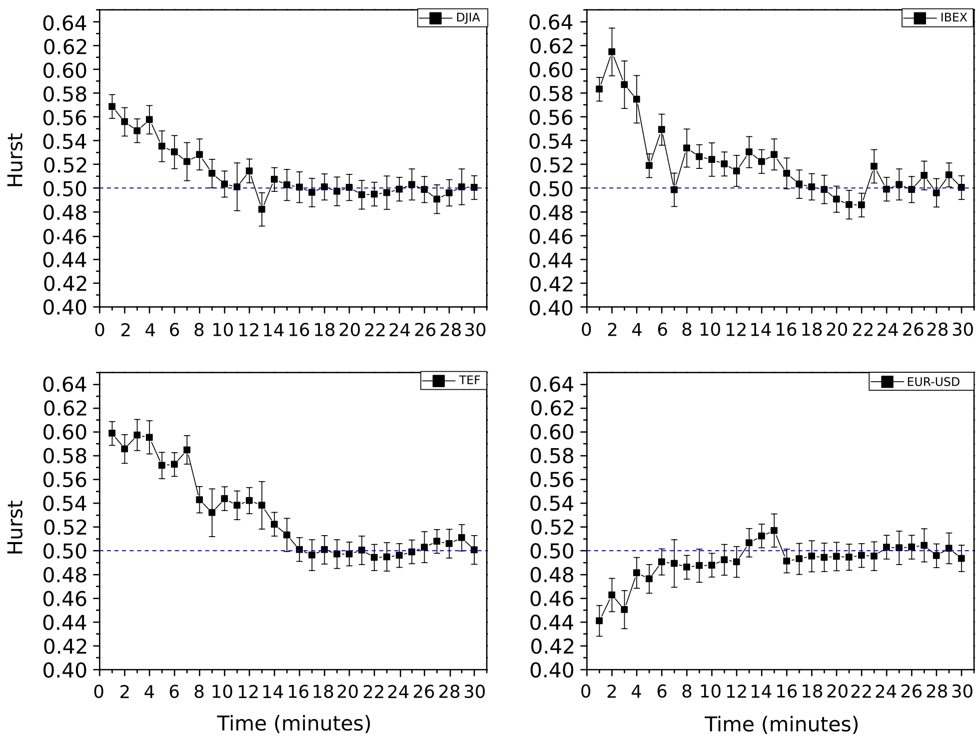

Fig. 3. Time series intraday scale convergence: upper left panel, DJIA index; upper right panel, IBEX-35 index; lower left panel, Telefónica España stock index (TEF); lower right panel, EUR–USD exchange rate index. The error bar is obtained from the standard error adjustment (ordinary least squares) for the Hurst exponent.

