MEAN-REVERTING STATE VARIABLES AS A FACTOR IN MEAN-REVERTING STOCK RETURNS

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This paper tests for mean reversion in macroeconomic and fundamental variables. We also contrast results derived from alternative methodologies. Tests of mean reversion using OLS regression, variance ratios, and Markov chain techniques are performed on S&P 500 returns, small stock returns, default premia, dividend yields, industrial production, inflation, and term premia. Findings indicate that mean reversion is not unique to stock returns. We also find that mean reversion results are highly sensitive to the methodology applied. Our findings suggest that mean reversion in stock returns may result from rational responses of investors to changing business conditions.

Financial theory suggests that if expected returns for firms are constant over time, then mean reversion in stock returns may indicate a market inefficiency. In particular, mean reversion in stock returns often is equated with systematic variation of stock returns around equilibrium values. Many studies find that stock returns are mean reverting. For example, McQueen and Thorley (1991), Fama and French (1988b), and Poterba and Summers (1988) find that stock returns are mean reverting over two to five year horizons. They also find that mean reversion is strongest in the period before World War II and is stronger for small firms than for large firms.

Many researchers, however, question the linkage between mean reversion in stock returns and market inefficiency. In particular, mean reversion in priced state variables may cause

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expected returns to be mean reverting. For example, Fama and French (1988b) argue that the predictable portion of long-term returns may vary over time because equilibrium expected returns may vary over time. Therefore, even in an efficient market, stock returns may appear to be mean reverting. Unfortunately, current studies concentrate more on the symptom of mean reversion in stock returns (e.g., negative autocorrelation) than on the underlying causes of mean reversion. A fairer assessment of the market efficiency implications of mean reversion in stock returns may emerge from an analysis of state variables during changing market conditions.

With the exception of Cecchetti, Lam, and Mark (1990), there has been no attempt to evaluate the impact of macroeconomic or fundamental forces on mean reversion in returns. These authors specify an equilibrium model and then "calibrate" it to reflect the impacts of consumption, output, or dividends on the time series behavior of returns. They evaluate the likelihood that the estimates derived from historical data could have been generated from the equilibrium process described by their model. As is well known, however, any test of market efficiency that relies on an equilibrium model is a joint test of both the model and market efficiency. Therefore, reliance on an equilibrium model may inject an additional source of error into the investigation. This study takes a simpler approach to examine mean reversion. We do not rely on equilibrium models. Instead, we propose that rational investors will elicit mean reverting stock returns if priced state variables also are mean reverting.

Fama and French (1988b) describe a mean reverting stock market as a combination of a random walk component and a stationary but mean reverting component,

$$R = \lambda + \delta, \tag{1}$$

where R is the market return, λ is the random walk component, and δ is a stationary but mean reverting component.

We argue that δ is based on the observable information contained in the fundamental and macroeconomic state variables,

$$\Omega_{t-1} = \sum_{i=1}^{N} b_t X_{i_{t-k}}, \tag{2}$$

Where Ω is the information set available at time t-1, $x_{i's}$ are the observable state variables, $b_{i's}$ are coefficients, and k is the number of lags. Thus, we argue that,

$$R_t = \lambda_t + (\delta_t \mid \Omega_{t-1}), \tag{3}$$

If we assume that investors assimilate market conditions via an examination of macroeconomic and fundamental data, then the linkage between priced state variables and stock returns can be based on the well known valuation formula which describes the stock price as the sum of the present values of all future discounted cash flows. In general, this formula can be written as:

$$P_0 = \frac{CF}{k}, \tag{4}$$

where the stock's price (P_0) is the present value of all future cash flows (CF). If this is a reasonable model, then any factor that impacts either cash flows or the discount rate (k) should also affect the stock price and, consequently, returns.

