Long Memory in the Indonesia Stock Exchange

Martin P. H. Panggabean
Faculty of Economics and Business, Universitas Katolik Indonesia Atma Jaya, Indonesia,
martin.panggabean@atmajaya.ac.id

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Martin P. H. Panggabean*
Faculty of Economics and Business, Universitas Katolik Indonesia Atma Jaya, Indonesia

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The aim of this study is to investigate the existence of long-memory process in the Indonesia stock market. This study provides two major contributions and one anomaly. First, this is the first study on long-memory conducted on the Indonesia Stock Exchange at individual stocks. Second, this study uses the method of Detrended Fluctuation Analysis (DFA), supplemented by empirical confidence interval introduced by Weron (2002) and Kristoufek (2010). Our analysis uncover an anomaly that three out of thirteen of the most liquid shares in the Indonesia Stock Exchange exhibit mild long memory process in the daily return data. This result, however, is not robust to length of series utilized. All thirteen stocks exhibit long memory process in the absolute daily return which represent risk.

Keyword: *Long Memory; IDX; DFA; Equity; Confidence interval*

JEL Classification: G1; G10; G14; C01; C12; C59

Introduction

According to the weak form of Efficient Market Hypothesis (EMH), current prices reflect all publicly available information (Malkiel, 2003). Accordingly, the markets are conjectured as following a random walk where price movements are unrelated to past activities. The absence of linear correlations between current price changes with past price changes provide a statistical support for the EMH (i.e. fast-decaying autocorrelation function of price changes). If the EMH is held to be true, then technical analysis to predict future prices are not useful (Eitelman & Vitanza, 2008).

In early 1960s Mandelbrot started writing a series of papers that challenged the market efficiency hypothesis and its assumptions. Mandelbrot (1963) argued for prices changes to be modeled as Levy Distribution. More important to our study, and in contrast to the efficient market hypothesis, Mandelbrot believed that price changes in speculative market behave as a biased random walk series (or, similarly, fractional Brownian motions or fractal time series).

One immediate implication of a biased random walk is that price changes are not independent. That is, price change today carried a memory of preceding events (Peters, 1994, p. 27). In other words, current data is correlated not only with data from recent past (say 2-3 days), but also from distance past (say, 6 months ago). Long memory, therefore, implies an ability of a time series to 'memorize' its distance past.

A time series with long-memory, therefore, provide an evidence against the efficient market hypothesis. In the stock market, this also implies that past data contains some useful information for making future decisions including using technical analysis for trading purposes.

Most of the long-memory early research per-

* Corresponding author's email: martin.panggabean@atmajaya.ac.id

tains to study on developed market. Only few studies relate to developing countries' data. One possible explanation is that there are not too many developing countries that have historically well established capital markets. As such, these countries do not have sufficiently long time-series data (or reasonably long economic time-series data) to be useful for long-memory testing.

Most of the recent studies on developing countries' capital market dealt only at the index level (i.e. asset class). Using data from 1988 to 2013, Tan, Chin, and Galagedera (2014) shows the existence long memory for return series of stock indices in Malaysia and Indonesia Hull. Eight other countries (Hong Kong, Japan, Korea, Singapore, the US, Philippines, Taiwan, and Thailan) return series do not exhibit long memory. For Indonesia, research conducted on stock market concentrates on the market index. The research results are mixed. Eitelman and Vitanza (2008), using 25 years of data, find that the Indonesia stock market index has no long memory. However, Navarro, Tamangan, Guba-Natan, Ramos, and de Guzman (2006), using data from 1994 to 2004, conclude that there is persistently mild long-memory with coefficient of 0.61. In contrast, Samadder, Ghosh, and Basu (2012) observe that there is anti-persistent mild long-memort with coefficient of 0.43. We note that none of these studies conducted results on the stock price level.

For Indonesia, stock market activities become more important, as government tries to induce foreign and domestic investors back to the Indonesia stock market. This study can provide indications on the efficiency of the Indonesia stock exchange, and thus helps the government and investors to formulate necessary strategies for the market.