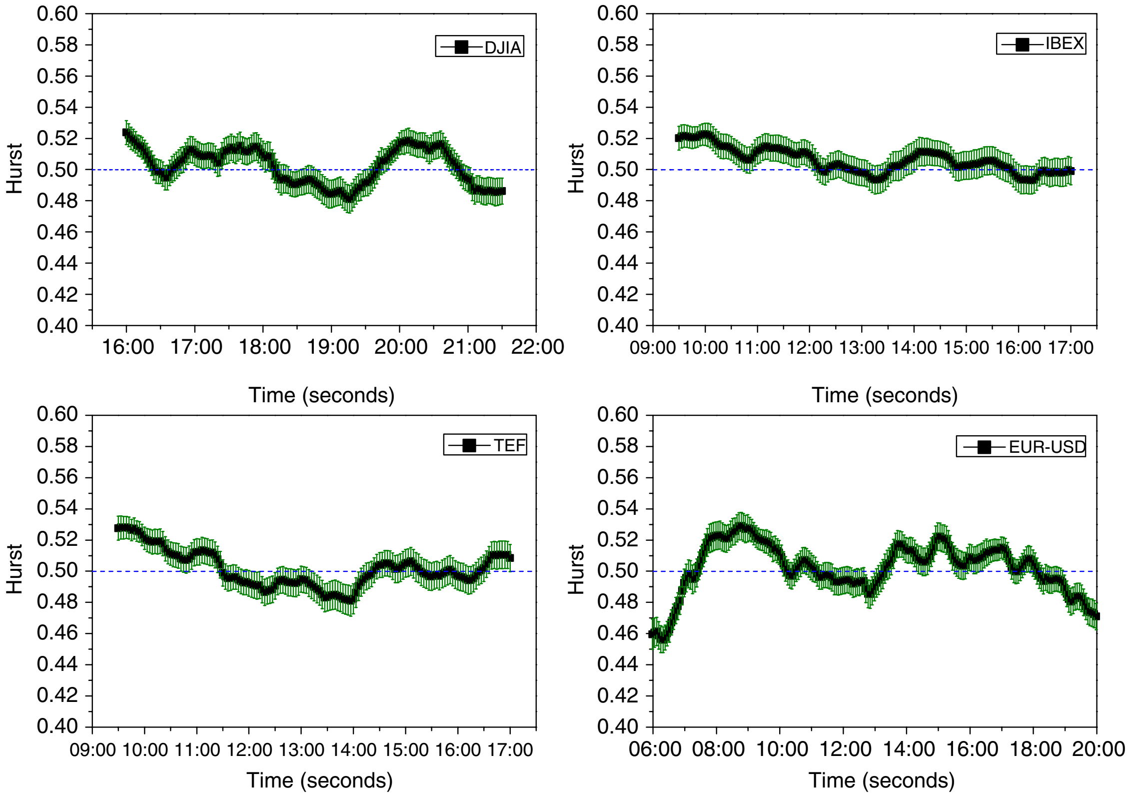

Fig. 4. Average time-varying Hurst exponent for 74 temporal intraday series days (30 s each): upper left panel, DJIA index; upper right panel, IBEX-35 index; lower left panel, Telefónica Españ stock index (TEF); lower right panel, EUR–USD exchange rate index. The solid black line and the green hashed area indicate, respectively, the Hurst exponent value and the Hurst exponent standard deviation during the 74 days. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

EUR–USD exchange rate lasted a mere 7 min. These results suggest different speeds of convergence in different markets and would corroborate the evidence that exchange rate markets converge to an fBm much more quickly than stock markets. This reaffirms the general perception that the exchange market is much more efficient than stock markets. Our results are also consistent with the evidence reported in the literature by Hillmer and Yu [43], Chordia et al. [3,44] and Visaltanachoti and Yang [45], suggesting that prices adjust quickly in the efficient market.

Fig. 4 depicts the behaviour of the mean Hurst exponent throughout the trading day by averaging the Hurst exponent calculated for each intraday time for the 74 trading days. Two different types of scaling behaviour can be observed. For the stock and the indexes, price differences were weakly persistent at the opening and closing trading times, with uncorrelated or unpredictable behaviour for the remainder of the day. This evidence is consistent with intraday volume, volatility and transaction time duration patterns [46]. On the other hand, anti-persistent behaviour can be observed for the EUR–USD series at the beginning and end of the trading day, indicating mean reversion at those times. At midday and in the afternoon, however, the series fluctuated around $H = 0.5$ (random walk). Comparing Figs. 3 and 4, it can be observed that Hurst exponent behaviour for small time scales in the DJIA, IBEX-35 and Telefónica stock series was produced by changes throughout the day. In Fig. 4 the Hurst exponent shows small changes throughout the day; in the EUR–USD series the changes in behaviour are much greater and interfere in the small scale fluctuations shown in Fig. 3.

5. Final remarks

We analysed the speed of convergence to market efficiency by using DFA to examine the scaling properties of intraday prices. We focused on estimating the Hurst exponent for different intraday time scales in order to determine the time scales during which price differences converged to an fBm.

The EUR–USD exchange rate, DJIA, IBEX-35 and Telefónica stock results indicate that there was rapid adjustment to fBm and, throughout the trading day and on small time scales, there was a tendency to assume random walk behaviour, meaning that traders could earn more only in those moments. The results also show that the exchange market is much more efficient than the stock market, since the former converges more quickly to a random walk. For small time scales the exchange market has anti-persistent behaviour, which means behaviour reverts to the mean; stocks, however, start to converge to an fBm with persistent behaviour, which means that future events would have the same behaviour as that previously observed.

