Journal of Empirical Finance 33 (2015) 104–113

Contents lists available at ScienceDirect

Journal of Empirical Finance

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

Long memory in log-range series: Do structural breaks matter?☆

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ARTICLE INFO

Article history:
Received 18 December 2012
Received in revised form 18 June 2015
Accepted 28 June 2015
Available online 3 July 2015

JEL classification:
C22
C58
G10

Keywords:
Structural breaks
Long memory
Log-range volatility proxy
Stock market

ABSTRACT

This paper examines whether the observed long memory behavior of log-range series is to some extent spurious and whether it can be explained by the presence of structural breaks. Utilizing stock market data we show that the characterization of log-range series as long memory processes can be a strong assumption. Moreover, we find that all examined series experience a large number of significant breaks. Once the breaks are accounted for, the volatility persistence is eliminated. Overall, the findings suggest that volatility can be adequately represented, at least in-sample, through a multiple breaks process and a short run component.

1. Introduction

The modeling of financial time series volatility has been a flourishing field of research. A number of theoretical and empirical studies focus on the apparent persistence in volatility manifested by slowly decaying autocorrelation functions which induces the frequent characterization of volatility as a long memory process (see Ding et al., 1993).

At the same time, many studies point out that structural breaks or regime switches may induce spurious long memory effects in time series (see for example Liu, 2000; Diebold and Inoue, 2001; Granger and Hyung, 2004; Stărică and Granger, 2005 and Davidson and Sibbertsen, 2005). They provide examples in which long memory can be easily confused with structural breaks, concluding that it is very difficult to distinguish between true and spurious long memory processes (see for instance Berkes et al., 2006 and Zhang et al., 2007). A growing strand of literature has tried to address the issue by developing tests that distinguish between true and spurious long memory. For example, we refer the Berkes et al. (2006), Ohanissian et al. (2008), Perron and Qu (2010), Qu (2011) and Shao (2011) tests. For reviews on structural breaks and long memory, we refer to Sibbersten (2004), Banerjee and Urga (2005) and Perron (2006).

From an empirical point of view, although the existing literature that examines long memory or structural changes is prominent, studies that focus on their interaction are limited but steadily growing. The distinction between long memory and structural breaks has not produced, yet, a clear answer as to which feature characterizes volatility time series or which feature is dominant. However

☆ We are grateful for the helpful and insightful comments to the editor and two anonymous referees. We would also like to thank the participants at the 5th CSDA International Conference on Computational and Financial Econometrics, University of London, UK, and at the 17th Annual International Conference of Macroeconomic Analysis and International Finance, University of Crete, Greece, for the useful suggestions on earlier drafts of this paper. We gratefully acknowledge the financial support from the University of Patras, Greece (Caratheodory Research Grant C.909). All remaining errors are the authors' responsibility.

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http://dx.doi.org/10.1016/j.jempfin.2015.06.003
0927-5398/

the correct classification of volatility as either long memory process or a process subjected to structural breaks or both can lead in measurable forecasting gains. Choi et al. (2010) examine the existence of structural breaks and long memory in daily exchange rate realized volatility series, establishing that part of long memory is due to structural breaks. McMillan and Ruiz (2009) find that the long memory property largely disappears when volatility time-variation is taken into account in absolute stock returns. Bisaglia and Gerolimetto (2009) examine the existence of long memory and occasional breaks in daily log absolute returns, concluding that the series is characterized by structural breaks and not by long memory. Morana and Beltratti (2004) find that while long memory is evident in the daily exchange rate realized volatility, this feature is partially explained once changes are accounted for.

This paper provides empirical evidence whether the long memory behavior observed in daily log-range series could be spurious and, drawing on these findings, investigates if the long memory behavior can be explained by the presence of (frequent) structural breaks. Using data from the US stock market, we find strong evidence of long memory in log-range series. The break analysis indicates that all series under scrutiny experienced a large number of structural breaks. After controlling for the mean level changes, the long memory feature is no longer supported.

The rest of the paper is organized as follows. Section 2 presents the log-range volatility proxy and the data. Section 3 presents the long memory approach and includes the discussion of our results. Section 4 provides the structural break analysis and the subsequent discussion while Section 5 concludes.

2. Volatility proxy and data

In this study, volatility is approximated by the log-range. The range based volatility proxies are considered more efficient compared to the classical return-based volatility estimators, a fact known since the work of Garman and Klass (1980) and Parkinson (1980). Following Alizadeh et al. (2002), we formulate the log-range volatility proxy as the difference between the highest and lowest log prices

$$R_t = \ln(\ln(H_t) - \ln(L_t)) = \ln(\ln(H_t/L_t))$$

where H_t and L_t denote the highest and the lowest price of the t day. The superior efficiency of the log-range is demonstrated by Alizadeh et al. (2002) who find that under benchmark assumptions on the data generating process, the log-range standard deviation is about one quarter of the standard deviation of the log absolute returns. As such, the log-range volatility proxy outperforms the usual volatility proxies of log absolute or squared returns since its adoption curtails the impact of noise present in the absolute or squared log-return measures of volatility. In addition, as shown by Alizadeh et al. (2002), range based volatility estimation can be powerful and convenient due to its apparent near log-normality. The log-range is nearly normally distributed[1] with mean $0.43 + h_t$ and variance 0.29^2, with h_t the daily log-volatility ($h_t = \ln \sigma_t$)

$$R_t \approx N\left(0.43 + h_t, 0.29^2\right)$$

while it is robust toward microstructure effects, particularly in liquid markets.

We study the S&P 500 and Dow Jones Industrial Average (DJIA) indices along with the thirty stocks that were components of the Dow Jones Industrial Average index as of 20/06/2011, namely AA, AXP, BA, BAC, CAT, CSCO, CVX, DD, DIS, GE, HD, HPQ, IBM, INTC, JNJ, JPM, KFT, KO, MCD, MMM, MRK, MSFT, PFE, PG, T, TRV, UTX, VZ, WMT and XOM. The data sample runs from January 2nd 2002 to June 20th 2011, covering the period after the dotcom bubble and the recent financial crisis, resulting in a total of 2384 daily observations.

Fig. 1 shows the AA log-range series and its autocorrelation function as an example.[2] The top panel presents the log range series, while the bottom presents the autocorrelation function up to T–1 lag. The autocorrelation function decreases to zero approximately at lag 400, reaches a minimum value at lag 1000 and goes back to near zero values at distant lags. Perron and Qu (2010) demonstrate that this shape of the autocorrelation function could characterize a short memory process with level shifts. Though, if we restrict our attention to autocorrelations up to lag 400, the function decays in a hyperbolic pattern akin to a long-memory process.

3. Long memory estimation

3.1. Long memory

Baillie (1996) provides a detailed survey of econometric work on long memory and its application in economics and finance. One definition of long memory for a stationary discrete time series process, y_t, is that

$$\lim_{n\to\infty} \sum_{j=-n}^{n} \left|\rho_j\right| = \infty$$

[1] See also, Brandt and Jones (2006).

[2] In order to save space, we use the AA DJIA component as a representative series for the figures.