Among the earlier research documenting the relationship between the state variables of this study and returns are: Chen (1991), Campbell and Shiller (1988 and 1989), Fama and French (1988), and Fama (1981) who find that dividend yields, inflation, and P/E ratios are associated with stock returns. Other studies by Chen (1991), Kaul and Seyhun (1990), Fama and French (1989), Keim and Stambaugh (1986), and Chen, Roll, and Ross (1986) find linkages between default premiums on bonds, industrial production, and term premiums on bonds and stock returns. We rely on these earlier works to identify potential variables for inclusion in this study.

To examine the efficient market implications of mean reverting stock returns we propose a two stage approach. In one stage, using three different empirical techniques, we examine the time series characteristics of both the state variables and returns for evidence of mean reverting behavior. In an additional step, we evaluate the linkage between a set of state variables and stock market returns using Granger causality tests (a form of OLS regression). Given the empirically demonstrated relationship between returns and state variables, and having demonstrated the presence of mean reversion in returns and mean reversion in the state variables, our argument that mean reverting returns can be explained by mean reverting state variables is based on the traditional interpretation of OLS regression: variability in the independent variable(s) *explains* or *accounts for* the variability in the dependent variable.

The remainder of the paper consists of four sections. Section I describes the data. Results of tests of stationarity of the variables also are presented. Section II provides the methodology. Section III presents the empirical findings and Section IV provides conclusions and implications for future research.

I. THE DATA

The data set consists of eight variables, each spanning the 1926-1991 period. For comparison with past research, we include returns on the S&P 500 and returns on an index of small capitalization stocks. The remaining six variables are default premia on bonds, dividend yields, industrial production, inflation, P/E ratios, and term premia on bonds. In each case, we consider horizons from one to five years. Default premia, dividend yields, inflation, S&P 500 returns, small stock returns, and term premia are taken from the *Stocks, Bonds, Bills, and Inflation: 1992 Yearbook* by Ibbotson Associates. The earnings-price ratio data are from Standard and Poor's *Trade and Securities Statistics*, and the industrial production series is taken from both the *Survey of Current Business* and *Business Statistics*. The raw data for each variable are measured monthly, except for the earnings-price ratio which is measured yearly. All series are converted to an annual basis to maintain consistency with previous research.

As argued by Fama and French (1988b) and Poterba and Summers (1988), to obtain reliable results, the data series must be stationary. Before applying any of the mean reversion tests, therefore, we examine the data for stationarity using correlograms and Dickey-Fuller tests. Correlograms provide a visual presentation of the autocorrelation coefficients that are subsequently examined for various patterns (see Pindyck and Rubinfeld, 1981). The Dickey-Fuller tests, on the other hand, provide an algebraic evaluation of stationarity (see Dickey and Fuller, 1979, 1981). Of the eight variables, dividend yields and inflation are found to be non-stationary. Therefore, we use first-differences for the dividend yield and inflation series, which, upon retesting, provide the requisite stationarity.

II. METHODOLOGY

The principal methods that have been applied separately to test mean reversion in returns are OLS regression (Fama and French, 1988b), variance ratios (Poterba and Summers, 1988), and Markov chains (McQueen and Thorley, 1991). We employ all three methods in order to compare our findings with past research and to determine the sensitivity of results to each method.

A. *OLS Tests for Mean Reversion*

In the OLS approach, observation t is regressed on observation t-1,

$$X_t = \alpha + \beta X_{t-1} + \epsilon_t, \tag{5}$$

where X_t is observation t on the variable being examined for mean reversion, observation t is based on horizon [t, t+T], and observation t-1 is based on horizon [t-T, t]. The slope coefficient, β, is the OLS estimate of the autocorrelation in the X series. The series is mean reverting if the estimate of β is significantly negative. Standard t-tests are used to evaluate the statistical significance of the β estimate.

Unfortunately, tests using OLS make various assumptions, including normality, which may not be met. Further, Poterba and Summers (1988) find that OLS tests are more likely to reject a null hypothesis of serial independence than other tests. Ultimately, OLS based tests are viewed as relatively weak tests of mean reversion.

