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Are Asia-Pacific Stock Markets Predictable? Evidence from Wavelet-based Fractional Integration Estimator

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***Abstract*—**This paper examines predictability in stock return in developed and emergingmarkets by testing long memory in stock returns using wavelet approach. Wavelet-based maximum likelihood estimator of the fractional integration estimator is superior to the conventional Hurst exponent and Geweke and Porter-Hudak estimator in terms of asymptotic properties and mean squared error. We use 4-year moving windows to estimate the fractional integration parameter. Evidence suggests that stock return may not be predictable indeveloped countries of the Asia-Pacificregion. However, predictability of stock return insome developing countries in this region such as Indonesia, Malaysia and Philippines may not be ruled out. Stock return in the Thailand stock market appears to be not predictable after the political crisis in 2008.

***Keywords*—**Asia-Pacific stock market,long-memory, return predictability, wavelet

I. INTRODUCTION

IN a long memory process (also called long range dependence) the correlations of the series decays hyperbolically over time. In other words, the process does not fade away in a short period with shocks taking a longer period to disappear. Thus, evidence of long memory in the returns of a stock indicates stock return predictability. However, evidence of predictability may notnecessarily violate the assumption of market efficiency as efficiency implies that the market is comprised of rational investors. The linearity test (such as autoregressive moving average and variance ratio test) for efficiency or return predictability is not suitable especially for emerging marketsas not all investors may be well informed due to poor information flow. In such situations a long range dependence test based on nonlinearityof stock return is more desirable.An interesting overview of market efficiency and return predictability is reported in Antoniou, Ergul and Holmes [1] and Pesaran and Timmermann [2].

Evidence of long-memory in stock returnsis documented in for example, Green and Fielitz [3], Lo [4], Peters [5], Cajueiro and Tabak [6] and [7],DiSario, Saraoglu, McCarthy and Li [8], Kang and Yoon [9], Bond and Dyson [10], Kasman, Kasman and Torun [11]. Some studies such as Aydogan and Booth [12], Lobato and Savin [13] and Kuswanto and Sibbertsen [14]have raised concern that long-memory may be observed as result of spurious effect of structural breaks and level shift in the return series.

We employ a wavelet-based maximum likelihood estimator to test presence of long-memory in ten Asia-Pacific countries. The wavelet-based technique for testing long-memory is more robust in terms of mean square error and asymptotic property compared to the conventional Hurst exponent and Geweke and Porter-Hudak (GPH) estimator. One of the concerns of spurious long memory is existence of structural change and trend in the time series.The wavelet approach is able to differentiate between trend, weak short-term dependence and long memory. Thus, the wavelet-based estimator is superior in detecting long-memory. We test presence of long memory using moving sub-samplesas return predictability may change over time.Pesaran and Timmermann [2] support this view.

The stock markets investigated in this study is fromseven developed countries (Australia, Hong Kong, Japan, Korea, New Zealand, Singapore and Taiwan) and four developing countries (Indonesia, Malaysia, Philippines and Thailand). The chosen set of developing countries record increasing market capitalization and share value traded in the recent years. The market capitalizationof the four developing countriesincreased from 86,510 million U.S. dollars in 1990 to 1,205,970 million U.S. dollars in 2010 which peaked in 1996. Economic integration among these developing countries has been strengthened through Association of Southeast Asian Nations (ASEAN) economic community, the ASEAN free trade area, the ASEAN framework agreement on services and ASEAN investment area.

We include the 1997 sample period to examine the impact of the 1997 Asian financial crisis on market predictability especially in the Asian countries, and the 2008 global financial crisis to examine its impact on the developed countries. The 1997 Asian financial crisis brought about changes to investment regulation with the intension of increasing market competitiveness. In March 1997, Philippines abolished the exemption of loans outside the banking system. This indirectly encouraged offshore lending. After the Indonesia rupiah plunged following depreciation of Thai baht, Indonesia announced control on capital and money market instruments in July 1997 by allowing foreign investors to invest in domestic shares except in the banking sector. During the same year in October, foreign investors were allowed to have full ownership of local financial institutions for up to 10 years. These initiativesinduced flow of foreign capital into the Indonesian stock market.Attracting foreign participation would not have been possible if the fundamentals such as rapid information flow, transparency and accountability were

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not met. In short, more participation indirectly implies positive sentiment on market efficiency. If so there would be no return predictability leading to no long memory in the return.