The aim of our study, therefore, is to investigate the existence of long-memory process in the Indonesia stock market's daily return and absolute daily return at the individual stock level. We further calculate confidence intervals of the estimators using formulas proposed by Weron (2002). As a prelude to future research on long-memory, we also investigate whether long-memory results on longer series carry over when calculated with shorter series.

After this introductory section, a review of relevant literatures regarding long-memory, including brief historical developments, is conducted. This paper then proceeds to the development of computational procedures as well as description of the data to be used in the analysis. Computation results are given for both the return data as well as for absolute return data (which proxies risk), and aslo computational results for different data lengths. Conclusions and implications of the research closes the paper.

Literature Review

Quantitative long memory analysis started in 1951 with the path-breaking work of Hurst (1951). Hurst noted that the Nile river discharge fluctuates with time. However, heavier floods is usually followed by above average floods, i.e. the flood shows persistence over a long period of time.

This type of persistence cannot be modeled by an ARIMA (Autoregressive Integrated Moving Average) process whose autocorrelation function (ACF) declined rapidly after several periods. In contrast, long-memory's ACF decayed hyperbolically, and gets close to zero only over a long period of time (Ding, Granger, & Engle, 1993). The hyperbolically decaying ACF means that a shock in distant past exerts its effect until now. The source of this phenomenon, however, is not a well-researched area. Complex nonlinear dynamic processes seem to be behind this long-memory process (Frechette & Jin, 2002). A thorough mathematical treatment for long-memory process as well as various estimators of long-memory process can be found in a recent work from Beran *et al.*(2016). (Beran, Feng, Ghosh, & Kulik, 2016).

In the economics and financial markets, studies of long-memory is still quite an active area of research. Among the pioneers in the field of long-memory analysis are Granger (1980) and Granger and Joyeux (1980). Since then, the concept has been applied to various topics in the broad field of finance and economics. For a macroeconomic application example, see Diebold and Rudebusch (1989).

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In the financial markets, studies of long-memory process have often yielded contradictory results, which are mainly caused by methodological differences. The most popular method to detect long-memory process is the Rescaled-Range. Other methods include Geweke-Porter-Hudak (GPH), Autoregressive Fractionally Integrated Moving Average (ARFIMA), and Detrended Fluctuation Analysis (DFA).

Using rescaled-range (R/S) statistic espoused by Hurst (1951), Peters (1994, p.60) found the existence of long-memory process in many stock indices in developed markets. Lo (1989), on the other hand, proved that the traditional R/S method may be biased in the presence of short-memory (i.e. ARIMA) process in the data.

While Lo (1991) modified R/S was able to correctly identify the existence long-memory process and provide confidence interval for the R/S statistics (something lacking in the traditional R/S statistics), it has a serious problem as well. Lo (1991) modified R/S depends crucially on knowledge of truncation lag needed to model the short-term dependence. Improper choice of truncation lag leads to a biased estimates of long-memory parameter.

Other estimators came from the spectral density function. This approach was proposed, for example, by Geweke and Porter-Hudak (1983). The Geweke-Porter-Hudak approach (GPH, hereafter) measures the long-memory parameter by regressing series of log periodogram against log of a function of frequencies. For details, the reader is referred to Weron (2002).

Yet another estimator is called ARFIMA, which stands for Autoregressive Fractionally Integrated Moving Average, model. In this model, proposed by Sowell (1992), all the parameters of short-memory and long-memory process are estimated simultaneously using maximum likelihood method of estimation. It is not clear, however, whether this method is superior to the GPH method. (Di Matteo, 2007) emphasizes that each estimator has its own deficiencies which implies that no estimator is uniformly superior to the other estimators..

There is a serious drawbacks of using ARFIMA. A method to choose appropriate lag length of autoregressive (p) and moving average (q) terms is still an unresolved research area (Bhardwaj & Swanson, 2006; Navarro et al., 2006; Reisen, Abraham, & Lopes, 2001). Thus, a wrong choice of p and q will lead to a biased estimate of the long memory parameter d.

