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Seasonality in Stock Price Mean Reversion: Evidence from the U.S. and the U.K.

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ABSTRACT

The evidence of slowly mean-reverting components in stock prices has been controversial. The hypothesis of stock price mean-reversion is tested using a regression model that yields the highest asymptotic power among a class of regression tests. Although the evidence that the equally weighted index of stocks exhibits mean-reversion is significant in the period 1926–1988, this phenomenon is entirely concentrated in January. In the post-war period both the equally weighted and the value-weighted indices exhibit seasonal mean-reversion in January. A similar phenomenon is also observed for the equally weighted index of stocks traded on the London Stock Exchange.

IN A RECENT PAPER Fama and French (1988) report that "25–45 percent of the variation of 3- to 5-year stock returns is predictable from past returns" and pose a serious challenge to the long-held view that stock prices follow a random walk. In a subsequent paper, Poterba and Summers (1988) use variance ratio tests on the stock price data from the U.S. and 17 other countries and conclude that "The results consistently suggest the presence of transitory components in stock prices." However, Kim, Nelson, and Startz (1988) and Richardson (1989) criticize the earlier papers on statistical grounds and suggest on the basis of simulation evidence that the results of Fama and French and Poterba and Summers do not violate the random walk model. The conflicting opinions expressed in these papers clearly highlight the controversy surrounding the interpretation of the seemingly large point estimates of long-term serial correlation in stock returns. The economic interpretation of the estimates in these tests is difficult because they have low precision, and hence more efficient tests are required.

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This paper examines the asymptotic power of a class of regression tests, which includes the Fama and French model and shows that the highest power against the form of mean-reverting alternative proposed by Summers (1986) is achieved with a regression model using 1-month returns as the dependent variable and lagged multiyear returns as the independent variable. This regression model is used here to test the hypothesis that stock prices contain a slowly decaying component.

The second objective of this paper is to test for seasonal patterns in stock price mean-reversion. The study of seasonality is motivated by the available evidence that a number of empirical regularities in stock returns are concentrated in the month of January. For example, Branch (1977) and DeBondt and Thaler (1987) report that the cross-sectional differences in January returns of selected securities are systematically related to their returns in the previous 1 to 5 years.

There is reliable evidence that the equally weighted index (EWI) exhibits mean-reversion in the sample period 1926–1988,[1] but there is little evidence of mean-reversion for the value-weighted index (VWI). On closer examination, it is found that the stock price mean-reversion is entirely concentrated in the month of January and the estimates of long-term serial correlation outside January are indistinguishable from zero. This pattern of long-term serial correlation is found for most size-based portfolio returns.

Fama and French (1988) and Kim, Nelson, and Startz (1988) report that the evidence of mean-reversion in stock prices is weak in the post-war period. The results here also suggest that there is little evidence of mean-reversion in this subperiod when all calendar months are considered simultaneously. However, there is reliable evidence that the stock prices exhibit mean-reversion in January in the post-war period as well. A similar phenomenon is also observed for the EWI of stocks traded on the London Stock Exchange, which suggests that the empirical regularity documented here is an international phenomenon.

My paper is organized as follows. The first section presents the specification of the mean-reversion hypothesis as proposed by Summers (1986) and later used by Fama and French, among others, and discusses the econometric issues.[2] Section II contains the empirical tests and the results using the data on stock returns from the U.S. and the U.K. The economic implications of the empirical results are examined in Section III, and Section IV concludes the paper.

[1] If the stock prices or the index levels contain a temporary component, then they tend to revert to their trends in the long run which is referred to as *mean-reversion*. If the stock price exhibits such a tendency, then the cumulative returns will also partially revert to the mean in the long run.

[2] The econometric issues related to the different specifications of the multivariate regression tests that examine the predictability of returns using variables such as the dividend yield and the default premium as in Fama (1990) are not considered in this paper. The evidence that the returns at various horizons can be predicted using these variables does not seem to be controversial.

I. Specification of the *Fads* Model and Econometric Issues

The *fads* model of stock prices as proposed by Summers (1986) hypothesizes that stock prices contain a slowly decaying temporary component. Let p_t be the natural logarithm of stock price at time t which consists of a permanent component q_t and a temporary component z_t. Let

$$\begin{aligned} p_t &= q_t + z_t, \\ q_t &= \mu + q_{t-1} + \psi_t, \qquad \psi \sim \text{i.i.d.}(0, \sigma_\psi^2), \quad \text{and} \\ z_t &= \lambda z_{t-1} + \eta_t, \qquad 0 < \lambda < 1, \qquad \eta \sim \text{i.i.d.}(0, \sigma_\eta^2), \end{aligned}$$

where η and ψ are independent random variables and μ is the expected rate of return. The continuously compounded stock return in period t is given by

$$\begin{aligned} R_t &\equiv p_t - p_{t-1} \\ &= \mu + \psi_t + \eta_t + (\lambda - 1)\textstyle\sum_{i=1}^{\infty}\lambda^{i-1}\eta_{t-i}. \end{aligned} \tag{1}$$

The fads model implies that the stock returns will exhibit negative serial correlation. As Summers (1986) points out, when λ is close to one, the negative serial correlation in returns is small in short horizons and hence will escape detection. Therefore, tests for slowly decaying components in stock prices typically focus on the behavior of long-horizon returns, using regressions of the form

$$\textstyle\sum_{i=1}^{J} R_{t-1+i} = a_{JK} + b_{JK}\sum_{i=1}^{K} R_{t-i} + u_{JK,t}. \tag{2}$$

Fama and French use a regression specification with the return aggregation intervals for both the independent and the dependent variables set equal, i.e., with $J = K$ in (2).

The probability limit of the slope coefficient in regression (2) can be computed in a straight-forward manner and is given by the following expression:

$$\text{plim}\ \hat{b}_{JK} = \frac{-(1-\lambda^J)(1-\lambda^K)}{2\phi K(1-\lambda) + 2(1-\lambda^K)},$$

where ϕ is the ratio of the unconditional variance of returns attributable to the permanent component to that attributable to the temporary component.[3] The asymptotic variance of the estimate of the slope coefficient under the

[3]The following relation is obtained from equation (1): $\sigma_R^2 = \sigma_\psi^2 + \frac{2\sigma_\eta^2}{1+\lambda}$, where σ_R^2, σ_ψ^2, and σ_η^2 are the variance of the stock returns and the variances of the random variables ψ and η, respectively. The second term on the right hand side is the variance of returns attributable to the temporary component.

null hypothesis is given by the expression[4]

$$N_{JK}\text{var}(\hat{b}_{JK}) = \frac{3KJ^2 - J^3 + J}{3K^2}, \tag{3}$$

where N is the number of time series observations and $N_{JK} = N + 1 - J - K$.

