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MEAN REVERSION IN THE INDONESIAN STOCK MARKET AND THE ASIAN CRISIS

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Key Words

Mean Reversion; Asian Crisis.

Abstract

This paper examines the long-run mean reverting behavior in the Indonesian stock market. Indonesia is one of the major countries in East Asia that witnessed an economic collapse and severe depreciation of their currency (rupiah) losing 80 percent of its value during 1997-1998. Indonesia has been in crisis longer than any other Asian stock market and the Indonesian stock market is yet to recover from its pre-crisis peak levels which happened in 1990. The bootstrap results show strong mean reverting behavior in Indonesia's index returns. The results remain robust after accounting for the financial crisis of East Asia which took place from 1997 to 1998.

Introduction

Long-run forecastability of stock markets is a major concern of investors, and financial economists who generally believe in the efficient market hypothesis (EMH) which is built on the idea of unpredictable returns and the notion that prices follow a random walk. Tests of long-horizon returns have reported pronounced negative long-term serial correlation, giving rise to the fad hypothesis which asserts that stock prices might overreact to relevant news. Fama and French (1988a) performed regressions of long-horizon returns on past long-horizon returns and conducted the classic autocorrelation tests using data from the 1960s. They found negative and significant lagged past returns coefficients, a result that support that stock market returns are unpredictable. Poterba and Summers (1988) considered a related variance ratio test statistic. They found variance ratios below one and reported a string of small negative return autocorrelations. These studies reveal a departure from

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a random walk view of stock prices (also see Kim, Nelson and Startz, 1991). Their evidence constitutes a major threat to the EMH and gives evidence that substantial parts of the variance in different-horizon returns are due to forecastable components (see Poterba and Summers, 1988). Recently , Caporale and Gil-Alana's (2002), using U.S. real stock returns, found a weak evidence of mean reversion in data but no permanent component in stock prices. On the other hand, Kiseok Nam et al. (2002) investigated the time-series evidence of asymmetric reverting patterns in stock returns that are attributable to contraries profitability by using asymmetric nonlinear smooth-transition (ANST) GARCH (M) models. They also found negative returns, on average, that are quick, with greater tendency of negative returns reverting to positive returns than vice versa. They interpret the asymmetrical reversion finding as supporting the stock market overreaction hypothesis.

In an effort to explain the observed price deviations from their fundamental values, several explanations have been suggested: (1) fads will cause such temporary deviation, (2) time-varying expected returns caused by macroeconomic factors (Fama and French, 1988), and (3) rational speculative bubbles, which is suggested by Blanchard and Watson (1982).

In this paper we test for the mean reversion hypothesis, using the Fama-French (1988a) return regressions and stock returns of Indonesia. Our estimations adjust for potential estimation bias, as well as structural breaks. This is accomplished using both bootstrapping and the One-Step Forecast tests.

Indonesia is classified as one of the major emerging markets by the Standard & Poor's and the International Finance Corporation (IFC). Indonesia is one of the major countries in East Asia which witnessed an economic collapse and severe depreciation of their currency (rupiah) losing 80 percent of its value during 1997-1998. Indonesia has been in crisis longer than any other Asian stock market, and the Indonesian stock market is yet to recover from its pre-crisis peak levels which happened in 1990. It was also the first stock market crisis that hit other Asian markets, such as Korea, Malaysia, the Philippines and Thailand. For this, we choose the Indonesian market for our analysis.

This paper is organized as follows. Section **2** discusses methodology and analysis. The latter includes an analysis of stock returns and different techniques for measuring the apparent deviation of stock prices from their long run equilibrium value suggested by economic fundamentals. Section **3** discusses data and descriptive statistics. Section **4** discusses estimation of these models and presents empirical results. Section **5** assesses the robustness of our results. Finally, Section **6** concludes the study.