Section II describes the research methodology for testing long-memory using wavelet analysis. Section III reports the empirical results and Section IV concludes the paper.

II. RESEARCH METHODOLOGY

A. Fractional Autoregressive Integrated Moving Average (ARFIMA)

The original work of long-memory process is from Hurst [15]. He proposed rescaled adjusted range statistics (R/S) in detection of long-memory process in a time series. Later, Granger and Joyeux [16] and Hosking [17] advanced the generalized ARIMA(p,d,q) models (ARFIMA) to analyze long-memory processes. The ARIMA model introduced by Box and Jenkins only allow the fractional integration parameter$d$ to be zero or one, where order zero indicates stationary time series and order one indicatesnonstationarity. However, the ARFIMA model allows$d$to take any non-integer value.

Let x_t denote the time series process. Then the fractionally integrated $I(d)$process can be expressed as

$$(1-B)^d x_t = \sum_{k=0}^{\infty} \binom{d}{k} (-1)^k x_{t-k} = \epsilon_t \quad (1)$$

where$d$ is the fractional integration parameter and $\binom{d}{k} = \frac{a!}{b!(a-b)!} = \frac{\Gamma(a+1)}{\Gamma(b+1)\Gamma(a-b+1)}$. $B$is the lag operator. $\epsilon_t$is a white noise process with zero mean and variance σ_ϵ^2. The process is invertible and stationary for $-0.5 < d < 0.5$. For $-0.5 < d < 0$, the time series process is an anti-persistent with intermediate-memory.For $0.5 \le d < 1$, it has infinite variancewith high persistency and for $0 < d < 0.5$, it is a stationary long-memory process (with Spectral density function approaches infinity at frequency zero). For $d < 1$, it is a mean reverting process.

B. Wavelet-based Fractional Integration Estimators

The wavelet-based maximum likelihood estimator (MLE) of the fractional integration parameter d is an alternative semi-parametric MLE. The method is proposed by Jensen [18], where the wavelet-based MLE estimator is invariant to unknown mean, model specification and contamination in the time series process. On the other hand, it is also efficient and it does not confound with the short-memory process. It also reduces the order of calculating the likelihood function from order N^2 to N where $N$is the number of observations.

The wavelet transformation decomposes a time series into series of different timescales. The lower scale is able to capture the abrupt change or jump in the series with high frequency while the higher scales is able to capture the low frequency data with smoother time series. The wavelet transformation is also localized in time and frequency. To begin the wavelet analysis, we must specify the wavelet filter,$\psi(t)$. A wavelet filter is any function that integrates to zero and is square integrable. Let $\psi(t)$denotes the wavelet filtersatisfying the admissibility condition where $C_\psi = \int_0^\infty \frac{|\Psi(f)|}{f} df < \infty$. To guarantee that $C_\psi < \infty$, the wavelet filter must satisfy the conditions where $\int_{-\infty}^{\infty} \psi(t) dt = 0$ and $\int_{-\infty}^{\infty} |\psi(t)|^2 dt = 1$. The first condition shows the changes in the data where all the coefficients must sum to zero and the second condition is to ensure the wavelet filter has unit energy.

Thediscrete wavelet coefficient is obtained by projecting any time series x_t onto wavelet function $\psi(t)$ through the discrete wavelet transform (DWT). It can be expressed as

$$W(u,s) = \sum_{-\infty}^{\infty} x(t)\psi_{u,s}(t) \quad (2)$$

where$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right)$ is translated by u and dilated by s from the original wavelet filter. This procedure has changed the time series process into frequency and scales through the translation and dilation process of wavelet filter. Then, we can reconstruct the original series as follows:

$$x(t) = \frac{1}{C_\psi} \sum_j \sum_k W(j,k)\psi_{(j,k)}(t) \quad (3)$$

where$s = 2^{-j}$ and $u = k2^{-j}$. $j$is the number of scales used.