The power of a particular regression test depends both on the expected value of the slope coefficient under the alternate hypothesis and also on the precision with which the estimate is obtained. For instance, increasing the aggregation interval J would, on average, result in a higher point estimate of the slope coefficient if the alternate hypothesis is true. However, increasing J would also increase the standard error of the estimate. Both these effects need to be considered simultaneously in order to choose the most powerful test among the class of regression tests specified above.

Geweke (1981) recommends the use of the approximate slope criterion for the purpose of relative power comparison. Geweke shows that when the limiting distribution of the test statistic is χ^2, then the approximate slope of the test is given by the probability limit of $\frac{1}{N}$ times the test statistic under the alternate hypothesis. In the present context, the approximate slope of a regression test with aggregation intervals J and K is given by

$$c(b_{JK}) \equiv \frac{3K^2}{(3KJ^2 - J^3 + J)} \frac{(1 - \lambda^J)^2(1 - \lambda^K)^2}{(2K\phi(1 - \lambda) + 2(1 - \lambda^K))^2}.$$

Geweke shows that, asymptotically, the test with the biggest approximate slope achieves the highest power among the class of tests considered.[5] Therefore, the aggregation intervals J and K should be chosen so that the approximate slope is maximized under the specified alternate hypothesis in order to achieve the highest asymptotic power. The optimal choices of aggregation intervals under different specifications of ϕ and λ are considered, and the results are presented in Table I. Specifically, ϕ is allowed to vary from 0.25 to 1.0, and the half life of the temporary component is varied from about

[4] This expression generalizes the result derived by Richardson and Smith (1988) for the case of regression tests with symmetric aggregation intervals, i.e., with $J = K$. Richardson and Smith specialize the general results of Hansen and Hodrick (1980) and derive the expressions for the standard errors of the autocorrelation estimates using overlapping observations. This expression assumes $J \le K$, which is usually the case of interest. If $J > K$ the expression for the asymptotic variance is $N_{JK}\text{var}(\hat{b}_{JK}) = \frac{3JK - K^2 + 1}{3K}$ (see Appendix A).

[5] Geweke's result is fairly intuitive. Note that the approximate slope is the probability limit of $\frac{1}{N}$ times the square of the usual t-statistic. Heuristically, in large samples, the t-statistic can be expected to be close to $\sqrt{Nc(b_{JK})}$ if the alternate hypothesis is true. Therefore, a test with a bigger approximate slope can be expected to be more powerful than one with a smaller approximate slope.

Table I

Choice of Aggregation Intervals

This table presents the aggregation intervals J and K in the regression model below that yield the highest asymptotic power against the alternate hypothesis of stock price mean-reversion, with different specifications of the parameters ϕ and λ. ϕ is the ratio of the unconditional variance attributable to the permanent component of stock returns to that attributable to the temporary component and λ is the mean-reversion parameter under the alternate hypothesis.

Regression model: $\sum_{i=1}^{J} R_{t-1+i} = a_{JK} + b_{JK} \sum_{i=1}^{K} R_{t-i} + u_{JK,t}$.

ϕ	λ	J	K
0.25	0.99	1	442
	0.98	1	221
	0.97	1	147
	0.96	1	110
	0.95	1	88
0.50	0.99	1	287
	0.98	1	143
	0.97	1	95
	0.96	1	71
	0.95	1	57
1.00	0.99	1	210
	0.98	1	105
	0.97	1	70
	0.96	1	52
	0.95	1	41

1 year to about 6 years (λ is varied from 0.95 to 0.99). It is found that the optimal choice of the aggregation interval for the dependent variable is always equal to one.[6] In other words, it is always desirable to use non-aggregated returns on the left hand side of the regression model (2). To see the intuition behind this result, note that increasing J has two opposing effects on $c(b_{JK})$. First, increasing J has the effect of making the probability limit of the point estimate of b_{JK} bigger by making λ^J smaller. However, an increase in J also leads to an increase in the variance of the estimate which makes the magnitude of the approximate slope smaller. The latter effect always dominates, and hence it is always optimal to set J equal to one.[7]

However, the optimal choice of the aggregation interval for the independent variable varies across different parametric specifications of the

[6] In addition to the results reported in Table I, the function $c(b_{JK})$ was numerically maximized for a number of other parametric specifications of the alternate hypothesis with $\lambda \in (0,1)$ and $\phi \in [0.01, 2]$. Function $c(b_{JK})$ always attained its maximum at $J = 1$.

[7] In a subsequent paper, Hodrick (1990) compares the regression test with aggregated returns as the dependent variable as in Fama and French (1988) with the specification using nonaggregated return as the dependent variable as proposed here, and he uses the dividend yield as the predictor variable. Hodrick suggests also that it is preferable to use nonaggregated return as the dependent variable.

alternate hypothesis. The optimal aggregation interval is large when λ is close to one. When λ is close to one, the temporary component of the stock price closely resembles a random walk in the short run, and hence serial correlation in stock returns can be uncovered only when long-horizon returns are considered. The optimal aggregation interval is small when the share of return variance attributable to the permanent component is large, i.e., when ϕ is big. When ϕ is large, the variance of aggregate returns increases rapidly when K is increased, which in turn makes the probability limit of the slope coefficient small. Based on the above analysis the following regression specification is used here:

$$R_t = a_K + b_K \sum_{i=1}^{K} R_{t-i} + u_{K,t}. \tag{4}$$

From the results in Table I it is found that the optimal aggregation intervals for the independent variable vary from 4 to 9 years for λ close to 0.95 and from 9 to 38 years for λ close to 0.99. The aggregation intervals used in this study are 4 to 9 years and 20 years.