B. Variance Ratio Tests for Mean Reversion

The premise underlying the variance ratio test is that if a series is random, its k-horizon variance, var(k), should be k times as large as its one-period variance, var(1). Therefore, for a random series we expect to find that var(1)/[var(k)/k] = 1. As demonstrated by Cochrane (1988), the variance ratio can be approximated by a linear combination of sample autocorrelations.

$$VR(k) \cong 1 + 2\sum_{j=1}^{k-1}\left(\frac{k-j}{k}\right)\rho_j - 2\sum_{j=1}^{11}\left(\frac{12-j}{12}\right)\rho_j \,, \tag{6}$$

where k is the horizon in months and ρ is the sample autocorrelation. A variance ratio of less than one implies negative autocorrelation and a variance ratio greater than one implies positive autocorrelation. Thus, the series is mean reverting if the variance ratio is less than one.

To test the variance ratio for statistical significance, we use a randomization approach. For each variable and for each horizon, the variance ratio, first, is calculated based on the actual data. Then, the data are randomly reordered to destroy any time dependencies and the variance ratio is recalculated. This process is repeated 10,000 times. Based on these results, we are able to evaluate the likelihood of obtaining a variance ratio (by chance) that is below the variance ratio observed from the actual series.

A sizeable ratio of repetitions to data set size is required to obtain stable randomization results. Our final data sets consist of 66 observations each, for years 1926-1991 inclusive, for a ratio slightly greater than 150 to 1 (10,000 ÷ 66). Small ratios can result in unacceptably high standard deviations of results in repeat trials. Cecchetti, Lam, and Mark (1990) use 1000 repetitions on a data set of 116 observations, providing a ratio of 8.6 to 1. Our experience suggests that this is materially low.

Note that the randomization technique is related to the Monte-Carlo methodology. However, in the Monte-Carlo approach, a hypothetical distribution must be specified. If the distribution specification is incorrect, then the empirical results may be suspect. Randomization, however, does not require assumptions about the distribution of the data.

C. Markov Chain Tests for Mean Reversion

In this study, Markov chains are a simple series of ones and zeros. Based on the original data series, if an observation is above the overall average, it is assigned a value of one; if it is below the overall average, it is assigned a value of zero. If a series is random, we should be just as likely to observe a "1,1,1" or a "0, 0, 0" sequence as a "1,1,0" or a "0,0,1" sequence. However, if the market is mean reverting, then the "1,1,0" or a "0,0,1" sequence should occur more frequently. Using the randomization approach, we determine the likelihood of obtaining the observed sequences. As in the variance ratio tests, each variable is evaluated using 10,000 repetitions.

D. Granger Causality Tests

Paraphrasing Granger's (1969) findings, we can say that Y_t is causing X_t if we are better able to explain time series X when utilizing the information contained in time series Y than if we ignore this information. In general, Granger causality tests are a form of OLS regression which enables the researcher to develop an understanding of the "causal" (in the Granger sense) and temporal nature of the relationship between returns and state variables. The Granger tests enable us to make inferences, not only about causality in general, but also about the *direction* of the causality. Further, as demonstrated by Geweke, Meese, and Dent (1983), Granger tests appear to be among the best available (from a statistical standpoint) for the investigation of causality.

The Granger test is computed by performing OLS regression on the following equations,

$$R_t = \alpha + \sum_{i=1}^{n} \psi_i (R_{t-i}) + \epsilon_t \tag{7}$$

$$R_t = \alpha + \sum_{i=1}^{n} \psi_i (R_{t-i}) + \sum_{i=1}^{n} \xi_i (X_{t-i}) + \nu_t \tag{8}$$

where R_t is the return in period t, X_t is the macroeconomic/fundamental variable in period t, α is a constant term, ψ and ξ are regression coefficients, n is the number of lags, and ϵ, υ are error terms.

