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IS MARKET FEAR PERSISTENT?
A LONG-MEMORY ANALYSIS

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June 2017

Abstract

This paper investigates the

1. Introduction

According to an old saying on Wall Street the market is driven by just two emotions: fear and greed. Shefrin (2000) in his famous book "Beyond Greed and Fear" claims that they are the most important of a number of heuristic-driven biases influencing investors and resulting in market inefficiencies. Zweig (2007) points out that agents are often in the grip of emotions without even realising it and provides an interesting example: a survey of 1,000 investors suggested that there is a 51 percent chance that in any given year the US stock market will drop by one third, whilst on the basis of historical data the odds that US stocks will lose one third of their value in any given year are only around 2 percent. This misperception of reality is a direct result of fear and represents evidence that investors are not fully rational.

Shefrin (2000) points to behavioural anomalies in individual investors, institutional money managers, and corporate managers regardless of their training or experience; moreover, such anomalies can be observed in all market sectors, including equities, fixed income, foreign exchange, commodities, and options. Shiller (2003) argues that some changes in prices occur not for fundamental reasons, but because of mass psychology instead. Other behavioural finance studies have provided more evidence that is inconsistent with the Efficient Market Hypothesis (EMH), according to which investors are rational, and asset prices fully reflects all available information and therefore should follow a random walk (see Malkiel and Fama, 1970).

Analysing investor sentiment and fear in particular is therefore crucial. Surprisingly, to date there is no study investigating the long-memory properties of the latter. The present paper aims to fill this gap in the literature by examining the degree of persistence of the very popular VIX index, also known as CBOE Volatility Index. This can be interpreted as a "fear" index, since according to Whaley (2000) it is an 'investor fear gauge' that reaches higher levels during periods of market turmoil. We use two different long-memory approaches (R/S analysis with the Hurst exponent method and fractional integration) to analyse persistence of the VIX over the sample period 2004-2016, as well as some sub-periods (pre-crisis, crisis and post-crisis) to see whether it varies over time depending on market conditions.

The results of our analysis are of interest to both academics and practitioners. They can be informative about the nature of financial bubbles and anti-bubbles, and provide evidence on whether there exist market inefficiencies that could be exploited to make abnormal profits by designing appropriate trading strategies. A better understanding of financial markets can be gained by applying quantitative methods to behavioural finance to analyse investor sentiment as in our study. Its layout is the following: Section 2 provides a brief review of the literature on market fear; Section 3 describes the data and outlines the methodology; Section 4 presents the empirical results; Section 5 provides some concluding remarks.

2. Literature

caused by the emotional reactions of investors affected their behaviour for years (for more details see Keim and Madhavan, 2000). According to Baba Shiv et al. (2005) after incurring losses agents are less inclined to invest and prefer to stay out of the market. There is plenty of evidence that losing streaks influence their behaviour (see, e.g., Zalla et al., 2000; Breiter et al., 2001 etc.).

Losses or market instability make investors more vulnerable to fear, which often results in irrational behaviour and costly mistakes. Johnson and Tversky (1983) find that 50 percent of agents can recognise when they have been affected by a bit of negative news, but only 3 percent admit that this may influence their degree of risk aversion. Slovic (1987) proves that fast and finite dangers (fireworks, skydiving, train crashes, etc.) feel more “knowable” (and less worrisome) than vague, open-ended risks such as genetically modified foods or global warming. Agents underestimate the likelihood and severity of common risks, and overestimate those of rare risks (see Zweig, 2007).

A few studies have attempted to analyse market fear empirically using measures such as the VIX index (also known as the CBOE Volatility Index or Fear index), the CNN Money Fear & Greed Index, the IVX and the CBOE Skew Index. By far the most popular is the VIX, which is derived from the prices of S&P 500 options and yields the expected annualised change in the S&P 500 index over the following 30 days. It is an implied volatility index: the lower its level, the lower is demand from investors seeking to buy protection against risk and thus the lower is the level of market fear.

Most papers analysing the VIX have focused on its predictive power for future returns. Giot (2005) finds that high (low) levels of the VIX correspond to positive (negative) future returns. Guo and Whitelaw (2006) and Chow et al. (2014) also show that there is a positive relationship between market returns and the VIX. Heydon et al. (2000) find that global equity markets outperform bond markets after periods of relatively high expected volatility in the US market and vice versa. Chow et al. (2016) estimate that approximately one-third of the VIX is attributable to the tail risk premium. Fleming et al. (1995) were the first t

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

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

window", where the size of the shift depends on the number of observations and a sufficient number of estimates is required to analyse the time-varying behaviour of the Hurst exponent. For example, if the shift equals 10, the second value is calculated for 10.04.2004 and characterizes the market over the period 10.01.2004 till 09.04.2004, and so on.

The second approach we follow to analyse persistence involves estimating

Hurvich and Ray (1995), Velasco (1999a, 2000), Shimotsu and Phillips (2002) etc. For our purposes we use another method, which is essentially a local 'Whittle estimator' defined in the frequency domain using a band of high frequencies that degenerates to zero. The estimator is implicitly defined by:

(8)

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

where m is a bandwidth parameter, and $I(\lambda_s)$ 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 (1995b) proved that:

$$\sqrt{\ }$$

where d_o is the true value of d. This estimator is robust to a certain degree of conditional heteroscedasticity and more efficient than other semiparametric alternatives; it has been further developed by Velasco (1999b), Velasco and Robinson (2000), Phillips and Shimotsu (2004, 2005) and Abadir et al. (2007).