A. Heteroskedasticity and Small Sample Considerations

The analytic variance of the estimate of the slope coefficient in (4) is $\frac{1}{K(N-K)}$ (set $J = 1$ in expression (3)). The assumption of homoskedasticity used to derive this expression is analytically convenient, but there is evidence that the series of stock returns is heteroskedastic (see Officer (1973)). The analytic expression for the standard error is consistent even under conditions of heteroskedasticity if the variance of returns at time t is uncorrelated with the past variances of returns.[8] However, to allow for more general forms of heteroskedasticity in the data, White's heteroskedasticity-consistent estimator is used in the tests. The small sample distribution of the White t-statistic under the null hypothesis, based on Monte Carlo simulation, is presented in Appendix B. The small sample distribution has a fatter left tail than the standard normal distribution, and hence the use of the asymptotic distribution will lead to excessive rejection of the null hypothesis. Therefore, the inferences drawn from the tests are based on the simulated distribution of the test statistic.

In small samples the estimate of the slope coefficient in regression (4) is biased downwards (see Marriot and Pope (1954)). Under the null hypothesis, the OLS estimate is biased downwards by $\frac{1}{N-K}$, and hence this factor is added to the OLS estimates both in the simulation and in the actual empirical tests.

[8]White (1980) shows that under this form of heteroskedasticity the OLS regression estimator of the standard error of the parameter estimate is consistent (see his Theorem 3, p. 826).

II. Empirical Tests and Results

This section examines the time-series properties of returns on the EWI and the VWI of stocks traded on the New York Stock Exhange (NYSE) using the regression model (4). The monthly returns data for the period 1926–1988 are obtained from the data set maintained by the CRSP.

The estimates of the slope coefficients in (4), using the returns on the EWI and the VWI, are presented in Table II.[9] The series of returns on the EWI is found to exhibit significant negative serial correlation (see Panel A of Table II). For example, the point estimate of the slope coefficient (t-statistic) is -0.018 (-2.27) when the aggregation interval is 84 months. The slope coefficients exhibit a U-shaped pattern across different aggregation intervals as observed by Fama and French using their regressions. The average of the slope coefficients in the regressions with different aggregation intervals, denoted by $\bar{b}$, is -0.009.[10] This statistic suggests rejection of the hypothesis that all slope coefficients are jointly equal to zero at the 10% level (one-sided) of significance.[11] However, there is little evidence that the VWI exhibits mean-reversion. The estimate (t-statistic) of the slope coefficient furthest from zero is only -0.007 (-0.75). The average of the slope coefficients is -0.003 which is not statistically different from zero.

Tests to examine the seasonal pattern in long-term return reversals are carried out next. The regression model (4) is fitted separately within and outside January. Specifically, to examine the extent to which the temporary components in stock prices decay in the month of January, the regression model (4) is fitted with only January returns as the dependent variable. The independent variable is obtained by aggregating the returns in all months in the aggregation interval. These regression estimates, adjusted for small sample bias,[12] are also presented in Table II. It is found that the long-term return reversals are entirely concentrated in the month of January. For example, for the EWI returns, the estimate (t-statistic) of the slope coefficient is -0.066 (-2.97) when the regression model is fitted in January with $K = 84$, while the corresponding estimate outside January is -0.012 (-1.48). The slope coefficients are never statistically significant in the non-January

[9] The results based on nominal returns are presented here. The results using returns in excess of the T-bill rate are qualitatively similar and hence are not reported.

[10] Richardson and Stock (1989) suggest the use of the statistic $\bar{b}$ to test the hypothesis that all the slope coefficients are jointly equal to zero. This statistic is recommended since it preserves the sign of the regression coefficients and hence may possess desirable power against the mean-reversion hypothesis.

[11] Critical values based on the distribution of $\bar{b}$ from the Monte Carlo simulation are used for statistical inference here and in the subsequent tests.

[12] The specification of the January regressions is somewhat different from the time-series regression considered by Marriot and Pope, where all observations except the end points enter both sides of the regression. However, the analytic expression for the small sample bias found by them can be extended in a straightforward manner to the case of the January regressions as well. The small sample bias in the OLS estimate of the slope coefficient is $-\frac{1}{N-K}$, where N is the number of months in the sample period including months other than January.

Table II

Regresions of 1-Month Returns against Lagged Multiperiod Returns: Equally Weighted and Value-Weighted Indices of the U.S. Stocks

The regression model below is fitted using continuously compounded monthly returns on the equally weighted and the value-weighted indices of stocks traded on the NYSE.

$$\text{Model:} \quad R_t = a_K + b_K \sum_{i=1}^{K} R_{t-i} + u_{K,t},$$

where K is the aggregation interval in months for the independent variable. The estimates of the slope coefficients are reported below. They are adjusted for small sample bias by adding to the OLS estimates the factor $\frac{1}{N-K}$ where N is the number of time-series observations in the sample period. The January regressions are fitted with only the returns in the month of January as the dependent variable. However, the independent variable is obtained by aggregating the returns in all months within the chosen aggregation interval. The non-January regressions are also fitted in a similar manner. The White t-statistics are presented in parentheses. $\bar{b}$ is the average of the slope coefficients in the seven regressions. This statistic is used to test the hypothesis that all slope coefficients are jointly equal to zero. Monte Carlo simulation experiments are run separately for each sample period and also for the January and the non-January subperiods in order to obtain the critical values for $\bar{b}$. $\bar{R}^2_{\text{adj}}$ is the average of the adjusted R^2 in the regressions with different aggregation intervals.