Another development in long-memory calculation is obtained through a technique called Detrended Fluctuation Analysis (DFA) as proposed byPeng et al. (1994). Thus far, there are only few studies utilizing the DFA approach in the finance areas, see Weron (2002) for an example. As shown by Weron (2002), DFA has many desirable properties over the previously mentioned indicators. As this is the method that will be used in this study, we will discuss its detail later.

Differences in methodology aside, there is yet another factor that contributes to the contradictory results in empirical works. The R/S method (and the DFA method) has no asymptotic distribution. Hence, no confidence interval can be attached to the parameter estimated using these two methods. Therefore, the robustness of various estimation results on long memory cannot be immediately verified and compared.

However, Weron (2002) and Kristoufek (2010) have conducted a Monte-Carlo simulation of various R/S statistics (including DFA), and came up with empirical confidence intervals for various long-range estimators. Weron (2002) result also shows that among three estimators considered (GPH, R/S, and DFA), the latter seems to be the most efficient (i.e. smaller confidence interval given the same amount of data). Hence DFA becomes our preferred choice of techniques in our empirical works.

Research Methods

In this section we will summarize the computational algorithm of the DFA. This will be followed by interpretation of the estimated long memory parameter H. A review on the Weron (2002) Monte Carlo study will show the strength of the DFA, and thus provide justification for its adoption in this study.

Detrended Fluctuation Analysis (DFA)

method is introduced in Peng et al. (1994). The computational method is explained in detail in Weron (2002), and is summarized here.

Given a time series Y of length L, we divide Y into d sub-series (windows) of length n. Thus, if L=1000, and n=50, we divide Y into 20 smaller (non over-lapping) sub-series. Further, for each sub-series m, we fit a polynomial (usually a linear or quadratic trend), and record the root mean square error of the fluctuation around the fitted trend. In other words, we calculate

$$F(m) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{i,m} - a_m \cdot i - b_m)^2} \qquad (1)$$

We then average the RMSE. Hence, continuing with our previous example, for window size n=50, we calculate 20 RMSE (one for each sub-series). And then we calculate the average of these 20 RMSEs as follows

$$\bar{F}(n) = \frac{1}{d}\sum_{m=1}^{d} F(m) \qquad (2)$$

We calculate the average RMSE above for every window-size, thereby generating two series that relate average RMSEs with the windows size.

With these two series, we run a regression of the log of average RMSEs against the log of window size, and take the estimated slope as our measure of the long memory parameter H.

Finally, the confidence interval for H is given in Weron (2002), and is replicated here for 95% confidence interval (where N is number of observations). The lower bound of H is calculated as 0.5 – exp(-2.93 log N + 4.45), whereas the upper bound of H is calculated as 0.5 + exp(-3.10 log N + 4.77).

The estimated value of parameter H ranges between 0 and 1. Value of H = 0.5 indicates that the data is a white-noise process (and has no memory), while value H 0.5 indicates presence of long memory. If a series has H > 0.5, then series is called persistent while H < 0.5 implies a series is anti-persistent.

An informal interpretation (Peters, 1996 p.64) is the following: H > 0.5 implies that an upward movement is likely followed by movement of the same sign. In contrast, H < 0.5 implies that an upward movement is likely to be followed by a downward movement.[1]

One major weakness of the DFA is that the methodology has no asymptotic distribution derivation. This is a weakness that is shared with other traditional R/S estimators. In contrast, asymptotic distribution theories have been derived for the GPH and Lo's modified R/S estimators.

Weron (2002) has done a Monte Carlo study on various long-memory estimators (R/S, DFA, and GPH). The study yielded several useful results. Firstly, Weron's (2002) study shows that the DFA estimator was the most efficient compared to the other two indicators included in the study. Secondly, the study was able to provide formulas for empirical confidence interval for each long-memory estimator. Thirdly, in the case of GPH where theoretical distribution exists, the empirical distribution lies very close to the theoretical distributions.[2] These provide justification for the use of the DFA in this study.