Following Jensen [18], we apply the DWT to a time series data with N observations ($N = 2^J$) with Daubechies least asymmetry length eight, LA(8), and Daubechies length 4, D(4), wavelet filterswith 4 and 2 vanishing moments, respectively. Longer wavelet filters yields more stationary wavelet coefficient and higher number of vanishing moments provide smoother wavelet. The chosen length of the wavelet filter should provide the shortest length with most reasonable result and LA(8) is often the optimum choice, see Percival and Walden [18] and Gencay, Selcuk and Whitcher [20] [21].

Jensen [18] [22]proposes the wavelet-based estimator of fractional integration parameter d using ordinary least square (OLS) and banded MLE application. It is named as banded MLE in which only the diagonal elements of the covariance matrix estimated via wavelet are used. The banded MLE is preferable against wavelet-based OLS where it produces smaller MSE. Thus, we only consider banded wavelet-based MLE in this study.

The approximate DWT covariance matrix has weak dependence in time and scale. Thus, the banded wavelet MLE utilizes the diagonal covariance of the approximate decorrelation of the DWT to replace the covariance matrix. This will reduce the computation burden of inverting the original covariance matrix. The approximate log likelihood function is

$$\hat{\ell}(d, \sigma_\epsilon^2 | x) = -\frac{1}{2} \sum \sum \left\{ \ln\left(2\pi\, \hat{\Sigma}_x\right) + \frac{\{W(j,k)\}^2}{\hat{\Sigma}_x} \right\} \quad (4)$$

where$\hat{\Sigma}_x$ is the diagonality on the covariance matrix of the DWT, and $\{W(j,k)\}^2$ is the covariance matrix of the wavelet coefficients.

III. DATA AND EMPIRICAL RESULTS

The data is daily stockmarket index obtained from DataStream from January 1, 1988 toDecember 31, 2010

TABLE I
SUMMARY STATISTICS ON PERCENTAGE STOCK RETURNS

	Mean	S.D.	Max	Min	Q1	Q3	Skew	Kurtosis	Q(24)
Panel A: Developed Country									
Australia	0.0219	0.9947	6.1010	-8.6790	-0.4972	0.5630	-0.4134	5.6885	32.23
Hong Kong	0.0334	1.6087	15.9800	-25.8500	-0.6600	0.7642	-0.8103	19.3125	78.62*
Japan	-0.0100	1.3275	13.0600	-10.4400	-0.6388	0.6490	0.0412	6.5089	77.72*
Korea	0.0295	1.9148	11.7200	-13.1000	-0.8579	0.9105	0.0676	4.4271	37.43**
New Zealand	-0.0029	1.1712	11.1400	-16.3400	-0.6192	0.5781	-0.3914	11.4680	43.35*
Taiwan	0.0193	1.8952	12.6500	-10.3100	-0.8454	0.9351	-0.0073	2.8600	98.13*
Singapore	0.0221	1.4109	15.0200	-9.9090	-0.6571	0.6862	0.0978	7.2424	95.49*
Panel B: Developing Country									
Indonesia	0.0636	2.0164	44.7500	-19.1500	-0.6788	0.7846	2.1867	53.5953	355.66*
Malaysia	0.0287	1.4433	23.2600	-24.1600	-0.5065	0.5678	0.5330	42.3783	139.54*
Philippines	0.0333	1.5234	16.2900	-13.6700	-0.7067	0.7996	0.2336	8.7801	199.69*
Thailand	0.0236	1.8943	21.4300	-18.0800	-0.8380	0.8425	0.4813	10.8609	178.287*

totaling6000 observations. We compute daily compounded returns,r_t, from the stock market index at day t, p_t,where $r_t \equiv \ln(p_t) - \ln(p_{t-1})$. The used stock market index is the adjusted closing price of the day. The stock markets studied here are: Australia (Australian securities exchange), Hong Kong (Hang Seng Index), Indonesia (Indonesia stock exchange), Japan (Nikkei 225 index), Korea (Korea exchange), Malaysia(Bursa Malaysia), New Zealand (New Zealand exchange), Philippines (Philippines stock exchange), Singapore (Stock exchange of Singapore), Taiwan (Taiwan stock exchange) and Thailand (Stock exchange of Thailand).

Table I reports summary statistics of percentage stock returns. The return distributions of all developing markets are positively skewed and in four out of the seven developed markets skewness is negative. Indonesia and Malaysia both reveal high kurtosis suggesting their return distributions have high peaks around the mean. The Ljung-Box statistics at lag 24 show significant autocorrelation in the return data in all sampled markets except Australia.