K	48	60	72	84	96	108	240	$\bar{b}$	$\bar{R}^2_{\text{adj}}$
Panel A. Equally Weighted Index									
1926-1988									
All	−0.005	−0.009	−0.016	−0.018	−0.009	−0.005	−0.003	−0.009*	0.007
	(−0.45)	(−0.93)	(−1.67)	(−2.27)	(−1.31)	(−0.75)	(−0.56)		
Jan. ($\hat{b}_K^J$)	−0.024	−0.041	−0.058	−0.066	−0.061	−0.023	−0.037	−0.044†	0.146
	(−1.30)	(−2.11)	(−2.94)	(−2.97)	(−2.55)	(−0.90)	(−1.74)		
Non-Jan. ($\hat{b}_K^{NJ}$)	−0.003	−0.006	−0.011	−0.012	−0.004	−0.004	0.001	−0.005	0.003
	(−0.23)	(−0.54)	(−1.09)	(−1.48)	(−0.52)	(−0.50)	(0.20)		
$t\,(\hat{b}_K^{NJ} - \hat{b}_K^J = 0)$	0.985	1.595	2.110	2.257	2.314	0.732	1.750		
1947-1988									
All	−0.008	0.000	−0.004	−0.004	−0.002	−0.003	−0.003	−0.003	0.002
	(−0.72)	(−0.03)	(−0.45)	(−0.47)	(−0.24)	(−0.43)	(−0.56)		
Jan. ($\hat{b}_K^J$)	−0.079	−0.072	−0.086	−0.079	−0.052	−0.037	−0.036	−0.063‡	0.211
	(−1.98)	(−2.29)	(−3.83)	(−3.23)	(−1.81)	(−1.18)	(−1.70)		
Non-Jan. ($\hat{b}_K^{NJ}$)	0.001	0.008	0.005	0.005	0.004	0.001	0.001	0.003	0.000
	(0.08)	(0.97)	(0.78)	(0.72)	(0.65)	(0.15)	(0.18)		
$t\,(\hat{b}_K^{NJ} - \hat{b}_K^J = 0)$	1.942	2.462	3.892	3.303	1.901	1.190	1.704		
Panel B. Value-Weighted Index									
1926-1988									
All	−0.003	−0.004	−0.007	−0.005	0.001	0.001	−0.001	−0.003	0.002
	(−0.30)	(−0.50)	(−0.88)	(−0.88)	(0.10)	(0.18)	(−0.37)		
Jan ($\hat{b}_K^J$)	−0.002	−0.010	−0.027	−0.027	−0.013	0.004	−0.011	−0.012	0.027
	(−0.14)	(−0.60)	(−1.54)	(−1.66)	(−0.75)	(0.27)	(−0.95)		
Non-Jan. ($\hat{b}_K^{NJ}$)	−0.003	−0.004	−0.005	−0.003	0.002	0.001	0.000	−0.002	0.001
	(−0.29)	(−0.41)	(−0.59)	(−0.49)	(0.30)	(0.12)	(−0.05)		
$t\,(\hat{b}_K^{NJ} - \hat{b}_K^J = 0)$	−0.040	0.340	1.148	1.371	0.807	−0.209	0.908		

Table II—*Continued*

Panel B. Value-Weighted Index									
K	48	60	72	84	96	108	240	$\bar{b}$	$\bar{R}^2_{adj}$
				1947-1988					
All	−0.007	0.003	0.001	0.001	0.004	0.002	−0.002	0.000	0.001
	(−0.75)	(0.36)	(0.12)	(0.14)	(0.62)	(0.35)	(−0.61)		
Jan ($\hat{b}_K^J$)	−0.032	−0.026	−0.048	−0.037	−0.013	−0.005	−0.010	−0.024*	0.038
	(−0.75)	(−0.71)	(−1.81)	(−1.41)	(−0.49)	(−0.19)	(−0.79)		
Non-Jan. ($\hat{b}_K^{NJ}$)	−0.005	0.006	0.005	0.005	0.005	0.003	−0.001	0.003	0.001
	(−0.52)	(0.64)	(0.68)	(0.65)	(0.88)	(0.46)	(−0.35)		
$t\,(\hat{b}_K^{NJ} - \hat{b}_K^J = 0)$	0.615	0.842	1.927	1.530	0.675	0.288	0.683		

*Significant at the 10% level (single-tailed).
†Significant at the 5% level (single-tailed).
‡Significant at the 1% level (single tailed).

sample period.[13] The average adjusted R^2 in January is 0.15 for the EWI returns, and the corresponding statistic outside January is only 0.003. The hypothesis that the slope coefficient in January is the same as the slope coefficient in the corresponding regression outside January is rejected at the 5% level of significance for aggregation intervals of 6 to 8 years. Even in the case of the VWI returns, the slope coefficients in January are statistically significant at the 10 and 5% levels (one-sided) when aggregation intervals of 72 and 84 months, respectively, are used in the regression model. The mean of the slope coefficients in the January regressions with EWI returns is −0.044 (p-value < 0.05). However, the random walk hypothesis cannot be rejected in the non-January months with the EWI returns, and the tests using the statistic $\bar{b}$ also do not suggest rejection of the random walk model for the VWI, both within and outside January.

A. Post-War Period Results

Fama and French and Kim, Nelson, and Startz report that in the post-war period there is no reliable evidence that the stock prices exhibit mean-rever-

[13]When the non-January months were individually considered, $\bar{b}$ was significant only in the month of August where $\bar{b} = -0.025$, which is significant at the 10% level (one-sided). The estimates of the slope coefficients (t-statistics) in the regressions with aggregation intervals of 4 to 9 years and 20 years were −0.07 (−1.5), −0.06 (−1.5), −0.07 (−1.6), −0.02 (−0.9), 0.01 (0.5), 0.03 (1.8), and 0.01 (1.1), respectively. However, the August estimates were driven by a single outlier in the month of August 1932. The return on the EWI in this month was 65.5% which followed a 4-year compounded market decline of 71.9%. The White standard errors are also large in this sample period since the White estimator places a large weight on the outlier which happens to follow a large market decline. When this observation is excluded, the estimates of the slope coefficients with aggregation intervals of 4 to 6 years were −0.01, −0.01, and −0.02, respectively. The slope coefficients in the regressions with aggregation intervals longer than 6 years are not affected by this exclusion since the outlier does not enter these regressions on the left-hand side.

sion. This section examines the behavior of stock returns in the sample period 1947–1988 using regression (4).

The slope coefficients in the entire subperiod are all close to zero for both the EWI and the VWI returns (see Table II). The negative slope coefficient furthest from zero is only -0.008 (t-statistic of -0.72), and there is little evidence that the stock prices exhibit mean-reversion. However, when the month of January is considered separately there is reliable evidence against the null hypothesis. For example, with the EWI returns the slope coefficients (t-statistics) with 72- and 84-month aggregation intervals are -0.086 (-3.83) and -0.079 (-3.23), respectively. The point estimates of the slope coefficients in January in the post-war period are generally further from zero than the corresponding estimates in the entire sample period. The average adjusted R^2 in January in this sample period is 0.21. The statistic $\bar{b}$ for the January regressions is -0.063 (p-value < 0.01). The point estimates of the slope coefficients in the January regressions with the VWI returns are qualitatively similar. The January slope coefficients are further from zero than the non-January slope coefficients, and the estimate of $\bar{b}$ is -0.024, which is significant at the 10% level.