Results and Discussions

Data

Long memory analysis is conducted on a subset of shares listed at the Indonesia Stock Exchange (IDX, henceforth). As of December 2016, there are 534 stocks listed in the IDX, with a combined market capitalization of domestically-listed companies equivalent to USD425.8 billion at an exchange rate of IDR13,473/USD. This is a large market in ASEAN, with the exception of Singapore (see Table 1). During the period between 2000-2016, the IDX capitalization grew by a rate of 17.7 percent per annum, the fastest among the six countries in Table 1 (with exception of Vietnam whose market just opened in 2008).

Despite the large number of listed stocks, this analysis only investigates a subset of the stocks listed in the Indonesia Stock Exchange (IDX). Specifically, we investigate shares that

[1] This interpretation is the same as in R/S analysis.

[2] The GPH estimator is normally distributed (Weron, 2002).

Table 1. Size of Several ASEAN Stock Market

Country	Members	Market Capitalization (USD billion)	CAGR 2000-2016 % p.a.
Indonesia		425,8	17,7
Malaysia		359,8	7,0
Philippine		239,7	14,0
Thailand		433,0	17,2
Vietnam		66,4	27,5*
Singapore		640,4	8,8

Source: World Bank (2017)
*Note : * Vietnam growth rate since 2008*

Table 2. Descriptive Statistics for Several JSX Stocks

No	Name	Observations	Standard Deviation (%)	Skewness Coefficient	Kurtosis Coefficient
1	AALI	6.988	2,69	0,56	17,29
2	ANTM	7.000	2,71	0,43	12,00
3	ASII	9.309	2,82	0,77	24,15
4	BBNI	7.367	3,20	0,34	12,46
5	GGRM	9.309	2,37	0,07	18,86
6	HMSP	9.309	2,67	0,49	55,99
7	INDF	8.232	2,69	0,25	32,18
8	INTP	9.309	2,38	0,60	20,54
9	KLBF	9.309	3,24	0,12	41,94
10	SMGR	9.309	2,36	0,42	25,87
11	TLKM	7.744	2,21	0,13	13,08
12	UNTR	9.309	3,15	0,60	31,08
13	UNVR	9.305	1,91	0,68	67,39

have long history. For our analysis, we use stocks that need to be listed prior to January 1, 1998 (hence providing approximately 20 years of data). This is to ensure that the stock in our sample have enough observations to capture the long-memory process. Further, we also choose stocks that are relatively liquid and included in the LQ45 index. As the name suggests, the LQ45 index represents the 45 most liquid shares traded in the IDX. The components of the LQ45 is reviwed every six months, leading to stocks being added and removed from the list. We use the July 2017 list to further subset our universe of stocks, which result in 13 stocks.

We collect closing price daily data from Bloomberg for these stocks, ignoring weekends but including non-trading days. Missing data are replaced with data from previous trading-day. Table 2 provides the name of each stock along with several descriptive statistics. In general, the stocks have a daily standard deviation of 2.6 percent, which is quite volatile.

In Table 2, we also present preliminary indication of non-normality of the daily return distribution of the stocks. Column 5 and 6 of Table 2 presents coefficients of skewness and kurtosis. Under the normal distribution, these coefficients should be at 0 and 3, respectively (Vose, 2000 p. 36). Although not presented here to conserve space, we also conduct the Jarque-Bera normality test. In all cases, normality is rejected in favor of non-normal distributions. Estimating the distribution of these stocks would distract us from our current goal of analyzing long-term memory. Distribution fitting, however, is the subject of our on-going project. This finding of non-normality is not uncommon in the financial-market literature, and is a well-documented phenomenon(see, for example, Bekaert et al. (1998)).[3]

Results

Given this data set, this paper calculated the DFA coefficients on two different series. The first series is daily return, defined as logarithmic differences of daily closing price data. The second series is Absolute return, defined as

[3] We also provide separate table of descriptive statistics for absolute returns of each stock. The table is not included in this paper but is available upon request.