Equations 7 and 8 are referred to respectively as restricted and unrestricted. Conceptually, if causality runs from the macro/fundamental variable to returns, then the ξ_i's in 8 will be significant and the prediction error will be smaller than that of the restricted case. Note that reverse causality (from returns to the macro/fundamental variables) can be evaluated by exchanging the equation positions of the two variables. Contemporaneous causality is examined by adding a current value of the explanatory variable (i.e., I = 0) to the lagged variable values and then reestimating the equations.

In summary, our mean reversion tests utilize various methodologies and extend the data sets of earlier research both in time and in number of variables. Further, our methods are designed to circumvent the use of potentially flawed equilibrium models and, hopefully, to enhance the rigor of standard tests associated with mean reversion. The Granger causality tests are well known and accepted and provide a vital link in our arguments about the underlying causes of mean reversion in returns.

III. RESULTS

Table I presents the results of the OLS tests. From left to right, the table presents the slope coefficient, standard error, t-value, and p-value from equation (1) for each horizon from one to five years. With the exception of term premia, the coefficients for each variable are generally negative, indicative of mean reversion. Small stock returns, default premia, dividend yields, inflation, and P/E ratios all have statistically significant negative autocorrelation for at least one horizon. S&P 500 returns, industrial production, and term premia provide no statistically significant autocorrelation.

Table II presents the variance ratio results. From left to right, the table presents the horizon, actual variance ratio, average randomized ratio (based on 10,000 randomizations), standard deviation of the average randomized ratio, number of times the randomized ratio was greater than or less than the actual ratio, probability value based on the randomization counts, and probability value based on traditional z-scores. Findings indicate that S&P 500 returns, default premia, industrial production, inflation, and P/E ratios all exhibit significant negative autocorrelation for at least one horizon. Small stock returns, dividend yields, and term premia provide no evidence of significant autocorrelation.

In almost all cases, the average variance ratio, estimated from the randomizations of the data, is quite close to the expected value of one. This result demonstrates the efficacy of the randomization approach. In general, if the autocorrelation of a particular horizon is insignificant, the randomized p-value is greater than the p-value based on the z-score (the normal p-value), suggesting that the randomization approach is more accurate. Moreover, when the autocorrelation of a particular horizon is statistically significant, the randomized p-value is typically smaller than that of the normal p-value. There is only one instance (inflation, horizon 5) in which the randomized p-value and the normal p-value do not agree on significance. In this case, the two p-values straddle the 0.10 significance level.

Table I presents the results of the regression $X_t = \alpha + \beta X_{t-1} + \epsilon_t$, for eight macroeconomic and fundamental variables, over the 1926-1991 period. The table presents the horizon period, the regression coefficient, standard error, t-statistic, and p-value, respectively.

Table II presents results of variance ratio tests on eight macroeconomic and fundamental variables over the 1926-1991 period. The variance ratio is approximated by a linear combination of sample autocorrelations:

$$VR(k) \approx 1 + 2\sum_{j=1}^{k-1}\left(\frac{k-j}{k}\right)\rho_j - 2\sum_{j=1}^{11}\left(\frac{12-j}{12}\right)\rho_j.$$

variance ratio less (greater) than one implies negative (positive) autocorrelation. A randomization approach is used to test the variance ratio for statistical significance. Horizon refers to the time period in years. Variance Ratio is the actual calculated ratio. Avg Ratio is the average ratio obtained from 10,000 random shuffles. σ is the standard deviation of the average variance ratio. > and < refer to the number of times, out of 10,000 shuffles, that the randomized variance ratio was greater than or less than the actual variance ratio. Random Pval is the marginal significance level based on the randomized findings, and Normal Pval is the significance level based on the normal distribution.

Table III presents the results of the Markov chain tests. The "Actual" column contains the actual number of occurrences of a particular sequence in the unshuffled data. The "Average" column is the average number of occurrences of a sequence based on 10,000 randomized samples (of size 66) of the data. The "pGt" and "pLt" columns are the probabilities of obtaining a count greater than or less than the actual count. For example, there are twelve occurrences of the "1,1,0" sequence for the actual S&P 500 returns series. The probability of observing a count greater than twelve from the random data is only 0.59 percent. The probability of observing a count less than twelve from the random data is 96.7 percent.