First, we report thefractional integration parameter,d using all the observations and compare the results obtained with rolling windows. Table II reports the d estimated with all observations in the sample and using theLA(8) wavelet filter with $J = 7$. We use D4 wavelet filter as robustness check of the results. Table II reports the estimated d and in the bracket the confidence interval of d at 5 per cent significance level. If the confidence interval of d contains zero, this implies that there is no long memory process in the time-series and if the confidence interval d include 0.5, the time-series is persistent. The resultsrevealthat only Australia, Korea and New Zealand stock returnsdo notshow evidence of long-memory with zero lying within the confidence interval. All the results estimated via LA(8) and D(4) filters are consistent except for Australia.

Next, we use moving windows to estimate $d$assuming that return predictability of the stock markets may change over time depending on the market condition, policy implementation and random events such as natural disasters. Each windowin which d is estimated consists of 1024 observations (multiple of 2^J) which is approximately 4 years. The increment for the next moving window is 21 days which is approximately one month. In other words, the first window is the first 1024 observations and the second window is from the 1045^{th}observation to the 2069^{th}observation and so on till the last observation which is the 5968^{th}. The rolling estimatesof $d$are plotted in Fig. 1. The rolling window estimated $d$gives a very different picture compared to what is revealed in the results in Table II. Each panel in Fig. 1 indicates three curves. The topcurvegives the upper limit of the parameter and the bottom curve gives the lower limit. The curve in the middle shows the estimated d. The rolling parameter of d shows no long-memory in stock markets in developed countries, such as Australia, Hong Kong, Korea, Japan, New Zealand and Taiwan. However, Singapore (a developed country) and all developing countries (Indonesia, Malaysia, Philippines, and Thailand) exhibit long memory in the stock return at the beginning of the 1990s. The parameter d shows downward trend suggesting weakening of long-memory behavior over time. In this we highlight that to obtain a better understanding of long memory in stock returns it is better to consider moving window analysis. This will give a better picture of howmarket predictability may evolve or disappear. Fig. 1 also demonstrates that although the$d$s are approaching zero towards the latter sample period, this is not a very strong indication of absence of long-memory. Nevertheless, stock market in Thailand shows very significant evidence of no long-memory starting from 2008. Thailand experienced political crisis in 2008.

TABLE II
ESTIMATES OF FRACTIONAL INTEGRATION PARAMETER

	$\hat{d}$ (Daubechies Least Square length 4)	$\hat{d}$ (Daubechies Least Square Length 8)
Australia	-0.0121 (-0.0323, 0.0079)	-0.0217 (-0.0418, -0.0016)
Hong Kong	0.0289 (0.0088, 0.0491)	0.0204 (0.0002, 0.0405)
Japan	-0.0029 (-0.0231, 0.0172)	-0.0100 (-0.0301, 0.0102)
Korea	0.0037 (-0.0164, 0.0238)	-0.0039 (-0.0240, 0.0162)
New Zealand	-0.0079 (-0.0280, 0.0122)	-0.0087 (-0.0288, 0.0115)
Taiwan	0.0406 (0.0204, 0.0607)	0.0447 (0.0246, 0.0648)
Singapore	0.0564 (0.0363, 0.0765)	0.0579 (0.0378, 0.0781)
Indonesia	0.1410 (0.1208, 0.1611)	0.1420 (0.1219, 0.1621)
Malaysia	0.0692 (0.0491, 0.0893)	0.0637 (0.0436, 0.0839)
Philippines	0.1048 (0.0846, 0.1249)	0.1027 (0.0826, 0.1228)
Thailand	0.0791 (0.0590, 0.0993)	0.0868 (0.0667, 0.1070)

IV. CONCLUSION

We test long range dependence of stock market returns in eleven countries (seven developed and four developing) using a wavelet-based fractional integration estimator. Adopting the proposed methodology in moving windows we highlight that the method of moving windows provide valuable insights that would be masked if the full sample information is used. We find that long-memory is not generally present in developed countries. The results suggest that in Indonesia, Malaysia, Philippines, Thailand and Singapore long-memory in the stock returns may not be ruled out. However, the stock markets in developing countries are becoming less predictable lately. This can be explained from the perspective of market integration and globalization where information sharingis virtually instant through the advancement of technology and government intervention for more transparency, accountability through regulation.