Empirical Model

Earlier studies included Fama and French (1988a) and Poterba and Summers (1988). Fama and French (1988a) conducted classic autocorrelation tests using data from the 1960s, while Poterba and Summers (1988) employed the variance ratio test of Cochrane (1988). These studies' findings indicated that the conventional view of the efficient market theory might have been jeopardized. However, in reaction to these studies and in an effort to defend the random walk hypothesis, several recent papers have questioned the significance of long-horizon mean reversion hypothesis and the rationale for it. Some observed have suggested that mean reversion statistics results may be misleading when the interdependence among these statistics at different return horizons is ignored (Richardson, 1989). On the other hand, other critics have stressed that using better asymptotic distribution of finite samples would support the random walk hypothesis (Richardson and Stock, 1989, McQueen, 1992).

This paper uses the Fama-French **(FF)** regressions of long-horizon returns and further extends to use Bootstrap technique of Efron (1982) in order to avoid the typical reliance on asymptotic distribution in earlier studies. The bootstrap technique also accounts for the downward bias in Beta coefficient (for more details, see Kendall, 1954 and Kim et. al., 1991). In addition, the use of the bootstrap technique avoids the dangers of data-driven inference which could be introduced by data-snooping biases[1]. Lo and McKinley (1990) note that the degree of such biases increases with the number of published studies performed on any single data set, resulting in the so-called "spurious" market patterns. Their Monte Carlo simulations indicate that the data snooping biases in asset pricing models can be substantial. In this study, the Bootstrap calculates the confidence intervals for 1,000 shufflings.

The long-horizon returns mean reversion propriety is tested using the following regression,

$$r_{t\rightarrow t+k} = a + b_k r_{t-k\rightarrow k} + \varepsilon_{t+k} \quad (1)$$

(1) Sullivan, Timmermann and White (1998) note that if researchers do not account for data-snooping biases, the assumptions underlying classical statistical inference will be invalidated. They claim that such problems may cause the presence of calendar effects in stock returns.

where:

- $r_{t\to t\to k}$ indicates the k-year return,
- $r_{t-k\to k}$ indicates the k-year return horizons

The confidence intervals for the lagged returns coefficients are calculated using the bootstrapping technique. Efron (1982a, pp. 35-36) suggests two methods of bootstrapping. In the first method, one first fits the model and then applies the bootstrap techniques to the residuals. The second method applies the bootstrap technique to the vector of the observed response variable and the associated predictor variable. These methods are very general. They can be applied to linear and nonlinear regression models and can be used for least squares or any other estimation procedure. In this paper, the bootstrapping of the residual method is used. Bootstrapping is a special Monte Carlo method designed to produce estimates of the bias and variance of an estimator. The technique is used to obtain a description of the sampling properties of the empirical estimator using the sample data itself, rather than broad theoretical results. The estimated values of coefficients are chosen to be the true (population) slopes of these estimated coefficients from the Monte Carlo study, and the errors for repeated sampling are chosen, with replacement, from the set of residuals of the original estimation. The estimate of the bias produced by this bootstrapping procedure can be subtracted from the original estimates to produce the bootstrap coefficient (Hsu et al., 1986).

The general linear regression model representation can be given by

$$Y_i = \Psi_i(\beta) + \eta_i \qquad (2)$$
$$for$$
$$i = 1, 2, ..., n$$

where Y_i and the row k-vector Ψ_i are observations on the dependent and independent variables, respectively. Y_i is a dependent return $r_{t\to t+k}$. The function, Ψ_i, is of known form and may depend on a fixed vector of covariates, Ω_i. The vector, β, is a $p \times 1$ vector of unknown parameters and the η_i are random errors assumed to be independently and identically distributed (*iid*) with some distribution, F. The distribution F is centered at zero(2). Given the observed vector:

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \bullet \\ \bullet \\ \bullet \\ y_i \end{bmatrix} \qquad (3)$$

$$y_i = \{r_{t\to t+k}\}$$

(2) Centering the F-distribution at zero means that the expected of ε_i is zero. And in cases where the expected value does not exist we may use the criterion that $p(\varepsilon < 0) = 0.5$.

