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Are Stock Returns Mean Reverting? The Case of Jordan (Evidence Using Bootstrap and GLS Randomization Techniques)

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ABSTRACT

This paper examines the mean-reverting behavior in Amman stock returns. Comparisons of two estimation techniques, the bootstrap and randomization, show strong mean reverting behavior in Jordan's index returns. Both the bootstrap and randomization methods have been used here to develop standard errors and significance levels for test statistics, which are free of distributional assumption.

I. INTRODUCTION

Efficient Market Hypothesis (henceforth EMH) is built on the idea of unpredictable returns and the fact that prices follow random walks. Recently, several departures from a random walk have been documented (Poterpa and Summers, 1988; Fama and French, 1988; Kim, Nelson and Startz, 1991). These departures prove to be true for both long and short-horizon returns (Conrad and Kaul, 1989). Their existence constitutes a major threat to the EMH and gives evidence that substantial part of the variance in different-horizon returns are due to forecastable component (Poterpa and Summers,1988). The first important evidence of long-run forecastability in stock market came from "clever ways" of looking at the long-run univariate properties of returns (Fama and French, 1988). It was simply a classic autocorrelation test from the 1960s to long-horizon returns data. Poterba and Summers (1988), on the other hand, considered using a related "variance ratio" statistic to test for near reversion. In both cases, the returns showed strong evidence of negative serial autocorrelation and a variance ratio statistic below one. It is important to mention that these two statistics are closely related and they reveal the same basic fact (for more details, see Asset pricing by Cochrane, 2001).

Within this environment, Caporale and Gil-Alana's (2002) application to U.S. real stock returns uses a test for unit roots and other nonstationary and stationary hypotheses. They found a weak support of mean reversion and no permanent component in stock prices, since the series examined is close to being integrated of order zero $I(0)$. On the other hand, Kiseok Nam et al. (2002) investigate 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 and these returns are quick, with a greater reverting magnitude to positive returns than positive returns reverted to negative returns. They interpret the asymmetrical reversion as evidence of stock market overreaction.

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

This paper investigates the mean reversion patterns of the Amman Stock market returns using Fama French (**FF**) return regressions test. Up to the present, this is the first paper that attempts to do so. This paper may also be of broader interest because we apply it on an emerging market.

Our paper is organized as follows: Section **I** discusses

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different techniques for measuring apparent deviation from fundamental price. Section **II** discusses estimation of these models and presents empirical results. The data are explained in section **III**. Conclusions and possible suggestions for possible future research are discussed in section **IV.**

II. Empirical Model:

Started with Fama and French (1988a) classic autocorrelation tests from the 1960s and Poterba and Summers (1988) variance ratio test of Cochrane (1988), the conventional view of the efficient market theory was jeopardized.

However, in an effort to defend the random walk hypothesis, several recent papers question the significance of long-horizon mean reversion and the necessity to explain it. Some suggest that we may reach misleading mean reversion statistics if we ignore the interdependence among these statistics at different return horizons (Rechardson,1989). Others stressed on the fact that using better asymptotic distribution of finite samples will lead us back to random walk (Richardson and Stock, 1989; McQueen, 1992).

This paper uses the **FF** regressions of long-horizon returns and further extends to use Bootstrap technique of Efron (1982) to avoid reliance on asymptotic distribution. The use of bootstrap technique is supposed to account for the downward biases in Beta coefficient (Kendall, 1954 and Kim et al., 1991).

In addition, the use of the bootstrap technique avoids the dangers of data-driven inference introduced via data-snooping biases.[1] Lo and MacKinlay (1990) note that the degree of such biases increases with the number of published studies performed on any single data set which will result in "spurious" market patterns. Their *Monte Carlo* simulations indicate that the data snooping biases in asset pricing models can be substantial. However, a Generalized Least Square (GLS) randomization technique is also used as a robustness test for the Bootstrap results. The Bootstrap and the GLS[2] Randomization calculate the confidence intervals for 1,000 shufflings.

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

$$r_{t\to t+k} = a + b_k r_{t-k\to k} + \varepsilon_{t+k} \qquad \ldots(1)$$

where

$r_{t\to t\to k}$ indicates the *k*-yeat return,

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

The confidence intervals for the lag returns coefficient are calculated using the bootstrapping technique. Efron (1982a: 35-36) suggests two methods of bootstrapping; one is to first fit the model and apply the bootstrap to the residuals, the second method applies the bootstrap to the vector of the observed response variable and the associated predictor variable. These methods are very general. They apply to linear and nonlinear regression models and can be used for least squares or any other estimation procedure. For the sake of this research, 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 true values of these coefficients for 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 estimate to produce the bootstrap estimate (Hsu et al., 1986).

The General Representation

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

A general linear regression model can be given by

Where Y_i and the row *k*-vector Ψ_i are observations on

[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.

[2] We use Hildreth-Lu consistent estimator for the asymptotic covariance matrix that adjust for the residual serial correlation.

the dependent and independent variables, respectively. Y_i is a dependent return $r_{t \to t+k}$. The function, $\Psi_{i,}$ 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.[3] Given the observed vector:

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

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

Where the i*th* component y_i is the observed value of the random variable Y_i.