B. Size-Based Portfolios

The regression results with the returns on size-quintile portfolios are presented in Table III. The size-based portfolio 1 is the equally weighted portfolio of the 20% of the smallest firms listed on the NYSE, and portfolio 2 is the portfolio of firms in the next size-quintile and so on. The extent of stock price mean-reversion for the small firm portfolios are generally more pronounced than those for the large firm portfolios. The results of the joint tests suggest rejection of the random walk hypothesis only for the size quintile 2 over the sample period 1926–1988. Again, it is found that the long-term return reversals are concentrated in the month of January, and no evidence of mean-reversion outside January is found.[14] In the post-war period the estimates of all the slope coefficients are close to zero when all months are considered simultaneously, and the estimate (t-statistic) of the coefficient furthest from zero is -0.009 (-0.84) in this period. However, all size-based portfolios exhibit significant January mean-reversion in the post-war period, and the point estimates of the January slope coefficients are generally further from zero than the corresponding slope coefficients in the entire sample period. The average adjusted R^2 in the January regressions are also bigger in the post-war period than those in the period 1926–1988.

C. Stock Returns in the U.K.

The robustness of the phenomenon of stock price mean-reversion in January can be examined by analyzing the behavior of the stock returns outside the U.S. This subsection examines whether the EWI of stocks traded

[14] To conserve space the non-January results for size-based portfolios are not reported here. These results are available from the author.

Table III

Regressions of 1-Month Returns against Lagged Multiperiod Returns: Size-Based Portfolios of U.S. Stocks

The regression model below is fitted using continuously compounded monthly returns on size-based portfolios of stocks traded on the NYSE.

$$\text{Model:} \quad R_t = a_K + b_K \textstyle\sum_{i=1}^{K} R_{t-i} + u_{K,t},$$

where K is the aggregation interval in months for the independent variable. Portfolio 1 is the equally weighted portfolio of the 20% of the smallest firms listed on the NYSE, and portfolio 2 is the portfolio of firms in the next size-quintile and so on. The estimates of the slope coefficients are reported below. They are adjusted for small sample bias by adding to the OLS estimates the factor $\frac{1}{N-K}$ where N is the number of time-series observations in the sample period. The January regressions are fitted with only the returns in the month of January as the dependent variable. However, the independent variable is obtained by aggregating the returns in all months within the chosen aggregation interval. The White t-statistics are presented in parentheses. $\bar{b}$ is the average of the slope coefficients in the seven regressions. This statistic is used to test the hypothesis that all slope coefficients are jointly equal to zero. Monte Carlo simulation experiments are run separately for each sample period and also for the January subperiod in order to obtain the critical values for $\bar{b}$. $\bar{R}^2_{\text{adj}}$ is the average of the adjusted R^2 in the regressions with different aggregation intervals.

	K	48	60	72	84	96	108	240	$\bar{b}$	$\bar{R}^2_{\text{adj}}$
					Panel A. Overall Period 1926-1988					
1	All	−0.001	−0.006	−0.013	−0.013	−0.006	−0.002	0.000	−0.006	0.005
		(−0.09)	(−0.82)	(−1.79)	(−2.12)	(−1.11)	(−0.50)	(−0.15)		
	Jan.	−0.003	−0.022	−0.036	−0.039	−0.032	−0.011	−0.019	−0.023*	0.071
		(−0.15)	(−1.09)	(−1.90)	(−2.27)	(−1.81)	(−0.50)	(−1.56)		
2	All	−0.003	−0.008	−0.015	−0.020	−0.011	−0.007	−0.001	−0.009*	0.008
		(−0.26)	(−0.85)	(−1.56)	(−2.37)	(−1.62)	(−0.91)	(−0.21)		
	Jan.	−0.019	−0.037	−0.053	−0.065	−0.072	−0.031	−0.039	−0.045‡	0.166
		(−1.11)	(−1.98)	(−2.69)	(−2.69)	(−3.03)	(−1.38)	(−1.76)		
3	All	−0.003	−0.007	−0.014	−0.016	−0.008	−0.006	−0.002	−0.008	0.006
		(−0.29)	(−0.76)	(−1.46)	(−2.06)	(−1.20)	(−0.81)	(−0.42)		
	Jan.	−0.026	−0.037	−0.051	−0.057	−0.047	−0.015	−0.031	−0.038†	0.128
		(−1.63)	(−2.19)	(−2.71)	(−2.94)	(−2.16)	(−0.69)	(−1.47)		
4	All	−0.004	−0.006	−0.010	−0.010	−0.003	−0.001	−0.001	−0.005	0.003
		(−0.34)	(−0.62)	(−1.14)	(−1.36)	(−0.49)	(−0.22)	(−0.27)		
	Jan.	−0.015	−0.025	−0.037	−0.039	−0.031	−0.005	−0.019	−0.024*	0.063
		(−0.81)	(−1.24)	(−1.80)	(−1.91)	(−1.55)	(−0.25)	(−1.18)		
5	All	−0.004	−0.006	−0.009	−0.007	0.000	0.000	−0.001	−0.004	0.002
		(−0.39)	(−0.63)	(−1.09)	(−1.06)	(−0.07)	(−0.03)	(−0.45)		
	Jan.	−0.008	−0.017	−0.033	−0.030	−0.014	0.005	−0.011	−0.015	0.036
		(−0.49)	(−1.02)	(−1.90)	(−1.77)	(−0.80)	(0.26)	(−0.85)		
					Panel B. Post-War Period 1947-1988					
1	All	−0.003	0.000	−0.003	−0.003	−0.001	−0.002	0.000	−0.002	0.001
		(−0.26)	(0.03)	(−0.44)	(−0.47)	(−0.28)	(−0.48)	(0.14)		
	Jan.	−0.065	−0.058	−0.067	−0.060	−0.041	−0.034	−0.022	−0.050‡	0.208
		(−1.60)	(−1.92)	(−2.61)	(−2.56)	(−1.86)	(−1.44)	(−1.83)		
2	All	−0.002	0.001	−0.004	−0.004	−0.003	−0.004	−0.002	−0.003	0.002
		(−0.24)	(0.16)	(−0.48)	(−0.62)	(−0.50)	(−0.66)	(−0.39)		
	Jan.	−0.067	−0.070	−0.085	−0.080	−0.059	−0.045	−0.038	−0.063‡	0.248
		(−1.84)	(−2.51)	(−4.28)	(−3.84)	(−2.30)	(−1.57)	(−1.64)		