where the ith component y_i is the observed value of the random variable Y_i. To find an estimate of β we minimize the sum of squared distance between $\boldsymbol{y}$ and $\lambda(\beta)$, (D ($\lambda(\beta)$)).[3]

Given the following relations,

$$D(y, \lambda(\beta)) = \sum_{i=1}^{n} \left[y_i - \Psi_i(\beta)\right]^2 \qquad (4)$$

$$D(y, \lambda(\beta)) = \sum_{i=1}^{n} [\eta]^2$$

and by minimizing the squared distance, we derive our parameter estimate of β. The elements η_i^* are created by re-sampling from η_i; that is, through drawing from η_i randomly but with replacement . Based on these procedures, an artificial (bootstrap) sample data set is created:

$$y_i^* = \Psi_i\left(\overset{\wedge}{\beta}\right) + \eta_i^* \qquad (5)$$

for

$$i = 1, 2, ..., n$$

For each such bootstrap data set y^*, a bootstrap $\beta^{\wedge *}$ is estimated on the artificial sample from Equation (4). The procedure is repeated N times and the sampling distribution of the difference between the bootstrap beta and the actual beta yield an estimate of the sampling distribution. Confidence intervals for β estimates from equation (1) can be obtained by several methods described in Efron and Tibshirani (1986, pp.67-70). They are the standard method, the percentile method, the bias-corrected bootstrap interval, and the acceleration constant method. In moving from the first method to the fourth, the assumptions become less restrictive, while the methods become more complicated; however, they generally become more applicable. In this paper the percentile method is used. The method uses confidence interval, which is the confidence interval below at which 2.5 percent of the bootstrap coefficients values lie and above which 2.5 percent of the bootstrap coefficients values lie. This confidence interval is used to test for the significances of the bootstrap betas.

Data and Sample Period

Monthly data are obtained from the Emerging Markets Data Base CD and the Kenneth French data library. The sample period spans from December 1989 through June 2002. Indonesia is classified as a major emerging market by Standard & Poor's and IFC. Data for value-weighted general share price index are taken from the same sources. There are a total of 127 monthly observations. To compute stock market returns, R_t, we use the log difference for the monthly general price index weighted by market capitalization as follows:

(3) $\lambda(\beta)$ is a column vector of the known functional form Ψ_i, $\lambda(\beta) = \begin{bmatrix} \Psi_1(\beta) \\ \Psi_2(\beta) \\ \bullet \\ \bullet \\ \Psi n(\beta) \end{bmatrix}$

$$r_t \equiv \log(1 + R_t) = \log \frac{P_t}{P_{t-1}} \quad ,$$

where P_t refers to the value of the Indonesia stock exchange price index for the period t or a particular month.

The continuously compounded multiperiod return (overlapping) is computed as follows:(4)

$$r_t(k) = \log(1 + R_t(k)) = \log((1 + R_t) \cdot (1 + R_{t-1}) \cdots + (1 + R_{t-k+1}))$$
$$r_t(k) = \log(1 + R_t) + \log(1 + R_{t-1}) \cdots + \log(1 + R_{t-k+1}))$$
$$r_t(k) = r_t + r_{t-1} + \cdots + r_{t-k+1}$$

Estimates of the multiperiod first-order autocorrelation coefficients are

calculated using different yearly time horizons. The time horizons are 1, 2, 3, 5, 7 and 10 years.

Empirical Results

Our primary interest in this study is to test whether stock prices in Indonesia follow a random walk or a mean-reverting process. Prior to running bootstrap results, we first test for the random walk hypothesis.

The most popular test for the random walk hypothesis is the augmented Dickey-Fuller (ADF) Test (1979, 1981) test and the Phillips and Peron (PP) test (1988).