While McQueen and Thorley (1991) use a likelihood ratio statistic in evaluating their Markov chain tests, our study deals only with randomization results. McQueen and Thorley note that there is an inherent small sample problem in their investigation of mean reversion. This problem leads to inconsistent findings across various test statistics (Lagrange multiplier test, Wald test, and likelihood ratio test). Instead, we focus exclusively on pure randomization results that do not rely on the knowledge of the distribution of the sample. We believe this approach is more prudent because the efficacy of the randomization approach does not depend on the sample being random or on the nature of the distribution (e.gs., Noreen, 1989, Kempthorne, 1966).

Table I

OLS Tests of Mean Reversion

Horizon	Coefficient	Std Error	t-value	p-value
1	-0.0017	0.1266	-0.014	0.9893
2	-0.2472	0.1725	-1.433	0.1621
3	-0.1822	0.2024	-0.900	0.3794
4	-0.0221	0.2628	-0.084	0.9343
5	-0.0290	0.3111	-0.093	0.9277
		Small Stock Returns		
1	0.0692	0.1263	0.548	0.5857
2	-0.0977	0.1819	-0.537	0.5950
3	-0.3790	0.2106	-1.799	0.0879*
4	-0.1797	0.2664	-0.674	0.5118
5	-0.5209	0.2423	-2.150	0.0570*
		Default Premium		
1	-02842	0.1207	-0.355	0.0216*
2	0.0155	0.1795	0.0860	0.9318
3	0.0715	0.2315	0.3090	0.7608
4	-0.0033	0.2874	-0.0120	0.9910
5	-0.0256	0.3239	-0.0790	0.9386
		Dividend Yield (1st Difference)		
1	0.0999	0.1262	0.791	0.4318
2	-0.2150	0.1787	-1.203	0.2386
3	-0.3963	0.2104	-1.883	0.0759*
4	-0.5277	0.2347	-2.248	0.0426**
5	-0.7246	0.2101	-3.449	0.0062**
		Industrial Production		
1	0.0901	0.1251	0.721	0.4739
2	-0.1772	0.1775	-0.999	0.3260
3	-0.0113	0.2293	-0.049	0.9612
4	0.0167	0.2663	0.063	0.9511
5	-0.0959	0.1821	-0.527	0.6100
		Inflation (1st Difference)		
1	-0.0294	0.1275	-0.230	0.8187
2	-0.5388	0.1566	-3.440	0.0018**
3	-0.7022	0.1694	-4.144	0.0006**
4	-0.1197	0.2732	-0.438	0.6686
5	-0.0647	0.2899	-0.223	0.8279