Table III—*Continued*

		Panel A. Overall Period 1926-1988								
	K	48	60	72	84	96	108	240	$\bar{b}$	$\bar{R}^2_{adj}$
3	All	−0.003	0.001	−0.003	−0.002	−0.002	−0.004	−0.003	−0.002	0.001
		(−0.37)	(0.16)	(−0.40)	(−0.35)	(−0.35)	(−0.70)	(−0.61)		
	Jan.	−0.067	−0.064	−0.078	−0.070	−0.046	−0.034	−0.030	−0.056‡	0.180
		(−1.95)	(−2.34)	(−3.83)	(−3.12)	(−1.77)	(−1.19)	(−1.37)		
4	All	−0.009	0.001	−0.003	−0.002	0.000	−0.002	−0.002	−0.003	0.001
		(−0.84)	(0.06)	(−0.38)	(−0.24)	(−0.06)	(−0.31)	(−0.62)		
	Jan.	−0.071	−0.062	−0.079	−0.069	−0.042	−0.029	−0.018	−0.053‡	0.134
		(−1.74)	(−1.83)	(−3.26)	(−2.62)	(−1.42)	(−0.93)	(−1.02)		
5	All	−0.009	0.002	0.000	0.001	0.003	0.001	−0.002	−0.001	0.001
		(−0.84)	(0.17)	(−0.06)	(0.07)	(0.43)	(0.10)	(−0.69)		
	Jan.	−0.032	−0.028	−0.050	−0.036	−0.014	−0.006	−0.009	−0.025*	0.038
		(−0.71)	(−0.76)	(−1.78)	(−1.25)	(−0.48)	(−0.22)	(−0.69)		

*Significant at the 10% level (single-tailed).
†Significant at the 5% level (single-tailed).
‡Significant at the 1% level (single-tailed).

on the London Stock Exchange exhibit mean-reversion. The sample period is 1955-1988.[15] The estimates of the slope coefficients in regression (4) with the U.K. data are presented in Table IV. As with the post-war period U.S. stock return data, there is no evidence of mean-reversion when the entire sample period is considered. In the January regressions with aggregation intervals of 4 to 6 years the slope coefficients are statistically significant, using single-tailed critical values. The statistic $\bar{b}$ in January is -0.041 which is significant at the 10% level. The average adjusted R^2 is 0.123 in the January regressions, while it is close to zero outside January. Therefore, it appears that the seasonality in stock price mean-reversion in the U.K. is qualitatively similar to that in the U.S.

The correlation between the U.K. stock returns and the returns on the EWI was 0.4 in the sample period 1955-1988. To the extent that the stock returns in the U.S. and the U.K. are correlated, large estimates of the slope coefficients in January observed with the U.S. data can be expected to carry over to the British data as well. The expectations of the slope coefficients in the regressions fitted with the U.K. stock return data, conditional on the estimates obtained with the U.S. data, can be analytically determined. Using asymptotic theory, it is shown in Appendix C that under the random walk hypothesis $E(\hat{b}_K^{UK} \mid \hat{b}_K^{US}) = \rho^2 \hat{b}_K^{US}$ where ρ is the correlation between the U.S. and the U.K. stock market returns, $\hat{b}_K$ is the estimate of the slope coefficient in the regression (4), and the superscripts denote the respective countries. For instance, if the estimate of a particular slope coefficient with the U.S. data is -0.08 then, under the random walk hypothesis, the condi-

[15]I would like to thank Jeremy Smithers of the London Business School for generously providing me with the data used here.

Table IV

Regressions of 1-Month Returns against Lagged Multiperiod Returns: Equally Weighted Index of U.K. Stocks

The regression model below is fitted using continuously compounded monthly returns on the equally weighted portfolio of stocks traded on the London Stock Exchange.

$$\text{Model:} \quad R_t = a_K + b_K \sum_{i=1}^{K} R_{t-i} + u_{K,t},$$

where K is the aggregation interval in months for the independent variable. The estimates of the slope coefficients are reported below. They are adjusted for small sample bias by adding to the OLS estimates the factor $\frac{1}{N-K}$ where N is the number of time-series observations in the sample period. The January regressions are fitted with only the returns in the month of January as the dependent variable. However, the independent variable is obtained by aggregating the returns in all months within the chosen aggregation interval. The non-January regressions are also fitted in a similar manner. The White t-statistics are presented in parentheses. $\bar{b}$ is the average of the slope coefficients in the seven regressions. This statistic is used to test the hypothesis that all slope coefficients are jointly equal to zero. Monte Carlo simulation experiments are run separately for the overall period and also for the January and the non-January subperiods in order to obtain the critical values for $\bar{b}$. $\bar{R}^2_{\text{adj}}$ is the average of the adjusted R^2 in the regressions with different aggregation intervals. The sample period is 1955–1988.

K	48	60	72	84	96	108	$\bar{b}$	$\bar{R}^2_{\text{adj}}$
All	−0.002	−0.006	−0.008	−0.007	−0.001	0.004	−0.003	0.004
	(−0.23)	(−0.61)	(−0.83)	(−0.66)	(−0.09)	(0.47)		
Jan. ($\hat{b}_K^J$)	−0.050	−0.048	−0.053	−0.039	−0.032	−0.025	−0.041*	0.123
	(−1.79)	(−1.57)	(−1.65)	(−1.21)	(−0.93)	(−0.79)		
Non-Jan. ($\hat{b}_K^{NJ}$)	0.003	−0.001	−0.003	−0.003	0.003	0.008	0.001	0.004
	(0.42)	(−0.13)	(−0.33)	(−0.27)	(0.30)	(0.82)		
$t\,(\hat{b}_K^{NJ} - \hat{b}_K^J = 0)$	1.837	1.383	1.484	1.080	0.973	0.994		

*Significant at the 10% level (single-tailed).

tional expectation of the slope coefficient with the U.K. data in the corresponding regression is −0.013. The estimates of the January slope coefficients with the U.K. data are generally further from zero than what can be expected under the random walk hypothesis, conditional on the estimates with the U.S. data.