P is a stationary series if $-1 < \rho < 1$ (where ρ is the lagged P coefficient). If $\rho = 1$, P is a nonstationary series or a random walk series (with or without drift); if the process is started at some point, the variance of P increases steadily with time and goes to infinity. If the absolute value of ρ is greater than one, the series is explosive. Therefore, the hypothesis of a stationary series can be evaluated by testing whether the absolute value of ρ is strictly less than one. The null hypothesis for both the ADF and the PP tests is: H_0: $\rho = 1$. Since explosive series do not make much economic sense, this null hypothesis is tested against the one-sided alternative $H_1: \rho < 1$. The model is estimated with and without trend. These results are reported in Table 1. Based on the ADF and PP tests, the null hypothesis of random walk can be rejected in favor of the mean reversion hypothesis when we use 1% significance level. We used different lag length up to 12 lags. It is apparent that the choice of lag length

(4) For more details on continuous compounding see , *The Econometrics of Financial Markets*, by Campbell, Lo and MacKinlay , Princeton (1997).

cannot affect the test results. All the results support the mean reversion against the random walk hypothesis. This result implies that it is possible to forecast long-run market returns in the Indonesian stock market.

Table 2 reports the mean, standard deviation, and five serial and partial

Table 1
ADF and PP tests for random walk in Indonesia stock market prices}

This table reports augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for the random walk hypothesis for emerging market stock prices. The one, five and ten percent critical values are -3.4545, -2.8716 and -2.5721, respectively for the model without a time trend; and --3.9930, -3.4266 and -3.1363 for the model with a time trend. The choice of lag length and lag truncation for Bartlett kernel is arbitrary.

ADF			PP		
Number of lags	**No Trend**	**With Trend**	**Lag truncation for Bartlett kernel**	**No Trend**	**With Trend**
4	-2.75745*	-3.080718*	4	-2.743253*	-2.80956*
6	-2.72741*	-3.146153*	6	-2.756233*	-2.82096*
8	-2.44253*	-2.867466*	8	-2.718582*	-2.77898*
10	-2.43812*	-2.738182*	1	-2.707850*	-2.76462*
12	-2.50914*	-2.842495*	1	-2.702308*	-2.75537*

* 1% level of significance

Table 2
Summary Statistic of Stock Market Returns}

The data covers the period from 1978:12 to 2003:08 with 297 monthly observations. Both the autocorrelations (AC) and partial autocorrelations (PAC) are for different lags ranging from 1 to 40

		Serial Correlations							
		1		**8**		**24**		**40**	
		AC	**PAC**	**AC**	**PAC**	**AC**	**PAC**	**AC**	**PAC**
Mean	0.006033	0.20	0.20	-0.058	0.006	0.097	0.073	0.093	0.085
S.D	0.094009	Q-stat 6.12 Prop (0.013)*		Q-stat 11.49 Prop (0.175)		Q-stat 28.24 Prop (0.25)		Q-stat 35.39 Prop (0.0.678)	
N	150								

* 1% level of significance

serial autocorrelations (AC and PAC, respectively) for the index return. Over the 13-year period, the monthly returns averaged 0.6 with a standard deviation of 9.4. The first-order serial correlation is quite large for the return index. and PAC is equal to 0.20. Higher order serial correlations are in general smaller in magnitude. The Q-statistics indicate no serial correlation in the stock market index.

Table 3 presents long-horizon return regressions and an estimate of the bias in beta when the standard method of constructing the confidence intervals is used. The long-horizon regressions show some interesting mean reversion cases, especially in the 1, 2, 3 and 7 year range. However, it weakens by the 5th year. The biased corrected beta estimates show downward biases in all the studied horizons but with a relatively small difference. We can conclude that the direct evidence for mean-reversion in index returns seems quite strong because we observe that all the beta coefficients lie outside the standard 95% confidence interval.

The Asian Crisis and Robustness of the results

The financial crisis of East Asia was surprising given that it contained some of the most successful emerging markets. Yet almost no one anticipated the size of the economic collapse that came in the years 1997 and 1998. Indonesia witnessed an economic collapse and severe depreciation of their currency which lost 80 percent of its value during 1997-1998. These developments likely caused some structural breaks in data. We therefore need to check the robustness of our results with respect to the crisis period. Doing so may allow us to spot the periods when our equation performs the least. To do so, we run One-Step Forecast Test (OSFT) to see whether the value of the dependent variable at time *t* might have come from the model fitted to the all data up to that point, so that each error can be compared with its standard deviation from the full sample. The OSFT option produces a plot of the recursive residuals and standard errors and the sample points whose probability value is at or below 15 percent. The plot will help us spot the periods when our equation is least successful. Plot 1 shows the result of this test.

