Department of
Economics and Finance

Working Paper No. 17-06

Economics and Finance Working Paper Series

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April 2017

http://www.brunel.ac.uk/economics

LONG MEMORY AND DATA FREQUENCY IN FINANCIAL MARKETS

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February 2017

Abstract

This paper investigates persistence in financial time series at three different frequencies (daily, weekly and monthly). The analysis is carried out for various financial markets (stock markets, FOREX, commodity markets) over the period from 2000 to 2016 using two different long memory approaches (R/S analysis and fractional integration) for robustness purposes. The results indicate that persistence is higher at lower frequencies, for both returns and their volatility. This is true of the stock markets (both developed and emerging) and partially of the FOREX and commodity markets examined. Such evidence against the random walk behavior implies predictability and is inconsistent with the Efficient Market Hypothesis (EMH), since abnormal profits can be made using specific option trading strategies (butterfly, straddle, strangle, iron condor, etc.).

Keywords: *Persistence, Long Memory, R/S Analysis, Fractional Integration*

JEL Classification: *C22, G12*

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** Luis A. Gil-Alana gratefully acknowledges financial support from the Ministerio de Ciencia y Tecnología (ECO2014-55236).

1. Introduction

The Efficient Market Hypothesis (EMH), according to which asset prices should follow a random walk and therefore not exhibit long memory (see Fama, 1970) has been for decades the dominant paradigm in financial economics. However, the available empirical evidence is quite mixed. Mandelbrot (1972), Greene and Fielitz (1977), Booth et al. (1982), Helms et al. (1984), Caporale et al. (2014), Mynhardt et al. (2014) among others all provided evidence of long-memory behaviour in financial markets. By contrast, Lo (1991), Jacobsen (1995), Berg and Lyhagen (1998), Crato and Ray (2000), Batten et al. (2005) and Serletis and Rosenberg (2007) did not find long-memory properties in financial series. A possible reason for such different findings is that the degree of persistence might change over time as argued by Corazza and Malliaris (2002), Glenn (2007) and others.

The present study aims to examine this possible explanation by estimating persistence in financial time series at three different frequencies (daily, weekly and monthly. The analysis is carried out for various financial markets (stock markets, FOREX, commodity markets), for both returns and their volatility, over the period from 2000 to 2016 using two different long memory approaches (R/S analysis with the Hurst exponent method and fractional integration) for robustness purposes. The hypothesis to be tested is that persistence is higher at lower frequencies.

The layout of the paper is the following. Section 2 describes the data and outlines the empirical methodology. Section 3 presents the empirical results. Section 4 provides some concluding remarks.

2. Data and Methodology

The R/S method was originally applied by Hurst (1951) in hydrological research and improved by Mandelbrot (1972), Peters (1991, 1994) and others analysing the fractal

$$R_{Ia} = \max(X_{k,a}) - \min(X_{k,a}), \quad 1 \leq k \leq n. \qquad (4)$$

4. The standard deviation S_{Ia} is calculated for each sub-period I_a:

$$S_{Ia} = \left(\left(\frac{1}{n}\right) \sum_{k=1}^{n} (N_{k,a} - e_a)^2 \right)^{0,5}. \qquad (5)$$

5. Each range R_{Ia} is normalised by dividing by the corresponding S_{Ia}. Therefore, the re-normalised scale during each sub-period I_a is R_{Ia}/S_{Ia}. In the step 2 above, we obtained adjacent sub-periods of length n. Thus, the average R/S for length *n* is defined as:

$$(R/S)_n = (1/A) \sum_{i=1}^{A} (R_{Ia}/S_{Ia}). \qquad (6)$$

6. The length *n* is increased to the next higher level, *(M - 1)/n*, and must be an integer number. In this case, we use *n*-indexes that include the initial and ending points of the time series, and Steps 1 - 6 are repeated until *n = (M - 1)/2*.

7. Now we can use least square to estimate the equation *log (R / S) = log (c) + Hlog (n).* The angle of the regression line is an estimate of the Hurst exponent *H*. This can be defined over the interval [0, 1], and is calculated within the boundaries specified below (for more detailed information see Appendix C):

- 0 Ò H < 0.5 ï the data are fractal, the EMH is not confirmed, the distribution has fat tails, the series are anti-

There are different approaches to calculate the Hurst exponent (see Appendix A). In most cases de-trended fluctuation analysis (DFA) produces the best results (Weron, 2002; Grech and Mazur, 2004), but for financial series the R/S analysis seems to be the most appropriate (see Appendix B), and therefore is used here. The interpretation of the Hurst exponent is as follows: the higher it

Phillips (2002). In this paper, however, we will employ instead another semiparametric method, which is essentially a local óWhittle estimatorô defined in the frequency domain using a band of high frequencies

Appendix F focuses on the semi-parametric approach, first for the return series (Table F.1) and then for their volatilities (Table F.2). We find again higher persistence at lower frequencies for the stock markets considered, but not the FOREX and the commodity ones. -

in all cases when persistence is higher at lower frequencies there exist profit opportunities (through appropriately designed trading strategies) that are inconsistent with market efficiency.

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Appendix A

Table A.1: Methodology for the Hurst exponent calculations: general review

Author(s)	Methodology*	Results
Taqquetal., (1995)	R/S, DFA	R/S overestimates the Hurst exponent, DFA underestimates it.
Weron, T7 90.24		

Appendix C

Appendix D

R/S analysis

Table D.1: Results of the R/S analysis for the different financial markets, 2004-2016

Appendix F

Semi-parametric method

Table F.1: Estimates of d for the return series

i) Daily

Table F.2: Estimates of d for the volatility series

i) Daily data										
		56	58	60	62	64	66	68	70	72
FOREX	Euro	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
	DJPY	0.448	0.462	0.483	0.493	0.500	0.500	0.500	0.500	0.500
Stock Market	D & J	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500