Table 3. Data to Calculate AALI's DFA

No	Windows	RMSE	log10(Windows)	log10(RMSE)
1	55	0,044366	1,7404	-1,3529
2	63	0,047639	1,7993	-1,3220
3	66	0,048904	1,8195	-1,3107
4	70	0,049945	1,8451	-1,3015
5	77	0,052377	1,8865	-1,2809
6	90	0,059737	1,9542	-1,2238
7	99	0,060194	1,9956	-1,2204
8	105	0,061861	2,0212	-1,2086
9	110	0,060534	2,0414	-1,2180
10	126	0,070654	2,1004	-1,1509
11	154	0,078827	2,1875	-1,1033
12	165	0,080642	2,2175	-1,0934
13	198	0,090932	2,2967	-1,0413
14	210	0,097197	2,3222	-1,0123
15	231	0,100005	2,3636	-1,0000
16	315	0,110390	2,4983	-0,9571
17	330	0,116740	2,5185	-0,9328
18	385	0,132089	2,5855	-0,8791
19	462	0,143597	2,6646	-0,8429
20	495	0,136179	2,6946	-0,8659
21	630	0,156448	2,7993	-0,8056
22	693	0,166602	2,8407	-0,7783
23	770	0,165209	2,8865	-0,7820
24	990	0,177385	2,9956	-0,7511
25	1155	0,188438	3,0626	-0,7248
26	1386	0,235315	3,1418	-0,6284
27	2310	0,288843	3,3636	-0,5393
28	3465	0,399502	3,5397	-0,3985

absolute value of daily return. This is a measure that is sometimes used by researchers as a proxy for risk (see Granger and Ding, 1995, and Grau-Carles, 2000).[4]

Before presenting the result, it is instructive to look at how this paper arrive at the estimation results. For this purpose, let us look at the case of Astra Agro Lestari (AALI, a palm-oil plantation company).

The AALI stock in this sample has 6,988 observations (for the period between 9 December 1999 – 25 January 2017) and thus 6,987 daily-return observations. In the first iteration the data must be divided into non-overlapping segments. Letting the length of segment (i.e. 'window size') equal to 50, we are left with 139 boxes (with 38 observations left over). If the window size is equal to 100, then we will have 69 boxes (with 88 observations left). Generalizing on this procedure, we have decided to include the final 6,930 observations and discard the first 47 observations. We have also chosen the window-size to be the following: 55, 63, 66, 70, 77, 90, 99, 105, 110, 126, 154, 165, 198, 210, 231, 315, 330, 385, 462, 495, 630, 693, 770, 990, 1155, 1386, 2310, 3465.

We have also decided not to use small window-size (less than 50) since we are interested in long-memory Please note that 6,930 divided by any of these window-sizes will yield round numbers (with no remainders).

Calculation of DFA of AALI is shown in Table 3. In Table 3, four calculated columns are presented. The first column is the series representing windows size. The second series is the AALI's actual DFA (empirical) for various window-size. Regression between log10 of these two series result in the slope of the regression data at 0.50628. This value indicates that daily return of AALI is close to being a random walk.

Table 4 shows the estimated long-memo-

[4] Squared of daily return has sometimes been used as well. We found that the DFA result using squared daily return highly correlate with DFA calculation using absolute return (see also Weron, 2002). Since our conclusion will not be affected substantially, we do not present the result for squared daily returns in order to conserve space.