To find an estimate of β we minimized the sum of squared distance between *y* and $\lambda(\beta)$, (D (*y*, $\lambda(\beta)$)).[4]

Now if

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

Now by minimizing the squared distance we have our parameter estimate of β. The elements η^*_i are created by re-sampling from η_i ; that is drawing from η_i randomly but with replacement. Now we can create an artificial (bootstrap) sample data set:

$$y_i^* = \Psi_i\left(\hat{\beta}\right) + \eta_i^*$$
$$for \qquad \ldots(5)$$
$$i = 1,2,\ldots,n$$

For each such bootstrap data set y^*, a bootstrap $\beta^{\wedge *}$ is estimated on the artificial sample from (4). The procedure is repeated *N* times and the sampling distribution of the deference between the bootstrap beta and the actual beta is an estimate of the sampling distribution.

Confidence intervals for β estimates from equation (1) can be obtained by several methods. The methods are described in Efron and Tibshirani (1986: 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 but more generally applicable. In this paper, the percentile method is used. The confidence interval, which 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.

III. The Data:

Values of value-weighted Amman Stock Exchange (ASE) general share price index as well as the sectoral share price indexes were collected from the Central Bank and ASE monthly statistical bulletins for the period between January, 1978 and October, 2002. As a result, there is a total of 286 monthly observations ranging from december, 1978 to August, 2003.

To compute stock market returns, R_t, we took the log difference for the monthly general price index weighted by market capitalization as in the following formula:

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

Where P_t is the value of the Amman stock exchange price index for the period *t* (*t* is time in months). The continuously computed multiperiod return (overlapping)is as follows:[5]

[3] 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 $p(\varepsilon<0)=0.5$.

[4] $\lambda(\beta)$ is a column vector of the known functional form Ψ_i,

$$\lambda(\beta) = \begin{bmatrix} \Psi_1(\beta) \\ \Psi_2(\beta) \\ \bullet \\ \bullet \\ \Psi n(\beta) \end{bmatrix}$$

[5] for more details on continuous compouding see,The Econometrics of Financial Markets, by Campbell, Lo and MacKinlay (1997), Princeton.

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

Estimates of multiperiod first-order autocorrelation coefficient are found using deferent yearly time horizons. The time horizons are 1,2,3,5,7 and 10 years.

Our primary interest in this study is to test whether stock prices in Jordan follow random walk or mean reverting processes. So, before running the bootstrap and the GLS randomization, we will test for random walk.

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

We can say that P is a stationary series if $-1<\rho<1$ (where ρ is the lagged P coeffeciant). If $\rho =1$, P is a nonstationary series or a random walk(it can be with and whithout 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. Both the ADF and the PP tests take the unit root as the null hypothesis : H_0: $\rho=1$. Since explosive series do not make much economic sense, this null hypothesis is tested against the one-sided alternative H_0: $\rho<1$. The model is estimated with and without trend.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 mean reversion at the 1% significance level. We used different lag length up to a maximum of 12 lags. It is apparent that the choice of lag length, cannot affect the test results. All the results support the mean reversion against the random walk hypothesis (The monthly stock market returns are also graphed at the apendix.).

IV. Empirical Results

Table (2) reports the mean, slandered deviation, and five serial and partial serial autocorrelations (AC and PAC, respectively) for the index return. Over the 24-year period, the monthly return averaged 0.0018 with standard deviation of 0.105. The first-order serial correlation is quite large for the return index with AC and PAC equal to –0.348. Higher order serial correlations are in general smaller in magnitude.

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, especially in the 2,3 and 7 year range. However, that turns around and disappears by year 5. The biased corrected beta estimates show either downward or upward biases but with a relatively small difference. We can conclude that the direct evidence for mean-reversion in index returns seems quite strong.

To determine whether our results change when using the randomization technique instead of bootstrap, we re-estimated the model under the assumption that data are sampled without replacement. Results of the randomization tests and estimates of the bias in beta are presented in table (4). The second row, which calculates the 95% confidence interval across the 6 time horizons, shows similar results of those from the bootstrap. In sum, the direct evidence for mean-reversion in index returns seems quite strong. All the beta coeffeciants lie inside the standard 95% confidence interval.

V. Conclusion

This paper examines the empirical evidence for mean-revering behavior in stock returns.

ADF and PP reject the null of random walk against mean reversion (or a trend stationary alternative).Comparisons of two estimation techniques, the bootstrap and randomization, show strong mean reverting behavior in Jordan's index returns. Both the bootstrap and randomization methods have been used here to develop standard errors and significance levels for test statistics that are free of distributional assumption. Using the impulse response function to test for higher order autocorrelations may further develop this research.

Table 1: ADF and PP Tests for Random Walk in Jordan 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	-8.265735	-8.258416	**5**	-25.20142	-25.17204
6	-6.033428	-6.032290	**7**	-24.95308	-24.92721
8	-6.006715	-6.007818	**9**	-25.01159	-24.98961
10	-5.075730	-5.076576	**11**	-24.98384	-24.96569
12	-4.464257	-4.463934	**12**	-24.93766	-24.92120

Table 2: Summary Statistics 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 autocorelation (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	0.0018	-0.348	-0.348	0.016	-0.019	-0.012	-0.036	-0.052	0.029
S.D.	0.105								
N	297								

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استخدام طريقتين في التقدير لدراسة (Mean-Reverting) في العائدات على الأسهم المتداولة في بورصة عمان

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ملخـص

تتفحص هذه الدراسة سلوك (Mean-Reverting) في العائدات على الأسهم المتداولة في بورصة عمان، وتبين نتائج استخدام طريقتين في التقدير هما (Bootstrap and Randomization) أن سلوك (Mean-Reverting) قوي في مؤشر العائدات في الأردن. وقد تم استخدام الطريقتين لحساب الأخطاء المعيارية ومستويات الثقة للقيم الإحصائية المستخدمة في الاختبارات، التي تخلو من الافتراض التوزيعي.

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