The upper portion of the plot (right vertical axis) displays the recursive residuals and standard errors. The lower portion of the plot (left vertical axis) shows the probability values for those sample points where the hypothesis of parameter constancy would be rejected at the 5, 10, or 15 percent levels. The points with p-values less than 0.05 correspond to those points where the recursive resi-

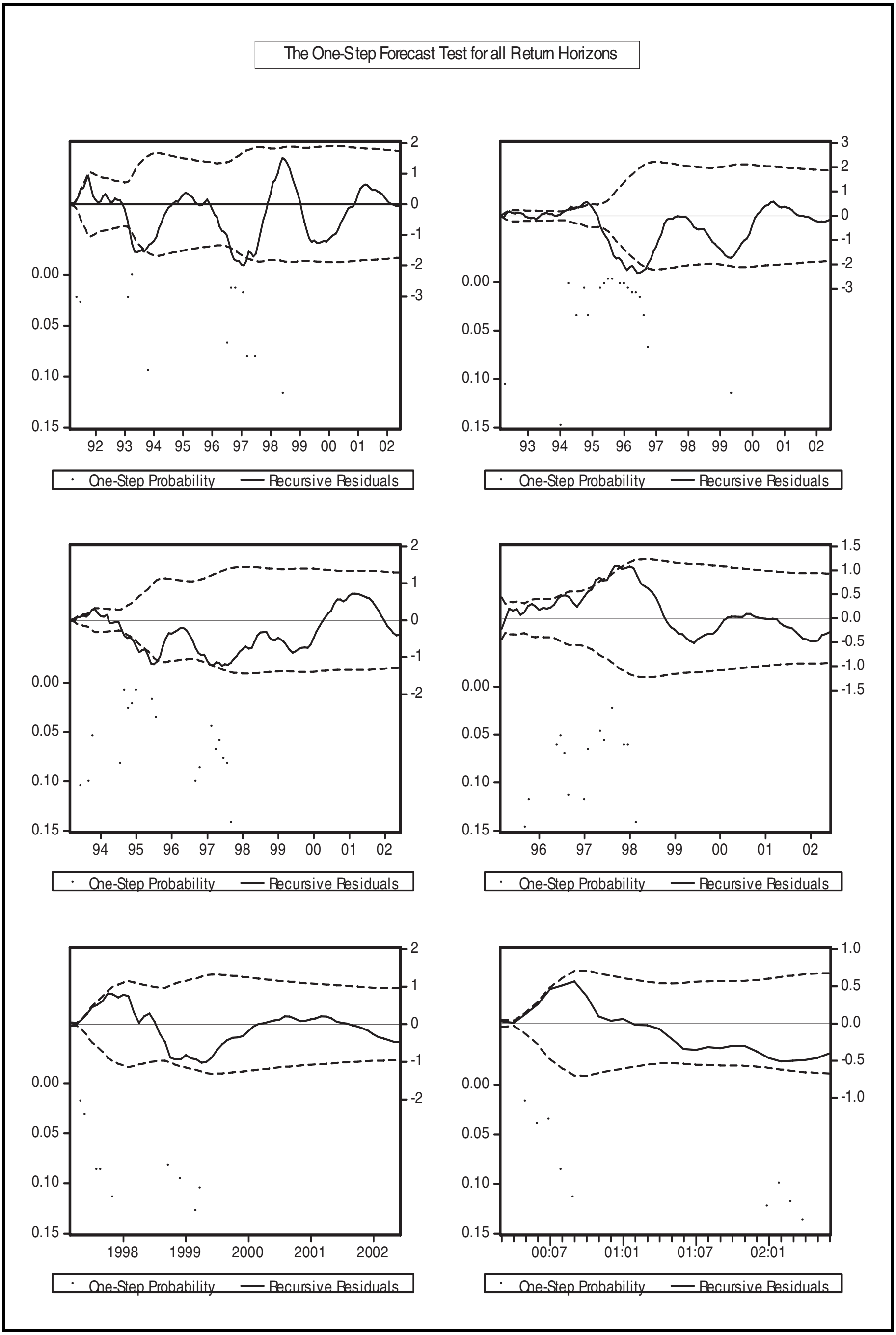
Table 3
Mean-Reversion using logs, 1989-2002: Bootstrap method