The parametric estimation of *d* and the other model parameters can be carried out either in the frequency domain or in the time domain. For the former, Sowell (1992) analysed the exact maximum likelihood estimator of the parameters of the ARFIMA model, using a recursive procedure that allows a quick evaluation of the likelihood function. Other parametric methods for estimating *d* based on the frequency domain were put forward by Fox and Taqqu (1986), Dahlhaus (1989) etc. (see also Robinson, 1994, Demetrescu et al., 2008, and Lobato and Velasco, 2007 for Wald and LM parametric tests based on the Whittle function).

In the following section we use both parametric (Robinson, 1994) and semiparametric (Robinson, 1995a, Abadir et al., 2007) techniques for testing and estimating the fractional differencing parameter *d*.

4. Empirical Results

The results of the R/S analysis on the return series for the whole sample and different sub-samples are presented in Table 1.

Table 1: Results of the R/S analysis for the whole sample and different sub-samples, 2004-2016

Period	Daily frequency	Monthly
Whole sample	0.41	0.53
Pre-crisis (2004-2006)	0.44	0.36
Crisis (2007-2009)	0.46	0.70
Post-crisis (2010-2016)	0.41	0.47

As can be seen, market fear does not follow a random walk, and the estimates depend on the data frequency. For the daily data it is anti-persistent (returns are negatively correlated). However, in the case of monthly data during the crisis period it exhibits persistence (returns are positively correh[( )] TJ8.51 Tmt-37(a)4(2BT)-21alf9t-37(1*372.3 TJET exponent estimates equals the number of dividing periods (156 months for the case of Figure 1 or 26 half-year case of Figure 2).

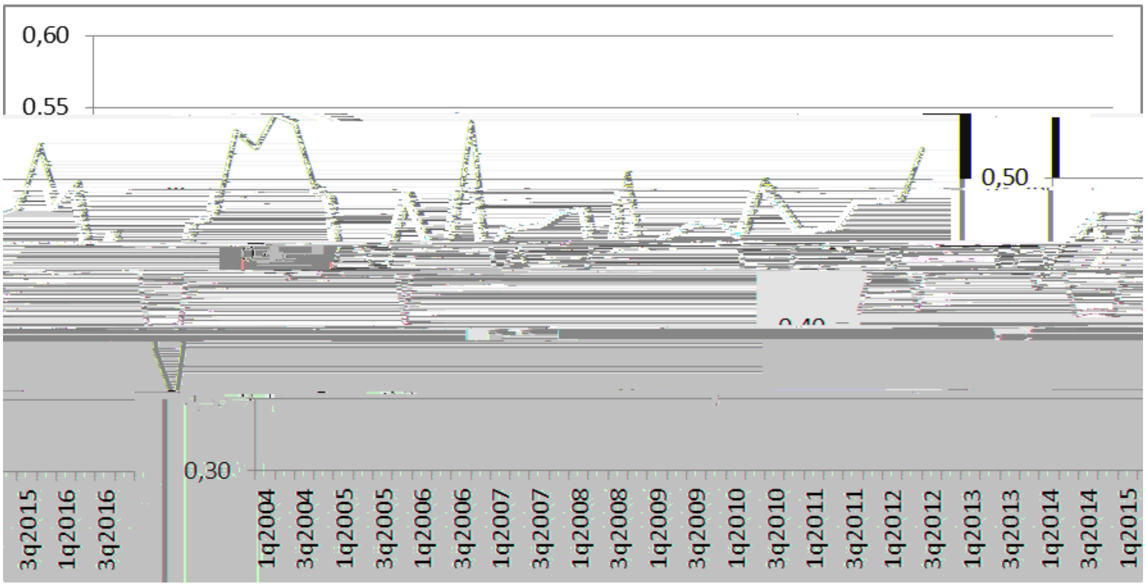

Figure 1: Results of the dynamic R/S analysis for the daily data, 2004-2016 (step=55, data window=300)

Figure 2: Results of the dynamic R/S analysis for the monthly data, 2004-2016 (step=4, data window=48)

As can be seen the degree of persistence varies over the time, being higher during the crisis period. This confirms the previous static findings.

The results for the fractional integration methods and using the index prices are presented in Tables 2 and 3. First, we display in Table 2 the estimates of d along with their corresponding 95% confidence interval based on a substantial differences between them, the highest degrees of persistence being found in the crisis period, during which the values of *d* are higher than 0.8 in virtually all cases and the I(1) hypothesis cannot be rejected. This is in contrast with the results for the pre- and post-crisis periods where mean reversion (i.e. $d < 1$) is found in all cases, which implies anti-persistent behaviour in the returns, consistently with the results from the R/S analysis.

Table 4a: Estimates of d based on a semiparametric method

Daily frequency	$m = (T)^{0.4}$	$m = (T)^{0.5}$	$m = (T)^{0.6}$
Whole sample	0.680	0.763	0.901
Pre-crisis (2004-2006)	0.588	0.578	0.652
Crisis (2007-2009)	0.958*	1.076*	0.990*
Post-crisis (2010-2016)	0.523	0.659	0.768

to 2016; using two different techniques, as well as analysing different data frequencies over a long sample including the most recent observations decreases the possibility of data snooping bias. Specifically, the R/S statistic is computed for the return series, whilst price indices are analysed applying I(d) techniques.

The results from the two approaches are consistent and indicate that market fear does not follow a random walk. It normally exhibits anti-persistence, but in crisis periods its persistence increases, which also suggests crowd effects. The fact that the long-memory properties of market fear are unstable and

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