*significant at the 0.10 level, **significant at the 0.05 level

Table II

Variance Ratio Tests of Mean Reversion

Horizon	Variance Ratio	Avg. Ratio	σ	>	<	Random Pval	Normal Pval
			S&P 500 Returns				
1	0.9663	1.0140	0.1774	6036	3964	0.3964	0.3964
2	0.8662	1.0232	0.2584	7091	2909	0.2909	0.2717
3	0.7744	1.0448	0.3320	7832	2168	0.2168	0.2076
4	0.5021	1.0724	0.3847	9568	432	0.0432**	0.0691*
5	0.6688	1.0875	0.4337	8343	1657	0.1657	0.1672
			Small Stock Returns				
1	0.9609	1.0132	0.1758	6125	3875	0.3875	0.3831
2	1.0748	1.0254	0.2510	4065	5935	0.5935	0.5779
3	0.7685	1.0810	0.3319	8234	1766	0.1766	0.1731
4	0.8483	1.0768	0.3865	6964	3036	0.3036	0.2772
5	0.9841	1.0871	0.4402	5502	4498	0.4498	0.4075
			Default Premium				
1	0.5045	1.0082	0.1796	9982	18	0.0018**	0.0025*
2	0.4338	1.0253	0.2559	9963	37	0.0037**	0.0104**
3	0.6349	1.0585	0.3238	9170	830	0.0830*	0.0954*
4	0.5605	1.0683	0.3863	9185	815	0.0815*	0.0944*
5	0.6186	1.0579	0.4224	8597	1403	0.1403	0.1492
			Dividen Yields (1st Difference)				
1	1.3424	1.0121	0.1791	329	9671	0.9671	0.9674
2	1.6708	1.0193	0.2639	104	9896	0.9896	0.9932
3	1.2813	1.0352	0.3298	2216	7784	0.7784	0.7722
4	1.0872	1.0661	0.3892	4415	5585	0.5585	0.5216
5	1.5292	1.0874	0.4577	1654	8346	0.8346	0.8328
			Industrial Production				
1	1.1247	1.1090	0.1696	2557	7443	0.7443	0.7333
2	1.2819	1.0303	0.2490	1529	8471	0.8471	0.8438
3	1.0096	1.0504	0.3326	5118	4882	0.4883	0.4511
4	0.5098	1.0860	0.3646	9613	387	0.0388**	0.0570*
5	2.0298	1.1040	0.4412	335	9665	0.9665	0.9821
			Inflation (1st Difference)				
1	1.1852	1.0185	0.1797	1712	8288	0.8288	0.8232
2	1.0040	1.0232	0.2588	5041	4959	0.4960	0.4704
3	0.7080	1.0564	0.3221	8623	1377	0.1378	0.1397
4	0.6596	1.0877	0.3706	8848	1152	0.1153	0.1240
5	0.5176	1.1072	0.4775	9119	881	0.0882*	0.1085
			P/E Ratio				
1	0.9021	1.0169	0.1825	7344	2656	0.2657	0.2647
2	0.6815	1.0398	0.2732	9129	871	0.872*	0.0948*
3	1.0402	1.0493	0.3337	4827	5173	0.5173	0.4891
4	1.0548	1.0458	0.3812	4526	5474	0.5474	0.5094
5	0.8038	1.0997	0.4747	7071	2929	0.2930	0.2665
			Term Premium				
1	1.1215	1.0172	0.1790	2815	7185	0.7185	0.7200
2	0.9010	1.0256	0.2550	6721	3279	0.3280	0.3125
3	1.8246	1.0378	0.3308	169	9831	0.9831	0.9913
4	1.1724	1.0456	0.3829	3420	6580	0.6580	0.6298
5	1.0196	1.1445	0.4282	5758	4242	0.4243	0.3852

*significant at the 0.10 level, **significant at the 0.05 level

Table III presents the results of second order Markov chain tests for eight macroeconomic and fundamental variables. In the present context, a Markov chain is a series of 1's and 0's. A 1 (0) represents an observation greater (less) than the overall average. The sequences being studied are "0,0,1" and "1,1,0". Actual refers to the actual count of the number of sequence occurrences based on the historical data. Average is the average count based on 10,000 repetitions. "pGt", and "pLt" are the probabilities of observing a sequence count greater or less than the actual count. A relatively large "Actual" count indicates the presence of mean reversion.

Table III

Markov Chain Tests of Mean Reversion

Sequence	Actual	Average	pGt	pLt
		S&P 500		
001	7	7	0.4424	0.2829
110	12	8	0.0059**	0.9666
		Small Stocks		
001	9	7		
001	10	8	0.0813*	0.7461
			0.0922*0	0.7292
		Default Premium		
001	5	6	0.7513	0.0689*
110	11	9	0.0823*	0.7791
		Dividen Yield		
001	12	8	0.0049**	0.9611
110	8	7	0.1322	0.6376
		Industrial Inflation		
001	9	6	0.0298**	0.8688
110	10	8	0.1604	0.6293
		Inflation		
001	9	8	0.1262	0.5404
110	12	7	0.0001**	0.9977
		P/E Ratio		
001	7	7	0.3598	0.3488
110	10	8	0.1247	0.6860
		Term Premium		
001	8	8	0.4002	0.3314
110	10	8	0.0464**	0.8357

*significant at the 0.10 level, **significant at the 0.05 level

S&P 500 returns, small stock returns, default premia, inflation, and term premia all have actual "1,1,0" counts that are significantly greater than expected to occur in a random series.

