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### Multifractal analysis of Moroccan family business stock returns



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#### h i g h l i g h t s

- Multifractality is investigated in Moroccan family business stock returns.
- Results are compared against Casablanca Stock Exchange main indices: MASI and MADEX.
- Evidence of multifractality is found in returns on family business stocks, MASI, and MADEX.
- Short and long dynamics in family business returns are different from those of market indices.
- Family business stocks are less risky than the market.

#### a r t i c l e i n f o

*Article history:* Received 6 April 2016 Received in revised form 1 May 2017 Available online 3 June 2017

*Keywords:* Multifractal Multifractal detrended fluctuation analysis Stock market Family business Emergent markets

#### a b s t r a c t

In this paper, long-range temporal correlations at different scales in Moroccan family business stock returns are investigated. For comparison purpose, presence of multifractality is also investigated in Casablanca Stock Exchange (CSE) major indices: MASI which is the all shares index and MADEX which is the index of most liquid shares. It is found that return series of both family business companies and major stock market indices show strong evidence of multifractality. In particular, empirical results reveal that short (long) fluctuations in family business stock returns are less (more) persistent (anti-persistent) than short fluctuations in market indices. In addition, both serial correlation and distribution characteristics significantly influence the strength of the multifractal spectrums of CSE and family business stocks returns. Furthermore, results from multifractal spectrum analysis suggest that family business stocks are less risky. Thus, such differences in price dynamics could be exploited by investors and forecasters in active portfolio management.

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#### **1. Introduction**

Hurst exponent [\[1–](#page--1-0)[3\]](#page--1-1) has been applied as a measure of long memory in time series to better describe the dynamics of its structural correlations with applications in engineering and science  $[4-16]$  $[4-16]$ , and also in econophysics  $[17-33]$  $[17-33]$ . In particular, multifractal detrended fluctuation analysis (MF-DFA) [\[3\]](#page--1-1) has become more attractive than conventional DFA [\[2\]](#page--1-6) as it allows detecting long range correlations that varies with time scale. Indeed, DFA [\[2\]](#page--1-6) is capable to detect presence of monofractal scaling properties in a given time series; however, it cannot be applied to detect presence of multifractality. In this regard, Kantelhardt et al. [\[3\]](#page--1-1) proposed the MF-DFA as a general extension of the classical DFA [\[2\]](#page--1-6) to characterize multifractality in non-stationary time series. In particular, MF-DFA is suitable to examine presence or absence of long memory in short and long variations of the time series contrary to standard DFA. In short, MF-DFA leads to a much better understanding of long memory complexity in non-stationary time series.

<http://dx.doi.org/10.1016/j.physa.2017.05.048> 0378-4371/© 2017 Elsevier B.V. All rights reserved.







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In econophysics, MF-DFA was effective in the analysis of economic and financial data where evidence of multifractality was found [17-[36\]](#page--1-7). In this regard, multifractal analysis by using MF-DFA is a common technique to investigate long-range dependence in short and long variations in asset prices. Such investigations are essential to build prediction models to improve portfolio management in terms of optimal asset allocation and risk management. For instance, one could determine whether or not prices possess long-memory to decide which type of forecasting model is appropriate.

Several works found in the literature have examined multifractal characteristics in stock markets [\[37,](#page--1-8)[38\]](#page--1-9). However, no attention has been given to family business stocks which are known to have a distinct ability for competitive advantage [\[39\]](#page--1-10), to attract customers and increase sales  $[40]$ , to exhibit high profitability  $[41]$ , and to grow at international level  $[41]$ . Certainly, these abilities are attractive for investors and managers. Therefore, the main purpose of this paper is to study long memory at different scales in Moroccan family business stock returns by using MF-DFA. Second, for comparison purpose, we also investigate this issue in returns of Casablanca Stock Exchange (CSE) major indices; namely, the MASI which is the all shares index and the MADEX which is the index of most liquid shares traded on CSE.

Indeed, our paper contributes to the literature by examining multifractal patterns in family business stock returns from different industrial sectors in an emergent stock market; for instance, the CSE in Morocco. In particular, we seek to investigate whether multifractal exists in these returns, and whether there are differences between dynamics of family business stock returns and dynamics of stock market returns. These interesting points surely help understanding the dynamics of family business stock returns in comparison with the market major indices. In addition, sources of multifractal are also investigated.

Our methodology is described as follows. The MF-DFA will be applied to return series of an index used to represent all family business listed on CSE. Similarly, MF-DFA will be applied to MASI and MADEX. Then, Hurst exponent is obtained at each scale for each market index; namely, family business index, MASI, and MADEX. In particular, we seek to check if the scaling behaviour of small fluctuations (corresponding to high scales) is different from that of the large variations (corresponding to low scales) in all indices under study. Thus, we can compare multifractal behaviour in returns on family business stock returns with multifractal behaviour in returns of CSE major indices. In this regard, the relationship between Hurst exponent and scale will be used to describe long memory in short and long fluctuations in return series of all three considered indices. In addition, for each market index, the time-varying singularity spectrum will be examined to assess the magnitude of multifractality. Furthermore, the standard multifractal mass function will be employed to examine multifractal spectrum distribution of return series at different scales. Finally, shuffled and surrogate return series are analysed to examine sources of multifractality.

Our paper is organized as follows. Next section briefly describes MF-DFA. Section [3](#page--1-13) presents the empirical results. Finally, last section concludes our work.

#### **2. Methods**

The multifractal detrended fluctuation analysis (MF-DFA) [\[3\]](#page--1-1) is an extension of the classical DFA [\[2\]](#page--1-6) used to estimate Hurst exponent of a time series at different scales. Let {*x<sup>k</sup>* : *k* = 1, 2, . . . , *N*} be a time series of length *N*. Then, MF-DFA is based on the following computational steps [\[33\]](#page--1-5):

*Step one*: the profile  $Y_i$  ( $i = 1, 2, ..., N$ ) is determined as follows:

$$
Y_i = \sum_{k=1}^i (x_k - \bar{x})
$$
\n<sup>(1)</sup>

where  $\bar{x}$  is the average of the time series  $x_k$ .

*Step two*: the profile  $Y_i$  ( $i = 1, 2, ..., N$ ) is divided into  $N_s$  non-overlapping segments (windows) of equal length *s* such that:

$$
N_s = \operatorname{int}\left(\frac{N}{s}\right). \tag{2}
$$

This procedure is repeated starting from the opposite end. Indeed, a small part at the end of the profile *Y<sup>i</sup>* could not be included in any time segment as *N* may not be an integer multiple of the time scale *s*. Consequently, 2*N<sup>S</sup>* segments (windows) are obtained.

*Step three*: a least square fit is employed to calculate the polynomial local trend for each of the 2*N<sub>S</sub>* segments. Then, the variance is calculated by eliminating the local trend of each sub-interval v (for  $v = 1, 2, \ldots, N_s$ ) as follows:

$$
F^{2}(s, v) = \frac{1}{s} \sum_{i=1}^{s} [Y((v-1)s + i) - P_{v}(j)]^{2}
$$
\n(3)

or, for  $v = N_s + 1$ ,  $N_s + 2$ , ...,  $N_s$  as follows:

$$
F^{2}(s, v) = \frac{1}{s} \sum_{i=1}^{s} [Y(N - (v - N_{s})s + i) - P_{v}(j)]^{2}
$$
\n(4)

where  $P_{\nu}(j)$  is the fitting polynomial in segment  $\nu$ .

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