Table 4. Long Memory Parameters of Daily Returns

No	Name	Lower Bound	H	Upper Bound	N	Windows
1	AALI	0,43	0,51	0,56	6987	28
2	ANTM	0,43	0,56	0,56	6999	28
3	ASII	0,44	0,52	0,55	9308	39
4	BBNI	0,43	0,54	0,56	7366	23
5	GGRM	0,44	0,55	0,55	9308	39
6	HMSP	0,44	0,57	0,55	9308	39
7	INDF	0,43	0,53	0,55	8231	28
8	INTP	0,44	0,52	0,55	9308	39
9	KLBF	0,44	0,60	0,55	9308	39
10	SMGR	0,44	0,51	0,55	9308	39
11	TLKM	0,43	0,45	0,55	7743	22
12	UNTR	0,44	0,60	0,55	9308	39
13	UNVR	0,44	0,51	0,55	9304	39

Source : Author's calculation

Table 5. Long-Memory Parameters of Absolute Returns

No	Name	Lower Bound	H	Upper Bound
1	AALI	0,43	0,87	0,56
2	ANTM	0,43	0,82	0,56
3	ASII	0,44	0,95	0,55
4	BBNI	0,43	0,88	0,56
5	GGRM	0,44	0,87	0,55
6	HMSP	0,44	0,89	0,55
7	INDF	0,43	0,90	0,55
8	INTP	0,44	0,83	0,55
9	KLBF	0,44	0,92	0,55
10	SMGR	0,44	0,83	0,55
11	TLKM	0,43	0,90	0,55
12	UNTR	0,44	0,97	0,55
13	UNVR	0,44	0,76	0,55

ry parameters for daily return data as well as the 95-percent confidence interval. In the case of AALI, the calculation estimated that the log-memory parameter is at 0.51. The null-hypothesis of no long-memory (0.5) has the lower-bound and upper-bound of the estimate at 0.43 and 0.56, respectively, as calculated by Weron (2002). This indicates that for AALI the estimated long-memory parameter of 0.51 is not statistically different from the value of 0.5 (no long-memory) since 0.51 is is between the lower-bound and upper-bounds. The calculation uses 6,987 data, and there are 28 window-sizes (as has been discussed in Table 3). The Table shows that three stocks show existence of long-memory: cigarette maker HM Sampoerna (HMSP), pharmaceutical company Kalbe Farma (KLBF), and heavy-equipment company United Tractors (UNTR). Thus daily return series of these 3 stocks indicates the presence of persistence and long memory in stock return. The price movements of the other ten stocks shows no evidence of the existence of long-memory.

Our result is somewhat surprising for two reasons. First, analysis done in other markets (for example: Barkoulas et al., 1999; Lo, 1991; Peters, 1994; Tan, Chin, and Galagedera (2014); Weron, 2002; Wright, 1999) rarely shows long memory in return data of index series, while Indonesia remains an exception. Secondly, our result shows that several stocks in the Indonesia stock exchange show the existence of long memory in daily return series. This is clearly in contrast with a recent study by Caporale, Gil-Alana, and Plastun (2017) which shows that long memory more likely to appear in monthly data, but not in daily return series.

Results on Absolute Returns

Table 5 presents our estimation results on absolute daily return. In the case of ANTM (second row in Table 5), the point estimate of

Table 6. Long-Memory Parameters of Daily Returns (Shorter Series)

No	Name	H (3000)	H (4000)	H (5000)	H (Full)
1	AALI	0,46	0,51	0,48	0,51
2	ANTM	**0,63**	**0,62**	**0,57**	0,56
3	ASII	0,48	0,51	0,50	0,52
4	BBNI	0,56	**0,61**	0,55	0,54
5	GGRM	**0,59**	**0,60**	0,55	0,55
6	HMSP	0,55	**0,62**	**0,60**	**0,57**
7	INDF	0,57	0,55	0,52	0,53
8	INTP	0,49	0,47	0,47	0,52
9	KLBF	0,48	0,57	0,55	**0,60**
10	SMGR	0,46	0,50	0,50	0,51
11	TLKM	0,45	0,47	0,45	0,45
12	UNTR	0,55	0,53	0,52	**0,60**
13	UNVR	0,46	0,44	0,41	0,51