III. Economic Implications

A. Rolling Forecasts

The extent of variability of the expected January returns implied by the evidence in the last section is examined in order to obtain some insights into the economic significance of the results. For this purpose, the average one-step-ahead forecasts of January returns based on the time-series regressions are examined over the sample period 1957–1988. To obtain the average one-step-ahead forecast of January return in the year t, regression (4) is first fitted in the sample period from 1926 to the year $t-1$ with January returns as the dependent variable. The lagged returns aggregated over 4- to 9-year intervals are used as the independent variables to fit six separate regressions and obtain six one-step-ahead forecasts of January return in year t.[16] The final forecast of January return in year t is obtained by averaging the one-step-ahead forecasts from the individual regressions. The average one-step-ahead forecasts of January returns on the EWI ranged from 1.41% to 9.07%. The forecasts of the VWI returns ranged from 0.57% to 2.48%. The wide ranges of the forecasts, particularly for the EWI returns, suggest that the variation in the expected returns in January is economically important. However, some caution in interpreting the results is in order since the range of the forecasts obtained here may overstate or understate the true variability in expected returns, depending on the signs of the measurement errors in the estimated parameters used in forecasting. To provide an alternate perspective on the magnitude of the changes in expected returns, the realized returns in two subperiods partitioned based on the predicted returns are examined. In the subperiod when the predicted returns are greater than the historic mean January returns, the average realized January return on the EWI was 6.75% compared with an average January return of 1.99% in the complementary subperiod. The VWI returns in the subperiods partitioned in a similar fashion were 2.48% and 1.33%, respectively. These results also suggest that the expected January returns on the EWI vary substantially depending on the return realizations in the previous 4 to 9 years.

B. *Tax-Motivated Trading?*

Market inefficiency and predictable changes in equilibrium risk premia are two competing hypotheses that have been proposed to explain the phenomenon of mean-reversion in stock prices. The evidence that the stock price mean-reversion is concentrated in the month of January suggests a third possible explanation, viz., that the empirical regularity may be related to year-end tax-motivated trading. For instance, it is possible that a large number of securities will be exposed to concentrated year-end tax-loss selling following prolonged periods of market decline. The subsequent turn-of-the-year rebound in the prices of these securities may result in high market returns in January.[17] However, the evidence of seasonal stock price mean-reversion in the U.K. casts some doubts on the plausibility of this explanation. Capital gains taxation was in effect in the U.K. during most of the sample period considered here, but the fiscal year ends on the fifth of April in the U.K.[18] However, British stock prices did not exhibit mean-reversion in April or any other month outside January. In spite of this evidence, the tax

[16]The regression with aggregation interval of 20 years is not used for forecasting due to limited data availability.

[17]See Branch (1977), Dyl (1977), and Givoly and Ovadia (1983), among others, for evidence in favor of the tax-loss selling hypothesis for individual securities.

[18]Taxes on short-term capital gains were introduced in 1962 in Britain and both long- and short-term capital gains were taxed from 1965 onwards.

hypothesis cannot be ruled out completely for two reasons. First, the U.K. stock market is open to the U.S. based investors, and secondly, many corporations in the U.K. end their fiscal years in the month of December. Therefore, it is possible that the stocks listed on the London Stock Exchange also experienced year-end tax-loss selling. Examining the relation between the volume of year-end transactions and lagged multiyear returns and also the relation between the former and January returns may shed some light on the viability of this explanation.

IV. Conclusion

The hypothesis that the stock prices contain slowly decaying components is tested using a set of regressions with 1-month returns as the dependent variable and lagged multiyear returns as the independent variable. It is shown that the regression model used here is asymptotically the most powerful test among a class of regression tests that includes the model previously used by Fama and French (1988) against a mean-reverting alternative previously considered in the literature. The seasonal pattern in the phenomenon of stock price mean-reversion is also investigated.

It is found that the EWI of stocks traded on the NYSE exhibits mean-reversion over the sample period 1926–1988, consistent with the earlier findings of Fama and French. However, it is found that the phenomenon of stock price mean-reversion is entirely concentrated in the month of January. In the post-war period there is no evidence of stock price mean reversion when all calendar months are jointly considered, but the January return reversals appear stronger in this subperiod. The EWI of stocks traded on the London Stock Exchange also exhibits a similar seasonal mean-reversion which suggests that the empirical regularity documented here is an international phenomenon.

Appendix A

The standard error of the estimate of b_{JK} in regression (2) is derived in this appendix.

Hansen and Hodrick (1980) show that the asymptotic variance-covariance matrix (1980) of the parameter estimates in (2) is given by $R_x(0)^{-1}S_0 R_x(0)^{-1}$, where

$$\begin{aligned} S_0 &= \textstyle\sum_{l=-\infty}^{\infty} R_u(l) R_x(l) \\ &= \textstyle\sum_{l=-J+1}^{J-1} R_u(l) R_x(l), \\ R_u(l) &= E[u_{JK,t} u_{JK,t-l}], \\ R_x(l) &= E[x_t' x_{t+l}], \quad \text{and} \\ x_t &= (1 \qquad \textstyle\sum_{i=1}^{K} R_{t-i}). \end{aligned}$$

Taking expectations under the null hypothesis and algebraic manipulation yields

$$R_u(l) = (J - |l|)\sigma^2,$$

$$R_x(l) = \begin{pmatrix} 1 & K\mu \\ K\mu & \max(0, K - |l|)\sigma^2 + K^2\mu^2 \end{pmatrix}, \quad \text{and}$$

$$S_0 = \begin{pmatrix} J^2\sigma^2 & J^2\sigma^2 K\mu \\ J^2\sigma^2 K\mu & \dfrac{3JKL - L^3 + L}{3K^2}\sigma^4 + J^2\sigma^2K^2\mu^2 \end{pmatrix},$$

where $L = \min(J, K)$. Using these expressions we find that $\mathrm{var}(\hat{b}_{JK}) = \dfrac{3JKL - L^3 + L}{3K^2}$.

Appendix B

This appendix presents the small sample distribution of the White t-statistics based on Monte Carlo simulations. The distribution of the t-statistics using simulated homoskedastic and heteroskedastic time series are presented in Table V in Panels A and B, respectively. A heteroskedastic time-series that roughly matches the properties of the EWI returns is generated using the method followed by Fama and French (1988). Specifically, 756 independent random numbers are generated, and the variance of the random numbers is changed every twenty-four observations to match the variance of the EWI returns in the corresponding period (the variance of the last thirty six observations is kept constant). The regression model (4) is fitted to the time-series with K varying from 48 to 108 and with $K = 240$. The distribution of the test statistics are based on 8000 replications.

The critical values of the White t-statistics for the subperiod regressions were close to those reported.

Appendix C

The expectation of the estimate of the slope coefficient when regression (4) is fitted with stock return data from country i, conditional on the estimate of the slope coefficient obtained from the corresponding regression fitted using the data from country j, is derived in this appendix.