This result indicates that the series are negatively autocorrelated. Moreover, small stock returns, dividend yields, and industrial production all have "0,0,1" counts greater than expected in a random series. This result also is an indication of negative autocorrelation.

Table IV presents a summary of the mean reversion findings by methodology, state variable, and horizon. One of the most striking findings of this paper is that, although seven out of eight variables produce evidence of statistically significant mean reversion at one or more horizons, there is no instance in which all three methodologies agree that the same variable is mean reverting at the same horizon. In fact, from Table IV, there are only two instances, default premia at horizon 1 and inflation at horizon 2, when any two methodologies agree that significant mean reversion is present. Even in those cases, there is considerable disparity between techniques with respect to the level of significance.

Table IV provides summary results for all three of the tests of mean reversion on eight macroeconomic and fundamental variables. Horizons, in years, are listed across the top row. Variables are listed down the first column. The intersection of a row and column (a cell) defines the variable that was tested and the horizon over which the test was performed. An "MC" in a particular cell indicates that the variable was found to be mean reverting, using the Markov Chain technique, at the indicated horizon. Likewise, an "OLS" indicates that the regression tests found mean reversion and "VR" indicates that the variance ratio tests found mean reversion, at the indicated horizon. An empty cell indicates that the variable was not significant, at the 0.10 level, using any of the 3 empirical techniques.

Table IV

Summary of Mean Reversion Tests

Variable/Horizon	1	2	3	4	5
S&P 500		MC		VR	
Small Stock			OLS		OLS
Default Premium	OLS, VR	VR	VR	VR	
Dividend Yield		MC	OLS	OLS	OLS
Industrial Production		MC		VR	
Inflation		MC, OLS	OLS		VR
PE Ratio		VR			OLS
Term Premium					

Table V provides summary findings for the Granger causality tests. Given the familiar nature of OLS statistics, we do not include the full set of results in this paper. As indicated in the table, dividend yields and P/E ratios are found to be significantly related to stock returns over the time period of this study. Lending support to our arguments, both dividend yields and P/E ratios are also found to be mean reverting. Although outside the scope of this paper, for future studies considering performance differences between large and small capitalization stocks, it may be interesting that returns of small stocks show evidence of contemporaneous influences with both industrial production and inflation, while large capitalization stocks show no such tendency.

Table V presents summary results for the direct, indirect, and contemporaneous Granger causality tests on both S&P 500 and small stock returns. D- Direct Granger test, I- Indirect Granger test, C- Contemporaneous Granger test. An empty cell indicates that the variable was not significantly related to returns using any of the three Granger tests. One of the above abbreviations in a cell means that significance was found at the 10 percent or better level using the indicated technique. No cell contains an "I" since no Indirect tests were significant

Table V

Summary of Granger Causality Tests

S&P 500 Returns

Variable/Lag	0	1	2	3	4	5
Default Premium						
Dividend Yield			D			
Industrial Production						
Inflation						
P/E Ratio		D				
Term Premium						

Small Stock Returns

Variable/Lag	0	1	2	3	4	5
Default Premium						
Dividend Yield			D			
Industrial Production	C					
Inflation						
P/E Ratio		D				
Term Premium						

IV. SUMMARY AND CONCLUSIONS

This paper examines whether or not mean reversion in stock returns may be consistent with weak-form market efficiency. We contend that stock returns in an efficient market may be mean reverting if priced state variables also are mean reverting. Mean reversion in stock returns, then, may be a rational consequence of business conditions that are also mean reverting. To test this proposition, we first perform three separate mean reversion tests on eight variables: S&P 500 returns, small stock returns, default premia, dividend yields, industrial production, inflation, P/E ratios, and term premia. Next, we evaluate the causal and temporal aspects of the relationships between returns and the state variables using Granger causality tests.