The intraday second analysis results show that, on average, behaviour over the trading day tends to converge to an fBm at the beginning and end of the day and does not tend to converge to a random walk as happens in the overall analysis. In conclusion, therefore, persistent behaviour is evident in the stock market, whereas anti-persistent behaviour features the exchange market.

Acknowledgements

We are grateful to three anonymous referees for their helpful comments. Any remaining errors are our own responsibility. The financial support provided by the Xunta de Galicia under research grant INCITE09201042PR and the Spanish Ministerio de Ciencia e Innovación under research grant MTM2008-03010 is gratefully acknowledged.

References

[1] E. Fama, Efficient capital markets: a review of theory and empirical work, Journal of Finance 25 (1970) 383–417.
[2] E. Fama, Efficient capital markets: II, Journal of Finance 46 (1991) 1575–1617.
[3] T. Chordia, R. Roll, A. Subrahmanyam, Evidence on the speed of convergence to market effciency, Journal of Financial Economics 76 (2005) 271–292.
[4] S. Grossman, On the efficiency of competitive stock markets where trades have diverse information, Journal of Finance 31 (2) (1976) 573–585.
[5] S. Grossman, J. Stiglitz, On the impossibility of informationally efficient markets, American Economic Review 70 (1980) 393–408.
[6] B. Cornell, R. Roll, Strategies for pairwise competitions in markets and organizations, Journal Bell of Economics 72 (1981) 201–213.
[7] D. Brown, R. Jennings, On technical analysis, Review of Financial Studies 2 (1989) 527–551.
[8] B. Grundy, M. McNichols, Trade and the revelation of information through prices and direct disclosure, Review of Financial Studies 2 (4) (1989) 495–526.
[9] R. Chakrabarti, R. Roll, Learning from others, reacting, and market quality, Journal of Financial Markets 2 (1999) 153–178.
[10] N. Barberis, A. Shleifer, R. Vishny, A model of investor sentiment, Journal of Financial Economics 49 (1998) 307–343.
[11] K. Daniel, D. Hirshleifer, A. Subrahmanyam, Investor psychology and security market under and overreactions, Journal of Finance 56 (1998) 921–965.
[12] Y. Hong, T. Lee, Inference on predictability of foreign exchange rates via generalized spectrum and nonlinear time series models, Review of Economics and Statistics 85 (2003) 1048–1062.
[13] J. Busse, T. Green, Market efficiency in real time, Journal of Financial Economics 65 (2002) 415–437.
[14] Y. Amihud, H. Mendelson, Trading mechanisms and stock returns: an empirical investigation, Journal of Finance 52 (3) (1987) 533–553.
[15] A. Lo, A. Mackinlay, Stock market prices do not follow random walks: evidence from a simple specification test, Review of Financial Studies 1 (1988) 41–66.
[16] D. Hsieh, Chaos and nonlinear dynamics: application to financial markets, Journal of Finance 46 (1991) 1839–1877.
[17] G. Mcqueen, S. Thorley, Are stock returns predictable? A test using Markov chains, Journal of Finance 46 (1991) 239–263.
[18] D. Kahneman, A. Tversky, Choices, Values, and Frames, Cambridge University Press, New York, 2000.
[19] J. Matias, J. Reboredo, Forecasting performance of nonlinear models for intraday stock returns, Journal of Forecasting 31 (2012) 172–188.
[20] J. Reboredo, J. Matias, R. Garcia-Rubio, Nonlinearity in forecasting of high-frequency stock returns, Computational Economics (2011) (forthcoming).
[21] H. Hurst, Long term storage capacity of reservoirs, Transactions of the American Society of Civil Engineers 116 (1951) 770–799.
[22] W. Brock, W. Dechert, J. Scheinkman, A test for independence based on the correlation dimension, unpublished paper, University of Wisconsin at Madinson and University of Chicago, 1987.
[23] C.K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Mozaic organization of DNA nucleotides, Physical Review E 49 (1994) 1685–1689.