log-memory parameter is at 0.87. The null-hypothesis of no long-memory (0.5) has a 95-percent confidence interval between 0.43 and 0.56, respectively. This indicates that for absolute daily return of ANTM long-memory is likely as its estimated value of 0.87 is outside the 95-percent confidence interval of no long-memory null hypothesis. Again, the calculation uses 6,987 data, and there are 28 window-sizes (as has been discussed in Table 3).We find that all stocks exhibit long-memory in absolute returns. The simple average of long memory coefficients for all stocks is at 0.88, with the lowest in our sample at 0.76 (for shares of Unilever, UNVR, a consumer goods company) and the highest at 0.97 (shares of United Tractors, a heavy equipment manufacturer).

Hence, there is a great deal of persistence in the absolute return of stocks. If we view absolute return as a proxy for risk, then this result imply a risk profile that is highly persistent In itself, this result is hardly surprising, and in fact corroborates similar studies done using Generalized Autoregressive Conditional Heteroscedasticity- (GARCH) type of models. Modeling exercises using GARCH shows that there is a great deal of persistence in stocks volatilities. Our result simply reaffirms such results, from an entirely different perspective. Using different methodologies, a study by Hull and McGroarty (2014) shows that long memory in equity index volatility exists for developing countries. Hull and McGroarty (2014) result is further strengthened by a study covering eighty-two countries conducted by Nguyen, Prokopczuk, and Sibbertsen (2017).

Results on Shorter Series

The length of original series in the thirteen stocks vary from approximately 7,000 to 9,300 observations. While the result in Table 4 shows that three stocks shows mildly persistent long-memory, this section investigates the robustness of such result. Our strategy is to estimate the long-memory parameters in Table 4, but instead of using the full data set Table 6 uses 3 different lengths: 3000, 4000, and 5000 observations. The result is presented in Table 6. In the case of AALI (first line in the Table 6), the estimated long-memory parameter now vary between 0.46 (using 3000 daily data) to 0.51 (using 4000 daily data) to 0.48 (using 5000 daily data). In all the three sub-samples, all calculations show the existence of long-memory for AALI.

Two facts stood out from Table 6. First, long-memory parameters clearly depends on sample size. In the case of UNTR, the stock exhibit long-memory using the full sample (coefficient at 0.60). However, when only 3000 until 5000 most recent observations are used, UNTR stopped exhibiting long-memory. The confidence interval of Weron (2002) clearly helps to separate the significance of each change. The second interesting feature in Table 6 is the fact that, even it exist, the long-memory parameters are only mild (between 0.4 and 0.6).

The results from this subsections suggests that, at individual level, long-memory exist albeit at a mild level. The results, however, is not robust to sample sizes. This corroborates results obtained by (Navarro et al., 2006).

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Conclusions

We investigate the presence of long memory process in the Indonesia Stock Exchange. Toward this end, we employ the Detrended Fluctuation Analysis (DFA) to analyze stocks in the Indonesia Stock Exchange.

Our analysis finds the presence of long memory process in several stocks in the Indonesia stock exchange. To our knowledge, this is the first study done at the individual stock level on the Indonesia Stock Exchange. Different from studies done elsewhere, this study shows that mild long memory process appears in daily return variables for several stocks. This result, however, is not robut to length of series. Result from volatility, on the other hand, confirms similar results reported elsewhere.

There are several implications for investors. First, given that daily returns in the Indonesia Stock Exchange exhibit mild long-memory (i.e. persistence), several stocks have a tendency to move in a certain direction. Once there occur a change in direction, such stock will continue in that direction for a long time. Hence a well-timed entry into the market can be beneficial. Secondly, and also as important, investors must note that the result is not robust to sample size. Hence more conservative strategy would be for investors to assume that EMH holds and no ex-ante excess-return should be expected from portfolio management. Third, our calculation truncates the lower (shorter) window at fifty days. Hence whether the EMH holds at window size of 50-days or less is something that is possible but is left open for future research.

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