Findings indicate that mean reversion is not unique to stock returns, extending also to important state variables. Evidence of mean reversion is found in all but one (term premium) of the state variables examined. We also find that mean reversion results are dependent on the methodology applied. For example, using a horizon of two years, S&P 500 returns, dividend yields, industrial production, and inflation are mean reverting according to Markov chain tests. According to variance ratio tests, only default risk premia and P/E ratios are mean reverting and, according to OLS tests, only inflation is mean reverting. This finding suggests that results of mean reversion derived from a single test may be misleading. Moreover, the results differ based on the horizon being examined. These findings point to the difficulty in drawing inferences on mean reversion. Further, these findings suggest the need for further research involving alternative statistical techniques and expanded categories of state variables.

Granger causality tests demonstrate that both dividends and P/E ratios are significantly related to returns of large and small capitalization stocks. Also significant, and providing crucial support for our arguments, movement in the state variables *always* precedes movements in returns. We interpret these findings in the traditional OLS manner: variability in the state variables, "explains" variability in returns.

Results of the mean reversion tests, in conjunction with the Granger causality tests, imply that mean reverting stock returns may be explained as rational investor responses to mean reverting state variables. These findings suggest that mean reverting stock returns are consistent with weak form efficient markets.

NOTES

1. Miller, Muthuswamy, and Whaley (1994) recently examine mean reversion in stock index basis changes and find that observed negative autocorrelations are not arbitrage-induced. Instead, they find that negative autocorrelation in basis changes arises simply because of differences in frequency of trade in stocks comprising the index.

2. The relationship between state variables and returns has also been considered within a consumption-based asset pricing framework (see Ferson, 1989) and a production-based pricing framework (see Cochrane, 1991). Although these models provide more detail about the mechanism through which state variables may impact returns, the focus of this paper is on *how* the state variables impact returns, not on *why*.

3. Earlier mean reversion studies consider returns series only. The returns series are stationary and, therefore, it has not been necessary to use first differences. Use of differences as opposed to levels does not pose a problem in this study. As discussed in Fama and French (1988b), Poterba and Summers (1988), and others, when evaluating a series for mean reversion, the focus is on a stationary yet mean reverting component in the series. First differencing assures that the series mean is stationary, but it does not preclude individual observations from systematically deviating above or below that mean (e.gs., see Pindyck and Rubinfeld (1981) or McCleary and Hay (1980)).

4 In repeated trials, the standard deviation of the test statistic was unacceptably high with ratios as low as 15:1 (1000 repetitions using 66 observations). This led to inconsistent findings of significance for the test statistic. Substantially increasing the ratio resulted in stable and consistent significance levels.

5. We also evaluated "0,1,0" and "1,0,1" sequences, however we do not report these findings since they relate to single period mean reversion and the focus of this study is on horizons of two to five years.

6. Evans, Keef, and Okunev (1994) examine data for the U.S. and the U.K. over the 1875-1975 period and find significant mean reversion in inflation and in real and nominal interest rates. Their findings for inflation are consistent with those reported in this paper for U.S. inflation during the 1926-1991 period.

7. Although the signs of the coefficient in Table I for S&P 500 returns agree with those of Fama and French (1988b), the significance levels are lower in this study. There are three possible reasons for the difference. First, Fama and French use the CRSP market index. Instead, we use the S&P 500 index, which is concentrated in larger capitalization stocks than those in the CRSP index. Second, our study includes a longer post-WWII period than that

examined by Fama and French. Their sample period ends in 1985 while our sample period extends through 1991. Third, Fama and French use overlapping observations and our study uses nonoverlapping observations.

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