This table presents the following regression: $r_{t\rightarrow t+k} = a + b_k r_{t-k\rightarrow k} + \varepsilon_{t+k}$. b_k is the long-horizon regression coefficient. The confidence interval, $\left(b^*_{0.025}, b^*_{0.975}\right)$, is the confidence interval below which 2.5 percent of the bootstrap coefficients values lie and above which 2.5 percent of the bootstrap coefficients values lie. }Results are based on 1,000 shuffles.

	Horizon k (years)					
	1	**2**	**3**	**5**	**7**	**10**
b	-0.19341	-0.27412	-0.28382	-0.43302	-0.27064	-0.077749
$\left(b^*_{0.025}, b^*_{0.975}\right)$	$[-0.146.b^\wedge, 0.136.b^\wedge]^*$	$[-0.139b^\wedge, 0.1404b^\wedge]^*$	$[-0.126b^\wedge, 0.1230.b^\wedge]^*$	$[-0.0831^\wedge, 0.0779b^\wedge]^*$	$[-0.182.b^\wedge, 0.1613b^\wedge]^*$	$[-0.4243b^\wedge, 0.487b^\wedge]^*$
Bias-corrected β	-0.19307	-0.27372	-0.28342	-0.43251	-0.27020	-0.077171

* Indicates that the coefficients lie outside the confidence interval

Plot 1: The One-Step Forecast test



duals go outside the two standard error bounds. As we can see the residuals outside the standard error bands suggest instability in the parameters of the equation at the period during the years 1997 and 1998. Hence, we conclude that at the time of the crisis our equation has less predictive values and thus is least successful.(5) In order to account for these periods of the crisis, other bootstraps are run for the periods 1989:12 to 1996:12 and 1999:01 to 2002:06, and the results are reported in Table 4 and 5 below. Regressions of table 4 show some mean reversion, for the period from 1989:12 to 1996:12, especially in the 2, 3, and 5 year range. However, the results are different around year 1. Table 5 shows similar results with the long horizon regressions showing mean reversion in the years 2, 5, and 7. In general, both tables show direct evidence of mean-reversion in the index returns of Indonesia.

Conclusion

This paper examines the long-run stock market forecastability in Indonesia. Unit root tests results reject the null hypothesis of random walk against that of mean reversion (or a trend stationary alternative) at the 1% significance level. We find that our results are robust to the choice of lag length. All the results support the mean reversion hypothesis against the random walk hypothesis.

The bootstrap results show strong mean-reverting behavior as well. The long-horizon regressions indicate some evidence of mean reversion, especially in the 1, 2, 3 and 7 year range. However, evidence weakens by year 5. The corrected beta estimates show downward biases in all the studied horizons but with a relatively small difference. Our results are robust to accounting for the financial crisis of East Asia.

Overall, we find strong direct evidence for mean-reversion in index returns in Indonesia. All the beta coefficients lie outside the standard 95% confidence interval, indicating that a string of good past returns are able to forecast bad future returns. These results are of significant importance to investors in Indonesia for two reasons. First, they can forecast the long-run trend of the general stock market index, which exhibits mean reverting behavior. Second, they can build profitable investment strategy based on evidence provided in this paper.

(5) These stability tests are based on OLS results which are not reported in this paper.