Express regression (4) in matrix notation as

$$R^i = \beta_K^i X_K^i + \varepsilon_K^i,$$

where the superscript denotes the country. Let σ_i and μ_i denote the mean and standard deviation, respectively, of the monthly returns in country i, and let σ_{ij} denote the covariance between the stock returns in the countries i

Table V

Small Sample Distribution of the Test Statistics: Simulation Evidence

	Panel A. Homoskedastic Time-Series						
K	48	60	72	84	96	108	240
$\hat{b}_{OLS}$-mean	−0.003	−0.003	−0.003	−0.003	−0.003	−0.004	−0.005
$\hat{b}_{\text{adj}}$-mean†	−0.002	−0.002	−0.002	−0.002	−0.002	−0.002	−0.003
	Distribution of t-statistics based on White standard errors						
0.01	−2.53	−2.60	−2.59	−2.59	−2.61	−2.61	−2.86
0.05	−1.80	−1.84	−1.88	−1.90	−1.93	−1.95	−2.15
0.10	−1.43	−1.48	−1.49	−1.52	−1.55	−1.57	−1.78
	Panel B. Heteroskedastic Time-Series						
$\hat{b}_{OLS}$-mean	−0.005	−0.005	−0.005	−0.004	−0.003	−0.003	−0.003
$\hat{b}_{\text{adj}}$-mean†	−0.003	−0.003	−0.003	−0.002	−0.001	−0.001	−0.001
	Distribution of t-statistics based on White standard errors						
0.01	−2.43	−2.51	−2.54	−2.44	−2.50	−2.47	−2.37
0.05	−1.81	−1.83	−1.85	−1.84	−1.80	−1.79	−1.70
0.10	−1.47	−1.50	−1.49	−1.49	−1.43	−1.45	−1.31

†The usual OLS estimate of the slope coefficient is biased downward by a factor $\frac{1}{N-K}$ where N is the number of observations in the simulation. Therefore, this factor is added to the OLS estimate to get $\hat{b}_{\text{adj}}$. The t-statistics are computed for $\hat{b}_{\text{adj}}$.

and j. The asymptotic covariance matrix between the parameter estimates $\hat{\beta}_K^i$ and $\hat{\beta}_K^j$, under the null hypothesis, is derived below. Letting the number of observations N tend to infinity,

$$\begin{aligned}
&\operatorname{plim} N\operatorname{cov}(\hat{\beta}_K^i, \hat{\beta}_K^j) \\
&= \operatorname{plim} N\left(X_K^{i\prime} X_K^i\right)^{-1} X_K^{i\prime} \varepsilon_K^i \varepsilon_K^{j\prime} X_K^j \left(X_K^{j\prime} X_K^j\right)^{-1} \\
&= \frac{\sigma_{ij}}{K^2\sigma_i^2\sigma_j^2}\begin{bmatrix} K\sigma_i^2 + K^2\mu_i^2 & -K\mu_i \\ -K\mu_i & 1\end{bmatrix} \cdot \begin{bmatrix} 1 & K\mu_j \\ K\mu_i & K\sigma_{ij} + K^2\mu_i\mu_j\end{bmatrix} \\
&\quad \begin{bmatrix} K\sigma_j^2 + K^2\mu_j^2 & -K\mu_j \\ -K\mu_j & 1\end{bmatrix} \\
&= \frac{\sigma_{ij}}{K^2\sigma_i^2\sigma_j^2}\begin{bmatrix} K^2\sigma_i^2\sigma_j^2 + K^3\mu_i\mu_j\sigma_{ij} & -K^2\mu_i\sigma_{ij} \\ -K^2\mu_j\sigma_{ij} & K\sigma_{ij}\end{bmatrix}.
\end{aligned}$$

The asymptotic variance of the estimate of the regression slope coefficient in regression (4) is $\frac{1}{K(N-K)}$ (see Appendix A). Since the regression estimates are joint normally distributed in large samples, we get

$$E(\hat{b}_K^i \mid \hat{b}_K^j) = \frac{\operatorname{cov}(\hat{b}_K^i, \hat{b}_K^j)}{\operatorname{Var}(\hat{b}_K^j)} \hat{b}_K^j$$
$$= \rho_{ij}^2 \hat{b}_K^j,$$

where ρ_{ij} is the correlation between the stock returns in the countries i and j.

REFERENCES

Branch, Ben, 1977, A tax loss trading rule, *Journal of Business* 50, 198–207.

De Bondt, Werner F. M. and Richard Thaler, 1987, Further evidence of investor overreaction and stock market seasonality, *Journal of Finance* 42, 557–581.

Dyl, Edward A., 1977, Capital gains taxation and the year-end stock market behavior, *Journal of Finance* 32, 165–175.

Fama, Eugene F., 1990, Stock returns, expected returns and real activity, *Journal of Finance* 45, 1089–1108.

——— and Kenneth R. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246–273.

Geweke, John, 1981, The approximate slopes of econometric tests, *Econometrica* 49, 1427–1442.

Givoly, Dan and Arie Ovadia, 1983, Year-end tax induced sales and stock market seasonality, *Journal of Finance* 38, 171–185.

Hansen, Lars P. and Robert J. Hodrick, 1980, Forward exchange rates as optimal predictors of future spot rates: An econometric analysis, *Journal of Political Economy* 88, 829–853.

Hodrick, Robert J., 1990, Dividend yields and expected stock returns: Alternative procedures for inference and measurement, Unpublished working paper, Northwestern University.

Kim, Myung, Charles R. Nelson, and Richard Startz, 1988, Mean reversion in stock prices? A reappraisal of the empirical evidence, Unpublished working paper, University of Washington.

Marriot, F. H. C. and J. A. Pope, 1954, Bias in estimation of autocorrelations, *Biometrica* 41, 390–402.

Officer, Robert R., 1973, The variability of the market factor of the New York Stock Exchange, *Journal of Business* 46, 434–453.

Poterba, James and Larry Summers, 1988, Temporary components of stock prices: Evidence and implications, *Journal of Financial Economics* 22, 27–59.

Richardson, Matthew, 1989, Temporary components of stock prices: A skeptic's view, Unpublished working paper, Stanford University.

——— and Tom Smith, 1988, Tests of financial models in the presence of overlapping observations, *Review of Financial Studies*, Forthcoming.

——— James H. Stock, 1989, Drawing inferences from statistics based on multi-year asset returns, *Journal of Financial Economics* 25, 323–348.

Summers, Lawrence H., 1986, Does the stock market rationally reflect fundamental values?, *Journal of Finance* 41, 591–601.

White, Hal, 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, *Econometrica* 48, 817–838.