[24] P. Ivanov, Scaling behaviors of heartbeat intervals obtained by wavelet-based time-series analysis, Nature 383 (1996) 323–327.
[25] P. Robinson, Interpretation of scaling properties of electroencephalographic fluctuations via spectral analysis and underlying physiology, Physical Review E 67 (2003) 032902.
[26] A. Bunde, Detecting long-range correlations with detrended fluctuation analysis, Physica A: Statistical Mechanics and its Applications 295 (2001) 441–454.
[27] D.O. Cajueiro, B.M. Tabak, Ranking efficiency for emerging equity markets II, Chaos, Solitions and Fractals 23 (2005) 671–675.
[28] D. Cajueiro, B. Tabak, N. Souza, Periodic market closures and the long-range dependence phenomena in the Brazilian equity market, Physica A: Statistical Mechanics and its Applications 351 (2–4) (2005) 512–522.
[29] D.O. Cajueiro, B.M. Tabak, Testing for predictability in equity returns for European transition markets, Economic Systems 30 (1) (2006) 56–78.
[30] D.O. Cajueiro, B.M. Tabak, Testing for long-range dependence in world stock markets, Chaos, Solitons and Fractals 37 (2008) 918–927.
[31] B. Podobnik, D. Horvatic, F. Pammolli, F. Wang, E. Stanley, I. Grosse, Size-dependent standard deviation for growth rates: empirical results and theoretical modeling, Physical Review E 77 (5) (2008) 056102.
[32] J. Alvarez-Ramirez, E. Rodriguez, J.C. Echeverria, A DFA approach for assessing asymmetric correlations, Physica A: Statistical Mechanics and its Applications 388 (2009) 2263–2270.
[33] B. Podobnik, D. Fu, T. Jagric, I. Grosse, E. Stanley, Fractionally integrated process for transition economics, Physica A: Statistical Mechanics and its Applications 362 (2) (2006) 465–470.
[34] J. Alvarez-Ramirez, J. Alvarez, E. Rodriguez, G. Fernandez-Anaya, Time-varying Hurst exponent for US stock markets, Physica A: Statistical Mechanics and its Applications 387 (24) (2008) 6159–6169.
[35] Y. Wang, L. Liu, R. Gu, J. Cao, H. Wang, Analysis of market efficiency for the Shanghai stock market over time, Physica A: Statistical Mechanics and its Applications 389 (8) (2010) 1635–1642.
[36] X. Lin, F. Fei, Y. Wang, Analysis of the efficiency of the Shanghai stock market: a volatility perspective, Physica A: Statistical Mechanics and its Applications 390 (20) (2011) 3486–3495.
[37] E. Abounoori, M. Shahrazi, S. Rasekhi, An investigation of Forex market efficiency based on detrended fluctuation analysis: a case study for Iran, Physica A: Statistical Mechanics and its Applications 391 (11) (2012) 3170–3179.
[38] T. Mills, The Econometric Modeling of Financial Time Series, Cambridge University Press, New York, 1999.
[39] J. Moreira, J. da Silva, S. Kamphorst, On the fractal dimension of self-affine profiles, Journal of Physics A: Mathematical and General 27 (24) (1994) 8079.
[40] C. Peng, L. Amaral, L. Glass, J. Hausdorff, P. Ivanov, R. Mark, J. Mietus, G. Moody, A. Goldberger, H. Stanley, Components of a new research resource for complex physiologic signals, PhysioNet 101 (3) (2000) 215–220.
[41] B. Podobnik, E. Stanley, Detrended cross-correlation analysis: a new method for analyzing two nonstationary time series, Physical Review Letters 100 (8) (2008) 084102.
[42] B. Podobnik, D. Horvatic, A. Petersen, E. Stanley, Cross-correlations between volume change and price change, Proceedings of the National Academy of Sciences of the USA 106 (52) (2009) 22079–22084.
[43] S. Hillmer, P. Yu, The market speed of adjustment to new information, Journal of Financial Economics 1 (1979) 321–345.
[44] T. Chordia, R. Roll, A. Subrahmanyam, Liquidity and maket efficiency, Journal of Financial Economics 87 (2008) 249–268.
[45] N. Visaltanachoti, T. Yang, Speed convergence to market efficiency for NYSE-listed foreign stock, Journal of Banking and Finance 34 (2010) 594–605.
[46] M. O'Hara, Market Microstructure Theory, Blackwell, Cambridge, 1995.