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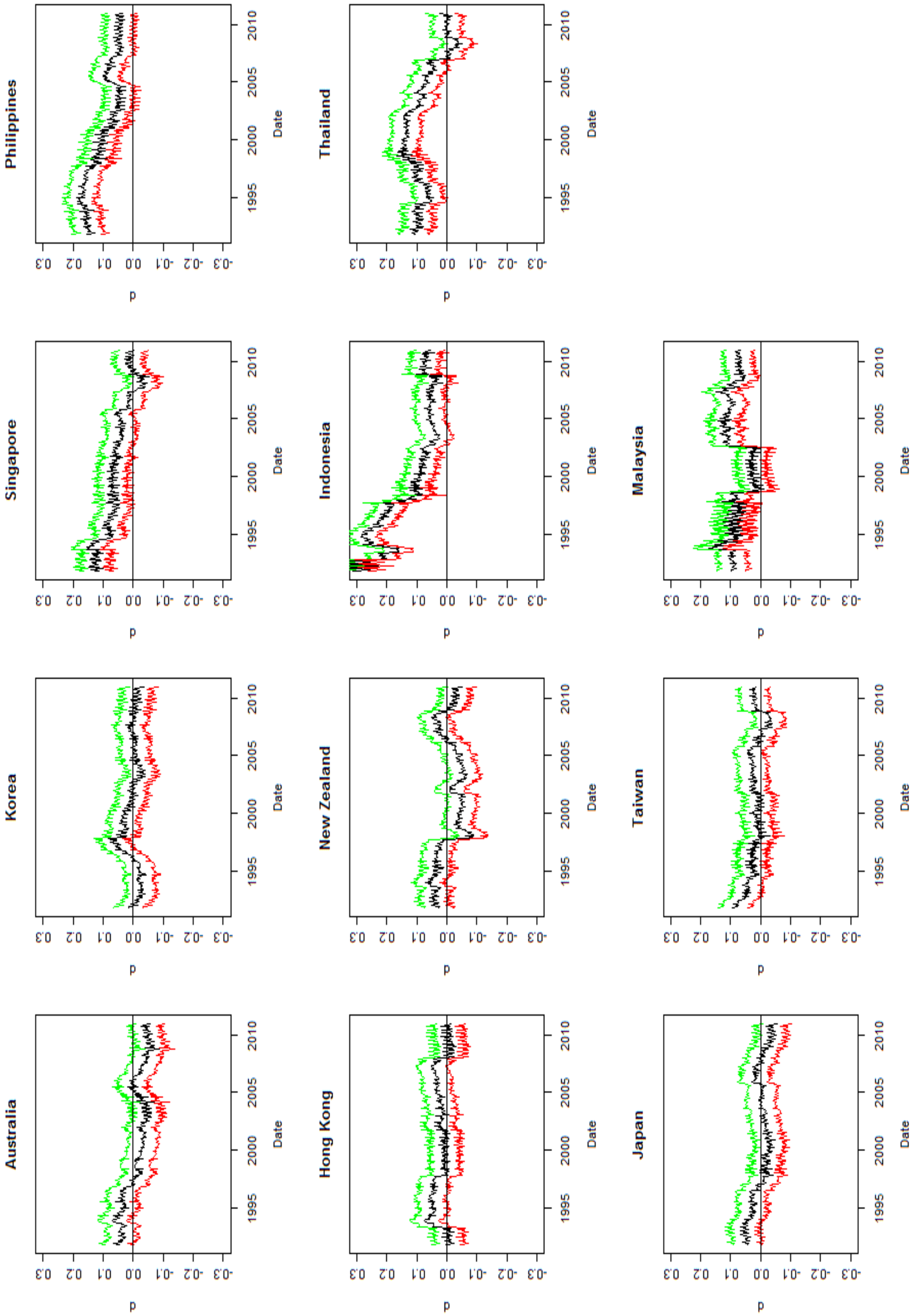

Fig. 1 Wavelet-based fractional differencing parameter in Asia-Pacific stock market returns