Table 4
Mean-Reversion using logs, 1989-1996: Bootstrap method

This table presents the following regression: $r_{t\to t+k} = a + b_k r_{t-k\to k} + \varepsilon_{t+k}$. b_k is the long-horizon regression coefficient. The confidence interval, $\left(b^*_{0.025}, b^*_{0.975}\right)$, is the confidence interval below which 2.5 percent of the bootstrap coefficients values lie and above which 2.5 percent of the bootstrap coefficients values lie. }Results are based on 1,000 shuffles. Long horizons 7 and 10 can't be run due to sample size

	Horizon k (years)			
	1	**2**	**3**	**5**
b	-0.0461	-0.3755	-0.64165	-0.38820
$\left(b^*_{0.025}, b^*_{0.975}\right)$	$[-0.1706.b^{\wedge}, 0.1877.b^{\wedge}]$	$[-0.2477b^{\wedge}, 0.1877b^{\wedge}]^*$	$[-0.2088b^{\wedge}, 0.1875.b^{\wedge}]^*$	$[-0.1914^{\wedge}, 0.1878b^{\wedge}]^*$
Bias-corrected β	-0.0459	-0.3749	-0.6408	-0.3876

* Indicates that the coefficients lie outside the confidence interval

Table 5
Mean-Reversion using logs, 1999-2002: Bootstrap method

This table presents the following regression: $r_{t\to t+k} = a + b_k r_{t-k\to k} + \varepsilon_{t+k}$. b_k is the long-horizon regression coefficient. The confidence interval, $\left(b^*_{0.025}, b^*_{0.975}\right)$, is the confidence interval below which 2.5 percent of the bootstrap coefficients values lie and above which 2.5 percent of the bootstrap coefficients values lie. }Results are based on 1,000 shuffles. Long horizons 10 can't be run due to sample size

	Horizon k (years)				
	1	**2**	**3**	**5**	**7**
b	-0.4322	-0.5239	0.3139	-0.53191	0.37194
$\left(b^*_{0.025}, b^*_{0.975}\right)$	$[-0.1781.b^{\wedge}, 0.1766.b^{\wedge}]^*$	$[-0.2798b^{\wedge}, 0.2712b^{\wedge}]^*$	$[-0.3588b^{\wedge}, 0.4238.b^{\wedge}]$	$[-0.0725^{\wedge}, 0.064b^{\wedge}]^*$	$[-0.3719^{\wedge}, 0.0408b^{\wedge}]^*$
Bias-corrected β	-0.4316	-0.5232	0.31409	-0.53132	-0.3715

* Indicates that the coefficients lie outside the confidence interval

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الملخص

ارتداد عوائد الأسهم نحو قيمها المتوسطية في السوق المالي الأندونيسي والأزمة الآسيوية

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تفحص هذه الدراسة نزعة عوائد الأسهم للارتداد نحو قيمها المتوسطية في السوق المالي الأندونيسي. وتعد أندونيسيا من أكثر دول شرق آسيا التي شهدت أزمة اقتصادية حادة وتراجعاً كبيراً في قيمة عملتها (الروبية)، حيث خسرت أكثر من ٨٠٪ من قوتها الشرائية في الفترة ما بين عام ١٩٩٧ و١٩٩٨. وأظهرت نتائج تحليل "bootstrap" وجود نزعة قوية في عوائد مؤشر أسعار الأسهم في الرجوع إلى قيمها الأساسية. وبعد الأخذ بعين الاعتبار الأزمة الآسيوية وما يمكن أن تحدثه من تغيير هيكلي في الأعوام ١٩٩٧ و١٩٩٨ ظلت النتائج على ما هي عليه، كما بدت ذات دلالة إحصائية قوية.

Samer A. Al-Rjoub (Ph. D., in Financial Economics, University of New Orleans, New Orleans, LA, 2002), Associate Professor of Finance, Department of Banking and Finance, 2002 - current, Hashemite University, Zarqa - Jordan. His Research Interests Include Risk Management and Derivatives, Macroeconometric Modeling, System Dynamics in Economic and Financial Models, Asset Pricing Models, Simulation-Based Econometric Methods.