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Can trade opportunities and returns be generated in a trend persistent series? Evidence from global indices

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HIGHLIGHTS

- Identified trend persistence in a series using time-varying Hurst exponent.
- Used a 12 month rolling window approach in 31 global indices.
- Developed trading strategies based on Hurst exponent and previous month return.
- Tested trading strategies and identified trading strategies that generated positive returns.

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ABSTRACT

In this study, we explore the possibility of generating trade opportunities and returns when a financial stock index series is trend persistent. Through application of Hurst coefficient based on the modified range to standard deviation analysis (Weron, 2002) in a sample of 31 leading global indices during the period December 2000 to November 2015, we found periods of trend persistence. We developed and tested a set of trading strategies on these periods of trend persistent in the financial series and found that significant positive returns can be generated when a series displayed upward trend persistence.

1. Introduction

Long memory has been a popular research topic in finance and economics. Long memory in stock return data means that higher-order correlation structures exist in the time series and that there is trend persistence in a series. Trend persistence means stock prices follow the same trend in the future as in the past months and consequently, there is a possibility of predicting returns of a financial series. A common technique used to detect long memory (trend persistence) in a financial time series is the Hurst exponent that is estimated through various methodologies. Academicians have used a rescaled Hurst exponent, modified Hurst exponent and various other methods to detect long memory (trend persistence). The estimated Hurst exponent (H) value lies between $0 \leq H \leq 1$. When H is greater than 0.5, a series displays trend persistence. Most of the studies have focused on detection of trend persistence in a financial series, but whether the trend persistence behavior can be used to generate positive return from the stock market is not established. In this paper, we add to the existing literature by exploring the possibility of generating return opportunities using a sample of 31 leading global indices based on a Hurst exponent criteria (i.e. $H > 0.5$ that implies a series displays trend persistence). Detection of trend persistence and its application in asset prices is vital for practitioners since its existence can have a significant impact on portfolio selection and trading strategies.

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The paper provides a systematic examination of using Hurst exponent value for trading in stock indices using the following three steps, First, we estimated the Hurst exponent for each stock index on a rolling window of past 12 months. Second, if the Hurst exponent of a series was greater than 0.5, a series implied trend persistent series. Based on the trend persistence behavior of a series and past month return trading strategies were developed. An open position in the index was initiated based on the trading strategies at the beginning of the month. All open index positions were closed at the end of the month. Third, returns from various trading strategies were analyzed and a strategy where Hurst exponent can be successfully used is identified.

The argument of this paper has been presented in 6 sections. Section 1 is Introduction, Section 2 discusses previous studies, Section 3 describes the data sources and data preparation, Section 4 discusses the methodology. Empirical results and discussion are presented in Section 5 and in Section 6 we present a brief summary and conclusion.

2. Previous studies

Most previous studies[1] show that long-memory implying trend persistence exists in various financial assets. Mandelbrot [5] and Greene and Fielitz [1] identified long memory in 200 daily stock return series using a rescaled Range to standard deviation (RS) statistic.[2] However, their method failed to distinguish between short and long memory. Lo[3] proposed that his modified RS statistic could capture the difference between short and long memory. However, Willinger et al. [13] and Jacobsen [14] found empirical evidence that Lo's modified range to standard deviation statistic was conservative and provided inconsistent results when short-memory existed along with long memory. Methods to calculate Hurst exponent were suitable for large data samples, and overestimated the Hurst exponent for a small sample. Hence, Annis and Lloyd [15] resolved the problem of over-estimation in small samples to a certain extent with Peters [4] and Weron [16] further improving the technique of estimation. Most academicians have estimated a static value of Hurst exponent over a fixed window, but the Hurst exponent may not remain a fixed value throughout.[4]

Some authors[5] suggest that calculating a fixed value of Hurst exponent over a fixed window may be misleading. Corazza and Malliaris [17] and Carbone et al. [20] find empirical evidence that the Hurst exponent value does not remain fixed throughout and a time-varying Hurst exponent is more apt to capture long memory (implying trend persistence) in return data. Granero et al. [21], Cajueiro and Tabak [18] have attempted to estimate a time-varying Hurst exponent; however, they did not consider the possibility of generating theoretical trading opportunities based on the trend persistent behavior of the financial series. The present paper tries to fill this gap to some extent by exploring the option of generating theoretical trading returns in 31 global indices based on the trend persistent behavior exhibited by these indices.

3. Data sources and preparation

In this section, we provide the description of the sample of 31 global indices. The data sample included monthly stock index data of 31 stock market indices belonging to major leading stock markets in twenty-five countries from December 1999 to November 2015. The data was extracted from Bloomberg data systems. These 31 indices belonged to 25 of the lower-middle income (LMI), upper middle-income (UMI) and high-income (HI) countries across the world.[6] High-income countries included United States, Canada, Australia, United Kingdom, Germany, France, Belgium, Greece, Switzerland, Ireland, Spain, Austria, Japan, Hong Kong, Singapore, Taiwan and Argentina. Upper-middle income countries included, Mexico, Brazil, China, Malaysia, South Korea and Turkey. Lower-middle income countries included India and Indonesia. A brief description of 31 global indices is mentioned in Table 1. Each index is either a capital weighted or price-weighted index. Each countries index comprises the largest capital stocks listed on a countries' stock exchange. These largest capital stocks represent 60%–90% of the respective countries' stock market capitalization.

A summary of descriptive statistics of 31 indices is presented in Table 2.

To arrive at the descriptive statistics the data was prepared using a 3-step procedure:

- **Step 1**: In the study, the stock index series was denoted as "i" ($i = \{1, 2, \ldots, 31\}$) and "ℓ" number of months ($\ell = \{1, 2, \ldots, 192\}$) corresponding months from December 1999 to November 2015. The stock index value of the

1 Greene and Fielitz [1]; Booth and Kaen [2]; Helms et al. [3] and Peters [4].

2 Peters [6,7,4], Crato [8], Crato and de Lima [9], Mills [10] and Goetzmann [11] found empirical evidence of long memory in select European and US stock returns.

3 Lo [12].

4 Corazza and Malliaris [17] find empirical evidence of long memory in the financial time series under study and also find that Hurst exponent varies with time. (Also see: Refs. [18,19]).

5 Cajueiro and Tabak [18] and Cajueiro and Tabak [19].

6 According to World Bank, 2017, High-income economies are defined in accordance with their Gross National Income (GNI) per capita per year. These countries have a GNI more than US Dollar 12,476 or more per year. Upper middle-income economies are those with a GNI per capita between US Dollar 4036 and US Dollar 12,475 $1025. Lower middle-income economies are those with a GNI per capita between US Dollar 1026 and US Dollar 4035. Low income economies are those with a GNI per capita below US Dollar 1025. Refer to GNI based classification available on the World Bank Website, https://datahelpdesk.worldbank.org/knowledgebase/articles/906519, accessed on 10 June 2016.